THREE ESSAYS IN RESOURCE ECONOMICS AND AVAILABILITY

by

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ABSTRACT

This dissertation investigates geologic, economic, social, and environmental barriers to the extraction of mineral resources. Minerals are critical inputs to society's modern way of life, but their short and long run supply often faces key constraints. Jointly considered, these barriers define the availability of minerals for society's use. This study adds to the existing literature on mineral resource availability through quantitative evaluation of three issues - geologic abundance as a supply metric, metal joint production, and social license to operate. The issues of geologic abundance and joint production are examined for a hypothetical new end-use for a specific material using estimated industry cost curves and long run availability cures. Joint production is found to be the key driver of low cost supply, not the material's abundance. The joint production relationship between minerals is then further examined using a flexible form dual revenue approach applied to a different set of materials. The results highlight the flexibility in a mine's ability to spatially target production from its resource in response to changing prices. Finally, social and political barriers are examined by econometrically estimating the relationship between increased environmental attitudes and mine closures in the United States. This analysis reveals a causal effect of increasing local preferences for environmental quality on nearby mine closures. Enactment of state-level policy is identified as a potential mechanism for earlier-than-expected closure.

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To Tyler and what we build together.

CHAPTER 1

INTRODUCTION

The scarcity of resources has been a long-running concern. Early economic thinkers like Malthus, Ricardo, and Mill all wrote about the limits to living standards and population growth imposed by the fixed quality and quantity of agricultural land. In the last several decades, anxiety over resource scarcity has tended to coincide with sharp increases in commodity prices (Tilton, 2003). When the Organization of Petroleum Exporting Countries (OPEC) imposed an oil embargo in 1973, price controls put-in-place by oil importing countries led to widespread shortages. While these shortages were a result of the export policy and not the signal of physical depletion of oil resource, it nonetheless triggered fears that oil resources might soon be exhausted. While the embargo was limited to oil, the prices of other commodities including metals, also experienced pronounced price increases (Tilton, 2003). These events were seen by many to validate the concurrent and pessimistic forecasts in studies like Meadows *et al.* (1972)'s *The Limits to Growth* which showed that resource depletion would lead to economic collapse by the middle of the twenty-first century. The embargo was short-lived, commodity prices eventually fell, and fears over depletion subsided. The calm lasted until the new millennium when demand growth in the developing world, particularly China, caused commodity prices and depletion fears to rise once again. When oil prices reached record highs in 2008, many speculated supply had reached its limits and production would decline as resources were depleted (Hirsch *et al.* (2005), Kerr (2011), Bardi (2009)). Soon after, innovations in shale oil and gas production proved the predictions of dire and immediate production declines moot.

While some still consider the physical depletion of resources to be a pressing threat, the past few decades have seen a turn in the debate of resource availability. With increasing recognition of the vast quantities of materials within the earth's crust, a new conversation has begun to take place over the economic, social and environmental availability of resources. Rather than being concerned that humanity will one day extract and use the last drop of oil or tonne of copper, we might instead worry that long before these resources are physically exhausted that they will be prohibitively expensive to extract and will be not be economically available. The large environmental externalities associated with resource extraction and the associated corrective policy may limit the environmental availability of resources. Finally, communities expressing their preferences for preservations of environments or ways of life may resist resource extraction and limit the social availability of resources

Despite several decades of recognizing economic, environmental, and social constraints around resource extraction many open questions remain regarding how these constraints impact resource availability. This dissertation investigates three important components of these constraints on the availability of mineral resources: geologic abundance, jointly produced minerals, and the social and environmental constraints around resource extraction. Firms that extract and produce multiple metals from their resource deposits are an important component of mineral supply. To better understand how this relationship might impact the availability of minerals, chapter 2 and 3 explore this issue in more detail. In chapter 4, social and environmental constraints are investigated.

To explore the issues of geologic abundance and mineral joint production Chapter 2 presents a case study for the mineral thorium. Thorium has been a proposed source of fuel for next-generation nuclear reactors. Thorium is more abundant on average than uranium in the earths crust and could theoretically extend the use of nuclear energy technology beyond the economic limits of uranium resources. This chapter provides an economic assessment of thorium availability by creating cumulative-availability and potential mining-industry cost curves, based on known thorium resources. These tools provide two perspectives on the economic availability of thorium. In the long term, physical quantities of thorium likely will not be a constraint on the development of a thorium fuel cycle. In the medium term, however, thorium supply may be limited by constraints associated with its production as a by-product of rare earth elements and heavy mineral sands. Environmental concerns, social issues, regulation, and technology also present issues for the medium and long run.

Chapter 3 explores the issue of joint production using an alternative methodology. The reaction of multi-product mining firms to changes in their relevant output prices is tested econometrically for five metals using a panel representing more than 100 mines across the time period 1991-2005. The estimation strategy is drawn from joint production theory, namely a flexible form, dual revenue approach with seemingly unrelated regressions (SUR) estimation. The results indicate that multi-product mines respond (in the short run) to higher prices of a particular metal by reducing output of that metal (indicative of low-grading behavior) and increasing and/or decreasing output of joint metal products. The price responses are not readily explained by a metal's classification as a by-product or main product based on revenue.

Chapter 4 fills a notable gap in the literature on community interactions with mining by econometrically estimating how local and statewide preferences for environmental quality affect mining firm behavior, specifically through the mines choice to permanently close. Using a sample of over 18,000 mines operating in the United States from 1966-2014 a Cox Proportional Hazard model is used to measure the impact of environmental preferences on mine lifetimes. Environmental preferences are measured using US Congress roll-call votes on environmental issues. Using a novel instrument, endogeneity is addressed by exploiting quasi-random office assignment in Congressional office buildings. The results show a significant impact of statewide environmental preferences enacted through state policy on mine life, and a significant impact of local preferences when state policy-making becomes less effective. These results provide new insight into which level of government, local, state, or federal, disputes over resource extraction take place.

CHAPTER 2

THORIUM: CRUSTAL ABUNDANCE, JOINT PRODUCTION, AND ECONOMIC AVAILABILITY

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There is renewed interest in the commercialization of a thorium fuel cycle for generating nuclear power (International Atomic Energy Association (IAEA) 2005; 2012). Growth in electricity demand, particularly in developing countries, combined with the threat of climate change have driven new or renewed interest in a host of power generating alternatives. Such interest includes conventional and advanced nuclear reactors and fuel cycles, of which thorium is a potential option (IAEA, 2005). The benefits and drawbacks of adopting a thorium fuel cycle compared to a uranium fuel cycle continue to be studied, but wide-spread agreement has formed that thorium is, on average, three to four times more abundant than uranium in the earth's crust (Kademani *et al.*, 2006). The implication is that thorium supply has the potential to last longer, or support a larger reactor deployment, than uranium supply. Crustal abundance, however, is an incomplete measure of potential supply. To draw a more complete conclusion about the potential supply of any resource, one must consider resource *availability*. This paper provides an assessment of the availability of thorium in the medium and long term.

Availability of any mineral resource can be defined in four dimensions. The geologic dimension, of which crustal abundance is a component, describes the physical quantity and

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characteristics of a resource. The technological dimension characterizes the ease or difficulty of recovering and purifying a resource. The social and political dimension of availability measures how resistant social and political institutions are to the recovering of a resource. Social and political resistance tend to increase as the environmental impact of a mine increases. Finally, the economic dimension measures whether or not a resource is profitable to recover. While these dimensions are interdependent, the focus of this paper will be on the economic measure of availability.

This analysis of economic availability uses two related analytical tools. The first is a cumulative availability curve (Yaksic & Tilton, 2009), which provides a perspective on availability over the longer term (decades). It is a plot of total resources grouped by the type of deposit and the associated costs of recovery. Analysis of the cumulative availability curve for thorium suggests that thorium cost could be comparable to historical average uranium prices. Thorium costs around this level should not be prohibitive to the development of a commercial fuel cycle.

The second tool, a potential mining-industry cost curve, illustrates availability over the medium term (some five to twenty years into the future). It is a more conventional, market-assessment tool, which plots the potential production rates of individual mines or deposits given capacity constraints and associated costs. In this study, we base the potential cost curve on known resources of thorium, essentially none of which are developed. The potential cost curve represents a medium-term perspective because the resources contained in the curve would take a number of years to be developed once (and only if) a market for thorium emerges. The potential cost curve highlights the role that by-product production plays in thorium availability. Likely sources of thorium are titanium-sand and rare-earth deposits, some of which would be the lowest-cost sources of thorium. However, by-product thorium supply depends on the profitability of the associated main products, titanium sands and rare earths.

The Background section below discusses briefly the potential demand for thorium and outlines issues relevant to its potential supply as a by-product. The Methodology and Data section describes the sources of data and the cost estimation method used in constructing the cumulative availability and potential cost curves. The Results section presents the outcomes from the cost estimation model by deposit or deposit type as well as the cumulative availability and potential cost curves. Finally, the Conclusions section places economic availability of thorium in the broader context of social, political and technical availability.

2.1 Background

Thorium's potential use as part of a nuclear fuel cycle has been known and studied for more than 50 years. Over this time, there have been experimental-scale applications in nuclear reactors, but thorium has never been utilized on a large, commercial scale.[6] There are several common reasons given for why a thorium fuel cycle has not been commercialized. First, uranium resources, for the most part, have not limited the development of uranium fuel cycles (Ünak, 2000; Van Gosen *et al.*, 2009). Second, technological hurdles exist that thorium must overcome. For example, thorium fuel fabrication and reprocessing technologies are not mature (IAEA, 2012). Third, some have argued that uranium has received more state support than thorium as nations looked to advance military goals alongside civilian goals (Hargraves & Moir, 2010). These three reasons are by no means a comprehensive listing. However, the drawbacks and merits of incorporating thorium into a nuclear fuel cycle are outside the scope of this paper's focus on thorium availability. Readers interested in issues related to the operations or back-end of a thorium based fuel cycle should refer to IAEA (2005) for a more comprehensive discussion.

Total historic thorium demand, and consequently supply, has been relatively small in terms of quantity. Thorium's primary commercial use until recently has been in mantles for gas lanterns. Over the last two decades thorium has been replaced by more inert materials in such non-nuclear applications (Gambogi, 2013). To meet limited thorium demand in the

[6] The World Nuclear Association's webpage on thorium includes a summary of past reactors (WNA, 2014).

past, by-product supply has been largely adequate.[7]

The role of by-product production of thorium, or joint production more generally, is key to thorium's historic and future supply. Joint production refers to situations in which multiple products are produced from one operation. At a mine, joint production can be characterized by three types of relationships: main product, co-product and by-product. A main product is a material that contributes such a large portion of revenue to a mine that investment and operating decisions are based almost entirely on the market (prices and production costs) for this material. A by-product, by contrast, is a material whose revenue contributes such a small portion to the total revenue of the mine that the mine largely ignores the by-product market when making investment and production decisions. Because by-products are produced as an indirect consequence of producing another resource, the only costs attributable to them are the additional costs incurred to separate and recover them from the main product of the mine. A by-product is recovered only if its price exceeds these additional costs. Finally, a co-product is a material whose own market, and that of one or more other materials, justifies mine decisions. For this study and in the interest of keeping the cost analysis simple, we consider thorium as either a main product or a by-product, although there might be instances of co-product thorium supply in the future.

Thorium's potential future supply could come in the form of main product, by-product or *twice by-product* (by-product of a by-product) production. Main product thorium could be supplied from thorium mines, as depicted on the bottom-most section of Figure 2.1. By-product thorium could potentially come from rare earth element mining and processing, as depicted starting in the middle section of Figure 2.1 and flowing down. And finally, twice by-product thorium could be derived as a by-product of rare earth elements, which in turn are a by-product of heavy mineral sand mining as shown starting at the top section of Figure 2.1 and flowing down.

[7]Main product thorium mines have existed. For example, Steenkampskraal, South Africa.

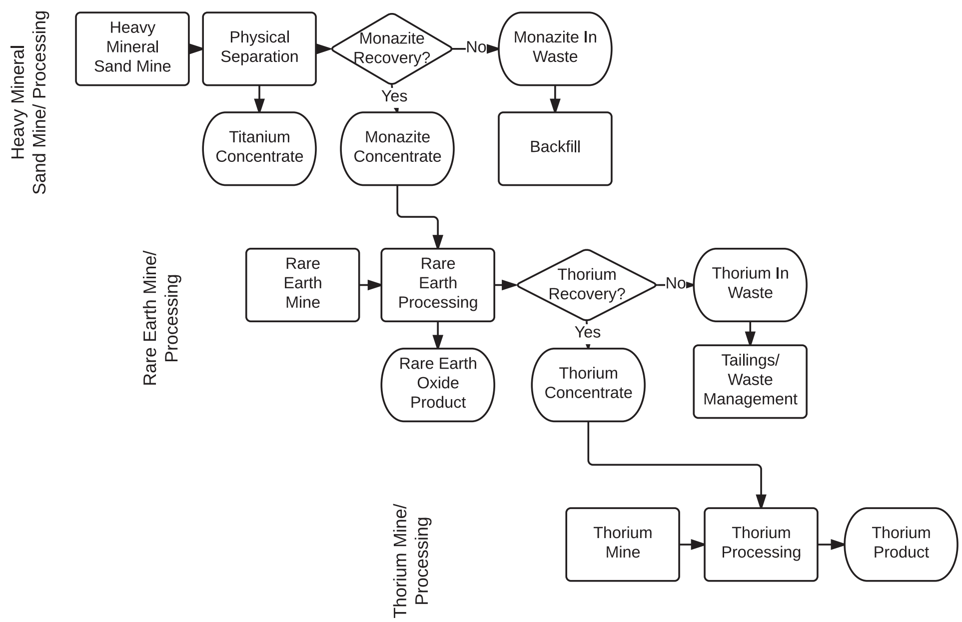


Figure 2.1: Generic Process Flow for Thorium Supply by Source

Source: Authors' Representation
This is a generic flowsheet designed to illustrate joint production relationships. These sources are inter-connected by the downward flows primarily to simplify the figure and avoid duplication.

As shown in the bottom-most section of Figure 2.1, thorium could be mined and processed as a main product from high-grade vein deposits of minerals such as thorite (a thorium silicate, $ThSiO_4$). The capital investment and operating decisions to mine these deposits would be determined by the market developments for thorium (with minor consideration given to potential joint products). As thorium has never been recovered on a commercial scale from thorite, many of the high-grade sources of thorium could require further technological developments in order to be recoverable.

The middle section of Figure 2.1, depicting rare earth mining and processing, shows that thorium could be produced as a by-product from rare earth processing. Once thorium is concentrated, thorium could be further processed on the mine site, or the concentrate could be sold to a downstream producer. Due to its radioactive nature and lack of a thorium market today, thorium is considered a deleterious element or nuisance in rare earth deposits and is treated as waste at rare earth mines. The majority of rare earth elements[8] are produced from the mineral bastnäsite (a rare-earth fluorocarbonate, $LaCO_3F$). The most notable bastnäsite mines are the Bayan Obo mine[9] in Inner Mongolia, China, and the Mountain Pass mine in California. The mineral monazite (a rare-earth phosphate, $LaPO_4$) contributes more modest quantities of rare earth supply, but typically has higher thorium concentrations than deposits which are mined for bastnäsite. The Mount Weld mine of Western Australia, which due to a unique weathering process actually has very low thorium content (IAEA, 2011), is the largest single producer of main product REE supplier from monazite. In addition to these three large rare earth deposits and other mines inside of China, many deposits in various stages of exploration could become rare earth mines. The capital investment and operating decisions of both the prospective and current rare earth operations will be almost completely dependent on the rare earth values recovered. In the absence of a thorium market, the

[8] REEs with lower atomic weights, typically called "light" REEs are produced and consumed in much greater quantities than "heavy" REEs. A major source of heavy REEs are ion-absorbtion clays in southern China. These clays are not a suitable source of thorium.

[9] The Bayan Obo mine is a main product iron ore mine, but is also the largest single producer of rare earth elements in the world (Long *et al.*, 2010). Thorium at Bayan Obo could be considered a twice by-product of rare earth elements and iron. However, the Bayan Obo case is relatively unique in this respect.

presence of radioactive thorium negatively affects the attractiveness of developing a rare earth deposit into a mine. Therefore there is a current trend of developing rare earth mines with low thorium content. There is no publicly available information about a commercial scale technology for recovering thorium from bastnäsite[10] deposits, but thorium has been recovered from monazite (principally from heavy mineral deposits) for many decades.

Finally, shown in the uppermost section of Figure 2.1, thorium could be produced as a twice by-product from titanium heavy mineral sand mines. While these mines would primarily be concerned with the recovery of titanium, market developments for rare earth elements (and thorium) could entice such producers to install and operate monazite concentration circuits which could then be further processed by the mine or sold (in specific cases) to rare earth mines and processing facilities. Monazite typically has the highest specific gravity among minerals in these deposits in addition to unique magnetic properties. Thus concentration of monazite requires only physical separation methods (Ferron *et al.*, 1991; Ito *et al.*, 1991) and not more expensive chemical separation. Monazite concentrate then could be further processed to recover rare earth elements as described previously. Twice by-product recovery of thorium has occurred for some time in India (Barthel & Dahlkamp, 1992), which currently produces and stores thorium for probable future use in the country's nuclear program. Because of the long history of thorium recovery from these heavy mineral deposits and current recovery taking place in India, the technology to recover thorium from monazite (in heavy mineral deposits) is more mature than the technology to recover thorium contained in bastnäsite or thorite deposits.

2.2 Methodology and Data

This section describes the sources of data and the cost estimation method used in constructing the cumulative availability and mining-industry cost curves. We first describe the cumulative availability and mining-industry cost curves and their use in assessing the eco-

[10] Bastnäsite in its most common form does not contain thorium, but is frequently associated with minerals that do in "bastnäsite deposits".

nomic availability of thorium produced as a main product, by-product, or twice by-product. We then characterize the data used for the horizontal (quantity) axes of the cumulative availability and of the mining-industry cost curves. Finally, we describe the method for determining the vertical (cost) axis values, which are the same for both curves, and illustrate this method with an example deposit.

2.2.1 The Cumulative Availability and Mining-industry Cost Curves

The cumulative availability curve is a tool for assessing material availability over the longer term, decades into the future (Tilton, 2003). The curve represents the costs of production of a non-renewable resource over the total (or cumulative) quantity produced. The analysis holds technology and known resources fixed. The curve is positively sloped because higher prices justify the recovery of higher cost, resources. Yaksic & Tilton (2009) illustrate the use of the cumulative availability curve for the case of lithium. They note that availability is influenced by three types of factors. First, geologic factors determine the shape of the curve. For instance, a steep curve indicates that there are only small quantities of low cost resources. Second, the nature of demand will determine how quickly society moves along the curve (from lower to higher costs sources). Finally, the third group of factors shifts the curve through changes in technology or quantity of resources (due to exploration).

The cumulative availability curve that we construct includes an additional feature: estimated recovery costs for three different types of thorium production from the same resource (main product, by-product, and twice by-product).

It is important to emphasize that the horizontal axis of the cumulative availability curve, cumulative production, is a stock variable. This is in contrast to flow variables, such as annual or monthly production, which appear on the horizontal axis of a supply curve. Another important feature of the cumulative availability curve is that technology and known resources are held fixed, but other variables, such as global refining capacity are ignored. In this way, the curve presents an analysis of the economic long run, the time frame in which variables under direct control of the mining firm such as labor, capital and land are not constrained, but external variables such as known resources, government policy and the state of technology are fixed. However, at present or at any given point in time in the future, mining firms are faced with a situation where at least one variable under their control is fixed and they are therefore constrained by production capacities.

To provide an alternative perspective on thorium availability, one that utilizes both a flow variable for production and incorporates fixed capacity that mining firms face at any given time, we construct a potential mining-industry cost curve. This curve uses the same vertical axis as the cumulative availability curve, the average total cost of producing one kilogram of 99.99% thorium oxide. Each mine or deposit is presented on the mining-industry cost curve as a bar, the width of which represents that mine's annual thorium production capacity. In this way, the horizontal axis represents potential annual production capacity of the thorium industry as a whole. Using the potential cost curve is particularly relevant in our application, because if thorium is produced as a by-product then the quantities of thorium that can be produced will be constrained by the quantities of rare earths or heavy mineral sands produced.

Both the cumulative availability and mining-industry cost curves are presented and discussed in Section 2.3, Results.

2.2.2 Data on Resources by Deposit Type

The resource data for the horizontal axis of the cumulative availability curve reflect the best estimates to date of known and undiscovered resources. Every two years the Nuclear Energy Agency (NEA) and IAEA publish *Uranium: Resources, Production and Demand* commonly called The Red Book, which includes estimates of thorium resources. The NEA/IAEA categorize these resources into levels of geologic confidence (including undiscovered) for resources deemed to be recoverable at less than $80/kg (a cutoff also used in their assessment of uranium resources). It should be noted however that because there is little standardization in the classification of thorium resources, these figures are not likely comparable to standardized resource figures for other minerals, such as uranium. Apart from their classification by geologic confidence and recovery cost, the NEA/IAEA also groups thorium resources by five types of deposits: carbonatite, placer (heavy mineral sand), vein, alkaline, and “other” (NEA & IAEA, 2012).

2.2.3 Data on Individual Deposits/Mines

For the horizontal axis of the mining industry cost curve, the data are deposit-specific. Data on thorium grades, quantities and joint products were collected for a selected set of individual thorium deposits and operating heavy mineral sand and rare earth mines around the world. Included in the selected deposits and mines are: the thorium stockpile accumulated by the United States government, major rare earth mines operating outside of China, a number of the operating heavy mineral sand mines globally (approximately 24% of world capacity), four rare earth projects that could come into commercial production before 2020, and six thorium deposits in the United States. Appendix A.2 discusses what quantities of thorium might be recoverable if all heavy mineral sand and rare earth capacity were to be included. Deposits and mines were generally selected based on their potential to produce thorium and on information on thorium grades and main product production being available.

2.2.4 Recovery Cost Model

For the vertical axis of both the cumulative availability and mining-industry cost curves we develop a cost model for thorium recovery as a main product, by-product, and twice by-product. To date, the only detailed attempt identified in the public domain to quantify the cost of thorium mining, milling and refining is Young *et al.* (1980). Young *et al.* (1980) used engineering-process-flow and discounted-cash-flow analysis to assess the costs of extracting thorium as a main product from deposits in the United States. Since the Young *et al.* (1980) study was conducted, the markets for rare earth elements have developed considerably as new end-uses for rare earth oxides (REOs) have developed. Such market developments could make it attractive for deposits to be developed primarily for their rare earth resources with thorium produced as a by-product. Depending on the deposit, considerable cost savings are associated with thorium being produced as a by-product as opposed to a main product.

To account for the effects of cost inflation since the Young *et al.* (1980) study was conducted, simple cost escalation factors were applied to modify the estimates from 1978 US dollars to 2013 US dollars. Details can be found in Appendix A.1. All costs presented in this paper are in 2013 US dollars.

2.2.5 By-Product Cost Estimation Example: Bear Lodge, Wyoming

The Bear Lodge deposit in northeastern Wyoming is currently being explored by Rare Element Resources, Ltd. as a potential rare earth mine. This deposit makes an excellent example to use for our by-product cost estimation method for several reasons: (1) the project is an advanced rare earth project in North America, with NI-43-101 compliant resource statements[11]; (2) of prospective rare earth mines, it has a reasonable chance of coming into commercial production; and (3) the deposit was one considered by Young *et al.* (1980) to be a potential thorium main product mine. These features allow comparison between the Young *et al.* (1980) study's estimated main product cost and quantity and those estimated by this paper. Figure 2.2 shows a simplified process flow diagram for the proposed Bear Lodge rare earth mine and associated processing facilities along with a hypothetical thorium recovery circuit.[12]

Bear Lodge's mine plan[13] calls for 620,000 tonnes of ore per year to enter the physical separation plant. This ore, on average, contains 20,000 tonnes of rare earth oxide, and an unspecified quantity of thorium. The physical separation plant creates 62,000 tonnes of "pre-produced concentrate" per year. Based on reported grades, the pre-produced concentrate contains 142 tonnes of thorium oxide. Next, the pre-produced concentrate is shipped to the hydrometallurgical plant which produces a final product of 21,000 tonnes of rare earth oxide

[11] A National Instrument (NI)-43-101 statement is one that complies with the Canadian Securities Administrators' set of standardized rules and guidelines for defining mineral resources and reserves for listing on Canadian stock exchanges.

[12] This example is hypothetical; Rare Element Resources has no announced plans to handle thorium in any way other than as a waste product.

[13] See bea (2012) for the Bear Lodge mine plan used in this study. While the Bear Lodge mine plan has since been modified, these changes would not materially change the conclusions of this analysis.

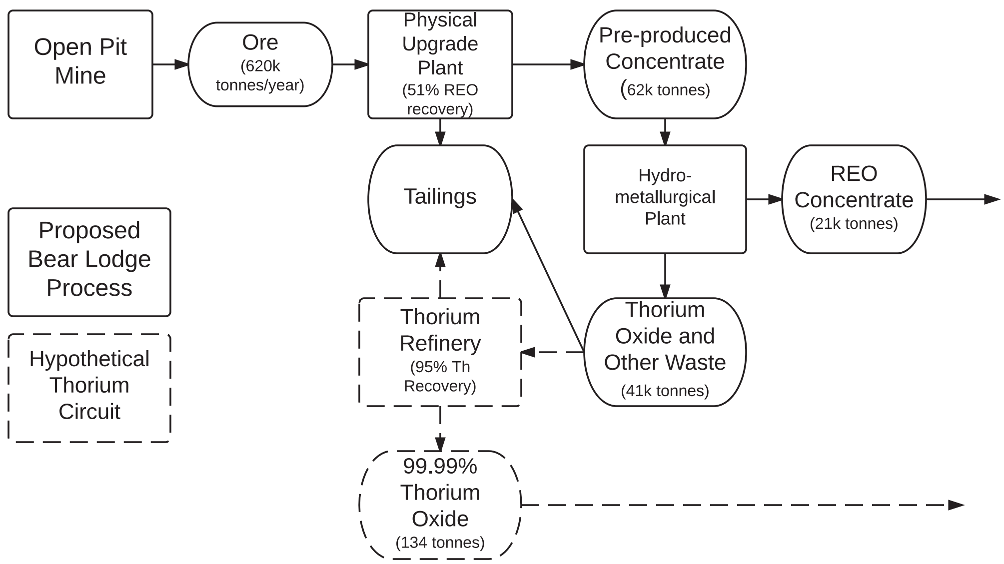


Figure 2.2: Proposed Bear Lodge Rare Earth Process with Hypothetical Thorium Circuit
Source: Authors' Representation based on process flow information in bea (2012)

concentrate. During processing at the hydrometallurgical plant, we assume all of the thorium is separated and combined with other material into a single waste stream. Therefore, a plant designed to recover all thorium from the waste stream would require a capacity of 41,000 tonnes of material per year. Thorium is assumed to be recovered and purified at a 95 percent rate (the rate used by Young *et al.* (1980)) from this waste material, yielding 134 tonnes of 99.99 percent purified thorium oxide product.

We use the capacity information from the materials flow described to scale the escalated costs for the hypothetical monazite recovery plant described in Young *et al.* (1980). There are two different factors required for this scaling calculation, one for fixed costs where economies of scale may exist and one for variable costs which change linearly with the quantity of ore processed. We use the following equation, typical in mining and chemical engineering cost studies (Darling, 2011; Green & Perry, 2008) to perform the scaling associated with fixed costs:

$$Cost_{new} = (Capacity_{New}/Capacity_{Old})^{0.7} Cost_{Old} \tag{2.1}$$

where $Cost_{new}$ is the cost for the Bear Lodge Th recovery facility, $Capacity_{New}$ is the required capacity of the Bear Lodge facility, and $Capacity_{Old}$ and $Cost_{Old}$ are the capacity and costs, respectively, of the hypothetical Palmer recovery facility estimated by Young *et al.* (1980). The parameter 0.7 is a term related to economies of scale, and is based on the "seven-tenths-rule" in engineering cost estimation (Green & Perry, 2008, pp. 9:13-14). The scaled Bear Lodge costs can be found in Table A.2 of Appendix A.1. Next, capital costs of the hypothetical plant are annualized to Bear Lodge's assumed mine life, 19 years, using a fixed charge rate, which incorporates tax effects and discounting. For simplicity, the rate calculated by Young *et al.* (1980) for the Palmer recovery plant, 0.2338, is used here.[14] After annual operating costs, annualized capital costs and unit production costs are discounted, these costs are escalated from 1978 dollars to 2013 dollars using appropriate escalation factors (See Appendix A.1 for these factors and their sources). The escalated costs are presented in Table 2.1. Depreciable Assets are calculated by multiplying the fixed charge rate of 0.2338 by the Total Depreciable Capital Investment of $8,438,000, found in Table A.2 of Appendix A.1. Working Capital of $700,000 is the only non-depreciable asset, and is spread out over a 10 year period.

Table 2.1: Bear Lodge Scaled Annual Production Costs

Depreciable Assets ($000s)	1,973
Non-Depreciable Assets ($000s)	70
Operating Costs ($000s)	10,302
Annual Production Costs ($000s)	12,345
Annual Production ('000 kgs)	134
Levelized Production Cost ($/kg)	92

[14] A sensitivity analysis was conducted for this fixed charge rate. A doubling of the rate resulted in an average change in cost of 16% across deposits. A halving of the rate resulted in an average change of 10% across deposits.

The final by-product cost of production for Bear Lodge, \$92/kg ThO_2 is significantly lower, as expected, than the escalated cost that Young *et al.* (1980) found for main product recovery from the same deposit, \$345/kg.

2.3 Results

This section presents the results of applying the cost estimation method described in the previous section for Bear Lodge to the other deposits selected for this study. The results are plotted on the cumulative availability and mining-industry cost curves. For both curves, we discuss the implications of the shape of the curves and the associated impact on availability. We then use a constructed demand scenario from Appendix A.3 to illustrate how society might move along the curves. Finally, we discuss how the curves might shift as a result of new exploration or changes in technology.

2.3.1 Cost Estimates for Individual Deposits/Mines

A process similar to that described for Bear Lodge was applied to selected deposits globally that would produce thorium as a by-product or a twice by-product. The costs to recover thorium as a main product are escalated without other modification from Young *et al.* (1980). Table 2.2 shows a summary of the deposits included in the cost estimation, grouped by joint production relationships and ordered by unit production cost. The cost and capacity figures shown in Table 2.2 relate directly to those in Figure 2.4, the mining industry cost curve. Complete sources of data and the assumptions used to calculate cost for each of these deposits can be found in Jordan & Eggert (2014).

2.3.2 Cost Estimates by Deposit Type

In order to construct the cumulative availability curve, costs are assigned to the four deposit types categorized by the NEA/IAEA.[15] Costs are further distinguished as either

[15] There are some deposits which categorization is more ambiguous. When available, we assign deposits based on the deposit type listed on the IAEA ThDepot database. These deposits are Bokan Mountain, Mountain Pass, Bear Lodge, Mt. Weld, Hall Mountain, Wet Mountains, and Lemhi Pass.

Table 2.2: Potential Sources of Thorium by Joint Product Relationship and Cost (2013 USD)

	Deposit/Mine	Country	Owner	Status	Mine Life	Cost ($/kg)	Capacity (tonnes/y)
Twice By-product	Richards Bay	S. Africa	RBM, Rio Tinto	Operating[1]	30	8	1683
	Murray Basin	Australia	Iluka	Operating	6.5	8	859
	Eucla Basin	Australia	Iluka	Operating	14	9	509
	Perth Basin	Australia	Iluka	Operating	12	14	177
	Concord, Virginia	USA	Iluka	Operating	20	19	93
	Orissa	India	Indian Rare Earths	Operating	NA[2]	19	240
By-product	Steenkampskraal	S. Africa	Great Western	Pre-feas.[3]	10	4	1176
	Bokan Mountain	USA	Ucore	PEA[3]	11	47	29
	Mountain Pass	USA	Molycorp	Operating	30	76	67
	Bear Lodge	USA	Rare Element Res.	Pre-feas.	19	92	134
	Mt. Weld	Australia	Lynas	Operating	20	128	94
	Araxá	Brazil	MBAC	Pre-feas.	40	197	373
Main Product	Stockplies	USA	US Government	"Deposit"[4]	NA[5]	18	3168[5]
	Hall Mountain	USA		Deposit	5	40	918
	Wet Mountains	USA		Deposit	5	49	693
	Lemhi Pass	USA		Deposit	14	85	1384
	Palmer	USA		Deposit	20	87	2918
	Bald Mountain	USA		Deposit	20	300	273
	Conway Granite	USA		Deposit	20	417	1289

Sources for costs and capacity: By-product and twice by-product: this study's estimates and various public sources, see Jordan & Eggert (2014). Main product: escalated from Young *et al.* (1980).

[1] Operating heavy mineral sand or rare earth mine.

[2] The Orrisa facility recovers rare earths and thorium from heavy mineral sands from across India. India's heavy mineral sand resources are extensive.

[3] Three stages of feasibility studies are generally conducted in succession to evaluate the economic acceptability of a mining project. The first stage, the preliminary economic assessment (PEA) has a large degree of associated uncertainty, +/- 40-50%. The next stage, the prefeasibility study, increases the confidence to around +/-25%. The final stage is the definitive or bankable feasibility which is designed to reduce uncertainty to +/-10%.

[4] The US thorium stockpile was disposed of in Nevada, but could be utilized if unearthed and refined.

[5] The capacity and longevity of stockpiles will depend on demand. The quantity has been modified from Young *et al.* (1980) to reflect the quantity that is actually contained at the Nevada site (Hermes & Terry, 2006).

being main product costs, by-product costs, or twice by-product costs (only in the case of placer/ heavy mineral sands). For example, the Mountain Pass rare earth mine is a carbonatite deposit containing minor amounts of thorium, which could be produced as a by-product.[16] Using the estimation process described earlier, the cost of producing pure thorium oxide as a by-product from Mountain Pass would be approximately $76/kg. These assignments, organized by deposit type, are described in the text below and in Table 2.3.

By-product recovery costs were estimated for three carbonatite deposits, Mountain Pass, Mt. Weld and Araxá. As shown in Table 2.2, these by-product recovery costs ranged from $76 to $197/kg. No main product recovery costs were estimated for this deposit type because such estimation would require "bottom-up," mine engineering which is outside the scope of this study.

By-product and twice by-product recovery costs were estimated for six placer deposits. As shown in Table 2.2, costs for twice by-product recovery in these six placer deposits ranged from $8 to $19/kg. If however, thorium justifies recovery as a once by-product, all of the joint rare earth and thorium refining costs should be allocated to thorium. This adjustment raises recovery costs for these same five deposits to the range $65 to $156/kg. Finally, if thorium were to be produced as a main product from placer deposits, its recovery cost would jump dramatically. This recovery cost estimate has been escalated from the one conducted by Young *et al.* (1980), who found main product placer recovery so expensive relative to other sources of main product thorium they give only one lower bound estimate for recovery. While co-product relationships have been ignored, co-product costs would fall between main product and by-product costs.

Five vein type deposits have estimates for by-product and/or main product recovery costs. The basis for the by-product recovery cost range presented in Table 2.3 are the Bokan Mountain and Steenkampskraal deposits, while the basis for the main product recovery cost range are the Hall Mountain, Wet Mountains and Lemhi Pass deposits.

[16]Mountain Pass has no current plans to recover thorium.

Only two alkaline rock type deposits were assessed, Bear Lodge as a by-product and as a main product (by (Young *et al.*, 1980)) and Conway Granite as a main product. These estimates come directly from those presented in Table 2.2.

Table 2.3: Potential Thorium Production Costs by Deposit Type (2013 USD)

Deposit Type	World Thorium Resources[1] (1,000 Tonnes)	Main Product Cost[2] ($/kg)	By-product Cost[2] ($/kg)	Twice By-product Cost[2] ($/kg)
Carbonatite	1,900	*Note A*	76-197	*Note B*
Placer deposits	1,500	>760	65-156	8-19
Vein-type deposits	1,300	40-85	3-47	*Note B*
Alkaline rocks	1,120	345-417	92	*Note B*
Other	258	*Note A*	*Note A*	*Note B*

1 Data from (NEA and IAEA 2012)
2 This study's estimates
Note A: No resource in this category had cost estimated in this study.
Note B: Twice by-product production is only applicable in the case of placer deposits.

2.3.3 Long Run Perspective: Thorium Cumulative Availability Curve

Figure 2.3 is a graphical representation of the information in Table 2.3. Deposit types are sorted on the figure by the most likely and least costly means of recovery. Under this organization: twice by-product recovery from placer is the lowest cost, by-product from vein is the second least cost, and so-on. The cost values presented in the figure represent the higher value from the range in Table 2.3.

Particularly important in analyzing the cumulative availability curve is the curve's slope. For a discrete curve like the one estimated in this paper, slope is measured by how much of a cost increase is associated with a move from a lower to a higher cost source. In Figure 2.3, there is an approximate doubling of cost at each of these points. Yaksic & Tilton (2009) place lithium production costs in the context of the total cost of battery and vehicle manufacturing, of which lithium is a small component. Producers of batteries and vehicles are therefore more insensitive to lithium price changes. For thorium availability, the impact of cost escalation is more uncertain because there is no reliable point of reference. An approximation might be the market for uranium, which like lithium, makes up a fairly small portion of total costs of electricity generation in nuclear plants. Econometric studies have shown nuclear power utilities to be insensitive to uranium fuel price changes (Kahouli, 2011).

The curve in Figure 2.3 also illustrates the dramatic savings associated with producing thorium as a twice by-product of titanium and rare earth elements in placer deposits and as a by-product of rare earth elements in alkaline deposits. Cost savings for vein deposits is more modest because thorium in these deposits tends to be of a higher grade.

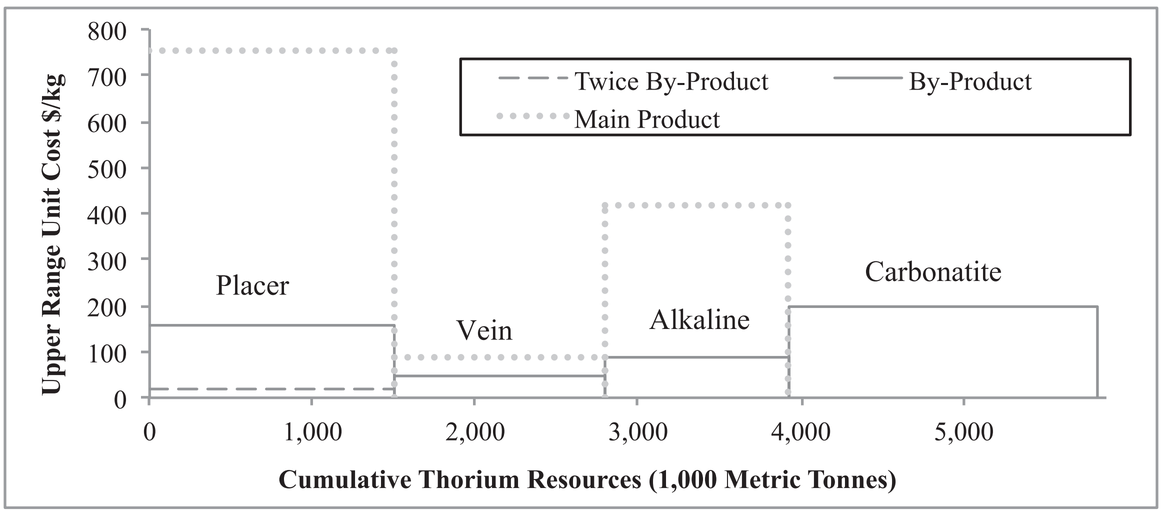


Figure 2.3: Cumulative Availability Curve: Thorium Resources by Deposit Type and Potential Production Costs

Source: Resource quantity data from (NEA and IAEA 2012). Cost data from this study: high value from each range in Table 2.3. Cost units are in 2013 US dollars.

To illustrate how society might move along the availability curve, we draw from a global demand scenario constructed in Appendix A.3. In the scenario, there is a 45 year "ramp-up" period where thorium demand grows. After 45 years we assume demand remains constant. Demand is based on a fuel consumption of 10 tonnes/GWe*yr. After the 45 year ramp-up, we assume a total installed capacity of 373 GWe (see Appendix A.3), a 100% capacity factor[17], and a steady state, once through, limited recycle fuel cycle. Using these assumptions,

[17] A 90% capacity factor is typically assumed for nuclear power. 100% is used here for simplicity.

cumulative demand is assessed at 100, 250 and 500 years after the beginning of the scenario. The calculated requirements are 0.313, 0.872, and 1.80 million tonnes of 99.99% ThO_2 for 100, 250 and 500 years of reactor operation, respectively. Note that the units of demand are not the same as the units in the cumulative availability curve. The cumulative availability curve uses resources on the horizontal axis, which are an in-situ quantity. Before the two can be directly compared, we must assume some rate at which in-situ resources can be recovered and purified. Young *et al.* (1980) estimate thorium mine recovery rates for various deposits between 60% to 100%, and mill recoveries between 40% and 98%. Average refinery recovery rates are higher, 95% in most cases. For simplicity, we will assume the same recovery rate as the hypothetical Palmer mine, 56%, but note the great deal of uncertainty around this rate.

With an assumed recovery rate of 56%, resources from placer deposits are sufficient for the 100 year scenario. In the 250 year scenario, vein and placer deposits are required. Finally, in the 500 year scenario, known resources from placer, vein and alkaline deposits are required. This assumes the constant demand rate and adequate production of main product rare earth and titanium mines in order to recover thorium as a twice by-product.

Shifts in the curve will also impact availability. The effects of changing technology over time, which are not accounted for in the discussion above, will have implications for both demand and supply. The importance of these effects to material availability have been demonstrated for other metals such as copper in Tilton & Landsberg (1999). For demand, technological improvement could make reactors more efficient, reducing their consumption. For supply, technology could improve recovery rates or facilitate the discovery of new deposits. The effects of technology over long time periods, such as those calculated above, are especially relevant, but their exact magnitude is unknowable. Technological uncertainty limits a more precise estimate of longevity, but the cumulative availability analysis suggests that thorium will be recoverable on the order of centuries at a low cost if by-product and twice by-product sources are available. More importantly, the limitations motivate thinking about thorium supply in the medium term where technology is more predictable and supply constraints are accounted for.

The perspective of availability in Figure 2.3 is also limited because it presents by-product supply and main product supply equally as if all by-product supply were available. For such a presentation to be valid, there would need to be sufficient main product production of rare earths and titanium such that all by-product resources were accessible. The cumulative availability analysis ignores the fixed capacity constraints mines face at any given time. These constraints are particularly important in the mining industry where it takes many years to finance, explore, plan, permit and construct facilities.

2.3.4 Medium Term Perspective: Potential Thorium Mining-Industry Cost Curve

To present a different perspective on thorium availability, incorporating some of the limitations noted about the cumulative availability curve in Figure 2.3, this section develops a mining-industry cost curve for thorium. Applying the cost estimation methodology developed in this paper, the deposits summarized in Table 2.2 are plotted on the cost curve presented in Figure 2.4.

More interesting than the physical quantities of recoverable thorium at given costs are the sources of those quantities. Figure 2.4 shows that annual production of by-product thorium from rare earth mines such as Mount Weld, Mountain Pass, Bear Lodge and Araxá are expensive relative to twice by-product heavy mineral sources and even some main product thorium mines, such as Hall Mountain and Wet Mountains. This finding can partially be explained by the concentrated state of thorium waste in twice by-product operations, but more importantly calls attention to the fact that thorium is an undesirable nuisance element in rare earth mines. It is not uncommon for rare earth projects to advertise their low thorium content as a benefit of their deposit over others. If demand for thorium arises, the desire to seek thorium-poor deposits may change, but absent this demand, deposits with low thorium concentrations may be more likely to be developed.

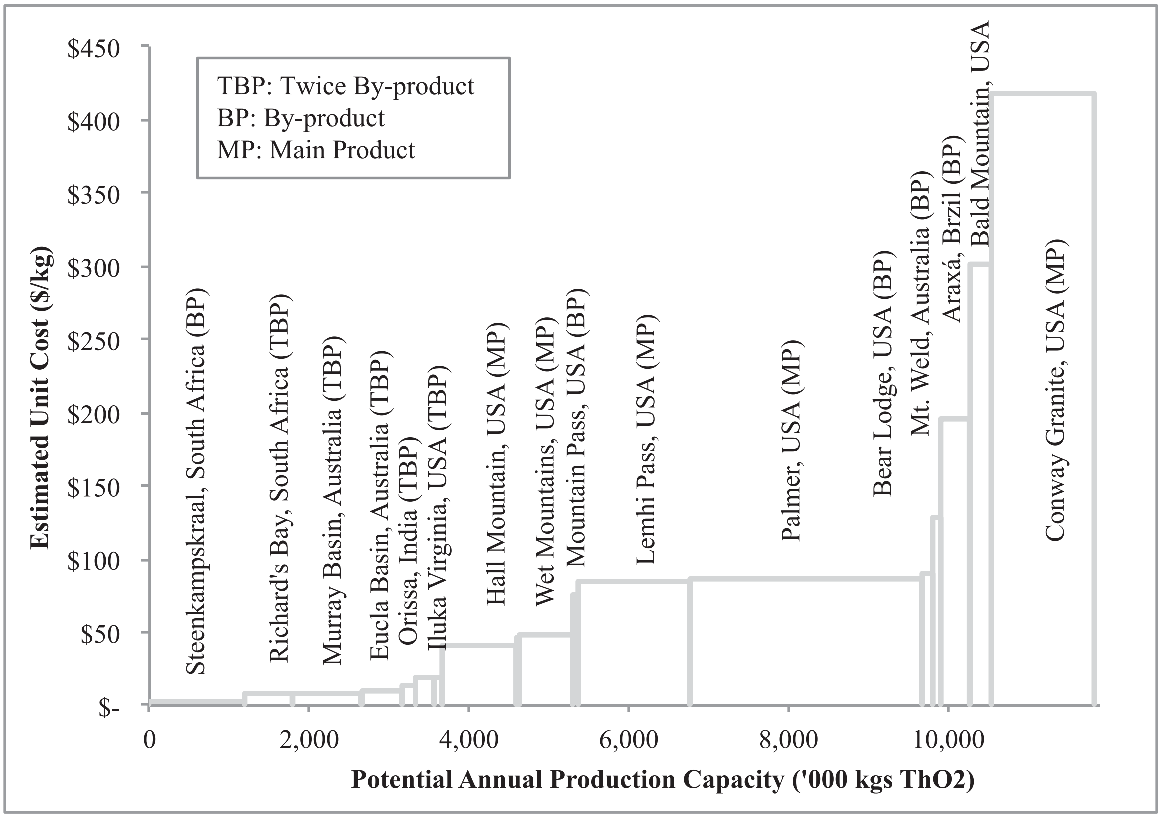


Figure 2.4: Potential Global Cost Curve for Selected Thorium Resources

Source: This study, see Table 2.2. Cost units are in 2013 US dollars.
Potential references both currently operating mines and projects in development. Only the Orissa Sands Complex, India, has installed capacity for thorium recovery.

The Steenkampskral deposit historically was one of the only main product thorium mines in the world and was profitable due to its very high grades. The low cost of the Richards Bay is due primarily to its large scale. The Richard's Bay mine also produced thorium until 1994. The Iluka heavy mineral sand mines of Australia, Murray Bay, Eucla Basin, and Perth Basin, have relatively low costs because of the assumed concentration of monazite entering the hypothetical rare earth and thorium separation plant. This concentration is assumed to be the same as the Orissa Sands Complex in India.[18] Mt. Weld has high estimated costs due to the low grade of thorium in the rare earth separation plant feed (40% REO, 0.13-0.16% ThO2). While the Araxá deposit has a 0.10% grade of thorium in-situ, the processing plan for the proposed mine does not include a physical separation plant, and the run of mine material will enter directly into the chemical separation plant leading to a large quantity of other waste material that thorium must be further separated from.

The cost to produce thorium rises slowly, moving from left to right in Figure 2.4, as more deposits are required to meet a higher levels of annual demand, but remains below $20/kg until the first main product mine, Hall Mountain, must enter production to meet demand. Hall Mountain has twice the production costs of the cheaper, by-product and twice by-product, sources of supply. However, as noted in Appendix A.2, more potential annual thorium supply from heavy mineral sand mines is likely to be available than is included in the selected deposits for Figure 2.4.

To place the mining-industry cost curve into context of annual quantities demanded, we again draw from the scenario developed in Appendix A.3. In this scenario, maximum annual demand for thorium is calculated to be 3,730 tonnes 99.99% ThO_2 per year. This maximum, plotted on the mining-industry cost curve, is presented in Figure 2.5.

Figure 2.5 shows that even the peak level of annual demand from the constructed scenario can be met from the selected by-product and twice by-product sources of thorium and only

[18] As the Orissa Sands Complex is currently the only known facility that concentrates monazite from heavy mineral sands before recovering thorium, it could serve as a model for other such plants. These plants could experience similar recovery factors. See Jordan & Eggert (2014) Appendix D and E for discussion of these assumptions.

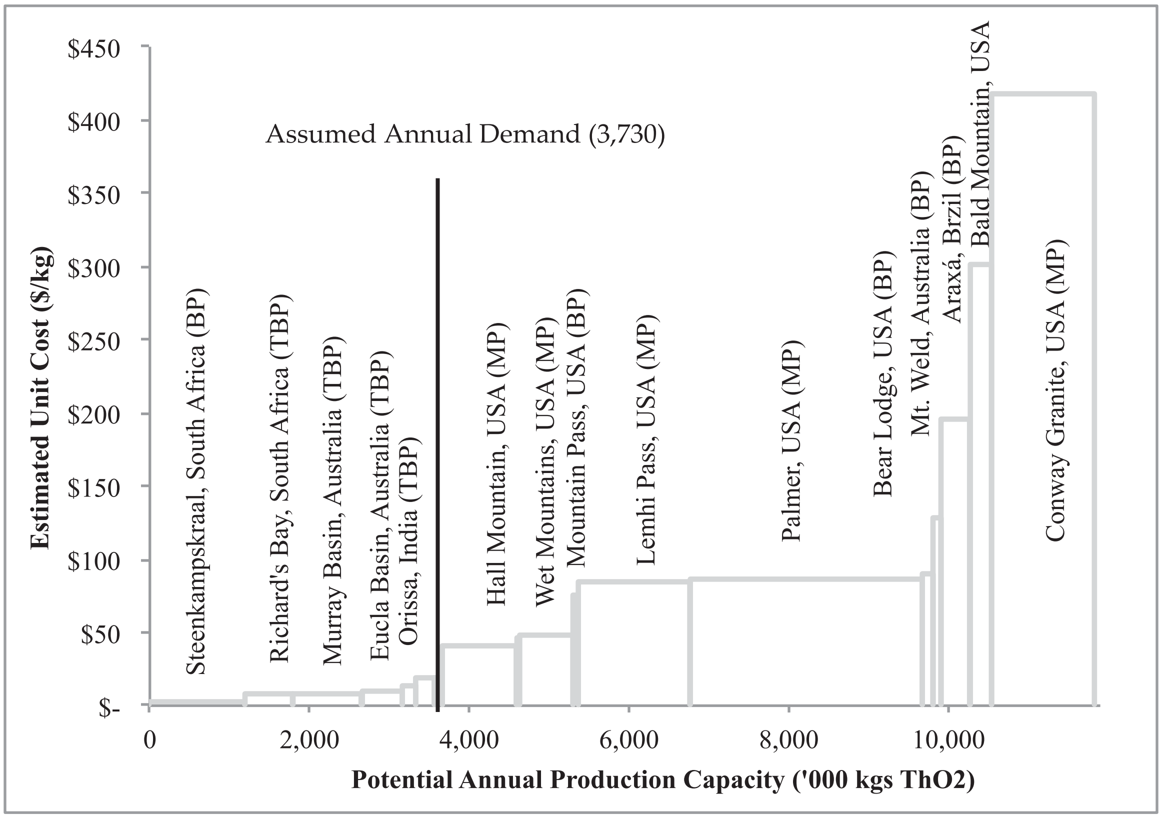


Figure 2.5: Mining-industry Cost Curve with Constructed Demand Scenario

Source: This study, see Table 2.2. Demand is calculated by assuming a 10 tonnes of ThO_2 are required per GWe per year, and a total installed global capacity of 373 GWe. See Appendix A.3.

one main product mine, Hall Mountain. However, the curve presented in Figure 2.5 does not incorporate all potential by-product production from rare earth and heavy mineral sand mines, as noted in Appendix A.2. The inclusion of omitted by-product production could meet demand without the need for more expensive main product mines, provided that omitted mines are similar in terms of costs and quantities to those included. Including additional sources would add additional “bars” to the curve, widening it overall. This does not override the basic point that for these sources to be low cost, thorium must be produced as a by-product or as a by-product of a by-product.

While by-product or twice by-product thorium could serve as an important (or sole) source of supply under certain scenarios, main product thorium mining has occurred historically and may be required again if demand is large. Main product thorium mining might also be required if the market for rare earth elements does not sufficiently justify recovery from heavy mineral sand deposits or if heavy mineral sand producers are simply not interested in deviating from their core business.

The mining-industry cost curve will also be affected by the same shifting factors as discussed with cumulative availability, namely technology and exploration.

2.4 Conclusions

Thorium is estimated to be between three to four times more abundant than uranium in the earth’s crust and has been identified around the globe in vein, placer, and carbonatite deposits and is almost always associated with rare earth elements as well as titanium minerals in the case of heavy mineral deposits. From the cumulative availability curve estimated in this study, sufficient quantities of thorium should be recoverable for many centuries at a cost that is unlikely to impede its use as a nuclear fuel. In the medium term, thorium availability may be more limited from by-product production constraints associated with rare earth and heavy mineral sand mining. In both the medium and long term; social, political and environmental considerations and technology could present issues for thorium supply.

Though we have found thorium production from by-product and twice by-product supply to likely be sufficient to meet the scenario of demand at a relatively low cost, several nuances are important to note. If rare earth producers continue the recent trend and seek less thorium-enriched sources of rare earth elements, then thorium may need to be produced as a direct by-product of heavy mineral sand operations rather than a by-product of a by-product. Such a development would involve a dramatic increase in recovery costs.

While not the direct focus of this paper, the other constraints to thorium availability (social, political, and environmental issues and the state of technology) are also important. Thorium is considered a nuisance material for rare earth operations because its radioactive presence can induce more stringent environmental regulations and increase the cost of tailings management. These concerns likely will persist into the future. Potential constraints also exist because of existing thorium recovery technology. Producing thorium at a large, commercial scale will likely require additional research and technological development which historically has received little investment.

Based on the findings of this study, it is unlikely that the potential development of a thorium based fuel cycle will be undermined by physical quantities of thorium resources or by the costs of extracting those resources. Current figures suggest that five to six million tonnes of thorium resources exist globally and these resources are found by this paper, given our demand scenario, to be physically sufficient for centuries. A significant portion of global thorium resources are contained in placer monazite, a supply source with some history of thorium recovery. Finally, thorium recovery costs are unlikely to be a major portion of total costs for plants, provided that thorium can be produced as a twice by-product, by-product or even, in select cases, as a main product.

A tremendous amount of uncertainty surrounds the future demand for thorium. A number of competing proposals for reactor designs, fuel configurations, and reprocessing options exist. On the front-end, it is uncertain how many more thorium-bearing deposits will be discovered, what kind of recovery technology will be developed, how political and social institutions could respond to thorium mining, or how mining firms will be react to a demand for thorium. What does seem to be clear is that, although thorium does not appear to a limiting factor for development of thorium-based nuclear fuel cycles, its availability is far more complex than its crustal abundance.

CHAPTER 3

COMPANIONS AND COMPETITORS: JOINT METAL-SUPPLY RELATIONSHIPS IN GOLD, SILVER, COPPER, LEAD AND ZINC MINES

A paper submitted to *Resource and Energy Economics*.

Technologies that produce multiple outputs are common across a variety of applications in economics. When the inputs for these technologies cannot be allocated to particular outputs, the process is considered joint production. There is a large body of literature on the implications of joint production for renewable resources such as fish and agricultural goods,[19] but only limited empirical treatment has been given to jointly produced non-renewable resources, such as metals.

The relationship between metal supply and joint production is intrinsic. Apart from the small amounts of copper and gold that were long-ago mined in native form, all metals mined and processed for use by society must be separated from other materials. Even recycled metals exhibit this characteristic, as many end-use products contain multiple materials (Stamp *et al.*, 2013). These other materials, which are often metals too, can also be valuable to society and whether they are marketed is an economic rather than geologic consideration. Given this important and intrinsic relationship, it is notable that economists have devoted considerable attention to the implications of the fixed-stock nature of metal resources,[20] but comparatively little attention to the joint production nature of metal supply.

The contemporary need for understanding the supply of jointly-produced metals comes as demand has increased sharply for geologically rare or specialized materials. For example, a smart phone today may use more than double the number of chemical elements as compared

[19] See literature surveys in Jensen (2002) for the case of fisheries and Shumway (1995) and Fox & Kivanda (1994) for agriculture.

[20] A seminal paper on fixed stock mineral extraction Hotelling (1931), for example, has been cited over 5,000 times.

to cell phones manufactured two decades ago (Rohrig, 2015), and the number of elements used in computers chips have increased by a factor of five over the same period (Eggert *et al.*, 2008). Analyzing the markets for these newly demanded elements, Nassar *et al.* (2015) finds a large number of them are dependent on other metals and joint production for the majority of their supply. The important role of joint production in the supply of these materials for key applications in clean energy and national defense is also noted in studies such as Bauer *et al.* (2010) and Graedel *et al.* (2015). Some empirical economic research, recently Fizaine (2013) and Afflerbach *et al.* (2014), has focused on joint production's role in minor metals markets, but many questions surrounding metal joint production remain unanswered.

This paper addresses the question of how a multi-product extracting firm responds when the prices of produced metals change. To answer this question, I estimate average short-run own and cross-price elasticities of supply for five commonly joint-produced commodities: silver, gold, copper, lead, and zinc. These specific markets are large and diversified, in contrast to those for the minor metals, but studying the behavioral response to price changes for these major and precious metals can still be informative in studying the supply for minor metals. The empirical model, a flexible-form dual revenue function, follows the approach of joint-production literature where it has been used extensively in the study of multi-product fisheries as shown in a literature survey by Jensen (2002). Three aspects of the estimated responses are of particular interest. First, I test the hypothesis that mines engage in "low-grading," where mining effort is redirected to a lower quality area of a resource in response to higher metal output prices. This behavior is measured by a negative sign on own-price elasticity of supply. I find that for three of the five studied metals, sampled mines engage in low-grading behavior. Second, I estimate how mines change their production levels for a particular metal when the price of another metal changes. This response is measured using cross-price elasticity of supply. I find large and significant cross-price responses for eight of the ten metal pairs studied. Additionally, the estimated signs on cross-price elasticity indicate metals produced as complements (higher production of one metal is associated with higher production of other metals) and substitutes (higher production of one metal is associated with lower production of others). Finally, I analyze whether the estimated own-price or cross-price supply elasticities have a strong relationship to a metal's contribution to mine revenue. Metals with very small revenue shares (sometimes classified as by-products or companion metals) are thought to have little impact on a mine's production behavior (Moss *et al.* (2013) and Bauer *et al.* (2010)). Metals with large revenues shares (sometimes classified as main products or host metals), on the other hand, are thought to drive the production decisions for the entire operation (Nassar *et al.*, 2015). I find that the relationship between revenue and elasticity does not generally hold for the metals and mines in this study.

This study expands and complements the existing work on metal joint production. It is the first identified study to estimate flexible functional forms for multi-product mines and includes the largest sample of firm level data to date. To place the findings of this paper in context with the existing literature, Section 3.1 describes how past work informs expectations of the behavior of joint metal supply. Section 3.6 describes and justifies the estimation strategy and the data used in the analysis. This section also qualitatively describes the distribution of metal revenues in the sampled mines. Section 3.7 describes the model results in the context of both the established joint production framework and the revenue distributions for the sampled mining operations. Section 3.8 presents possible limitations of the analysis. Section 3.9 discusses conclusions and potential future work.

3.1 Characteristics of Metal Supply Elasticities

This section discusses how past work translates to expectations of elasticity values as they relate to the three main findings of the paper. Section 3.2 first describes metal production as a multi-stage process and the implications for conducting this paper's analysis at the mining stage. Section 3.3 and Section 3.4 describe work that informs the own-price results and the cross-price results, respectively. Section 3.5 discusses how observed characteristics of metal supply such as metal grades, revenues, and profits are often used to infer elasticity response when data limitations prohibit statistical estimation.

3.2 Multi-stage Metal Supply

Metals are produced through a process which can generally be divided into three stages: mining, milling, and refining. At the mining stage a producer chooses the quantity and quality of ore to extract from the ground. Because absolute and relative metal concentrations vary across the resource, choosing a particular place to mine allows the producer to chose the quality of extracted resource. This choice will be constrained by the geology of the deposit, the mining method, and past mining decisions. In open pit surface mines a particular slope angle must be maintained to prevent failure. In underground mines the roof overburden must be supported to prevent collapse. For both types of operations the ability to access deeper resources depends on first extracting areas closer to the surface. Once the ore is mined it is transported to the mill. At the milling stage a producer uses physical and chemical processes to upgrade ore into a higher quality concentrate product. The concentrate contains one or more metals of economic value and waste. Finally, at the refining stage concentrate is separated into salable metal products. Each of these stages involve production choices which can affect the final supply of refined metal. Additionally, these decisions are not entirely independent; the recovery efficiency experienced by a mill can depend on the quality of material received from the mine. However this paper will abstract from the complications of this multi-stage process by focusing solely on the location and quality decision made at the mining stage, while controlling for the quantity mined. The short run supply elasticities estimated in this paper only reflect the supply of "in-situ" metal, or the metal contained within the extracted ore. A more complete elasticity value would further include the milling and refining decisions. If one assumes that choices in the milling and refining stages are relatively fixed in the short run (a reasonable approximation if there is no existing technology for changing preferential recovery of metals), then the estimated mining stage elasticity values will approximate the final supply elasticity of refined metal.

3.3 Own-Price Elasticity

The short-run relationship between a metal's price and its produced grade has been the subject of some debate over the last three decades, both in terms of optimality for profit maximization and empirical realities. A negative relationship between price and supplied metal quantity was first noted in the economics literature for the case of gold by Keynes (1936) and Paish (1938). This observation was followed by more sophisticated models on grade choice, each offering their own set of assumptions which make the negative relationship between price and grade optimal (or not).

Studies which have examined the issue of optimal grade choice in mining using optimal control models have found conflicting results, both in terms of why firms might optimize by low-grading and whether a negative relationship is optimal at all. Shinkuma (2000) proposes that the negative relationship of metal price to grade is due to "disorderliness"[21] in the composition of the deposit which impacts the mine's cost. If the highest quality portions of the deposit are arranged in a disorderly way, targeting these geographically scattered areas of the deposit will be necessarily more expensive than mining a single location due to scale economies. Slade (1988), on the other hand, finds that the negative relationship is optimal when there is uncertainty in future prices. Similarly, Krautkraemer (1989) models a situation where negative own price response is optimal when low grade ore must be mined "now or never," price changes are unanticipated, and the mine life is endogenous. Cairns & Shinkuma (2003) approach the problem differently by creating a more general and complex model without a predetermined optimal response. The authors find an ambiguous relationship between price and grade depending on parametrization. Providing dissent to the low-grading rule, Napier (1983) and Lane (2015) argue the behavior is not optimal for discounted profit maximization. Lane (2015) suggests that observation of low-grading behavior arises from mineral firms' desire to maximize the extracted quantities of resource and extend mine

[21] In Shinkuma & Nishiyama (2000), deposits with little or no pattern in ore quality distribution are said to be disorderly. For copper, the authors consider porphyry copper and sedimentary deposits to be orderly, while skarn and volcanogenic massive sulfide deposits are disorderly.

longevity.

Past empirical tests for the relationship between grade and price have utilized relatively small samples over a limited number of commodities. Farrow & Krautkraemer (1989) utilize a probit model and sample of 38 South African gold mines over eight years and 5 Idahoan silver, lead, and zinc mines over twelve years to test the relationship between price and grade. For the Idaho mines, variables are added to account for cross-price effects. The authors find a negative relationship between price and grade in South Africa. For the Idaho mines, they find a negative own-price relationship for silver, lead, and an insignificant negative result for zinc. Marsh (1983a) statistically tests for the negative price-grade relationship using a sample of 29 South African gold mines over seven years. In a similar analysis Marsh (1983b) looks at gold and uranium mines (including potential cross-price effects). Both Marsh (1983a) and Marsh (1983b) find evidence of the negative relationship between price and grade in the short run. The results found by Marsh (1983a), Marsh (1983b), and Farrow & Krautkraemer (1989) for South Africa are mandated by policy which is designed to maximize the quantities of extracted gold resource (Slade (1988) and Farrow & Krautkraemer (1989)) and are not particularly useful in making inferences about behavior in other settings. Finally, Shinkuma & Nishiyama (2000) use graphical analysis of copper deposits to test the theory of a negative price-grade relationship in disorderly deposits proposed by Shinkuma (2000); results are mixed. In a sample of 51 mines, they find that nearly all disorderly deposits exhibit (weakly) the low-grading response, but some "orderly" deposits do as well.

Generally speaking, while there have been divergent findings for the theoretical optimality for low-grading, the empirical evidence has found that producers do engage in low-grading.

3.4 Cross-Price Elasticity

Unlike the literature for the own-price effect where some developed theory prescribes low-grading behavior, the existing theory around cross-price responses tends to assume (rather than prescribe) that metals act as complements in supply. In other words, past theoretical studies have assumed that rising prices of one metal will spur increased production of joint products. Empirical studies have generally found results consistent with this assumption. In Campbell (1985) and Afflerbach *et al.* (2014), the signs of own and cross-price elasticities are assumed to be positive implying metals are produced as complement goods. Pindyck (1982) assumes a similar complementary relationship in supply. Afflerbach *et al.* (2014) argue for a complementary relationship in supply because the ratio of the grade of one metal to any other metal in a deposit is fixed. Farrow & Krautkraemer (1989) and Marsh (1983b) both empirically find evidence for metals being supplied as complement goods, but with a negative own-price response and negative cross-price response.

What if the grade ratio is not fixed across the space of a resource deposit? If the grade of one metal in a deposit is relatively uncorrelated with the grades of other metals, there may be little cross-price response at all. A mine choosing to low-grade one metal may be able to preferentially mine a different area of the deposit with lower concentrations of that metal without substantially altering the extracted grades of other metals. Alternatively, if relative grades exhibit a negative correlation, metals may be extracted as substitutes. A mine desiring to low-grade one metal may need to extract from an area of the deposit with higher grades of their other metals. Such deposits can be formed by more complex formation events such as multiple magma intrusions, hydrothermal events, zonation, or overprinting.

An example deposit with complex geology is shown in Figure 3.1. The Pebble project in Alaska, USA is a proposed gold and copper mine (also molybdenum and silver) where geologic events have created a heterogeneous distribution of grades across the resource. Certain areas of the deposit are enriched in both copper and gold, while other areas are poor in both copper and gold. Most importantly, specific areas have high grades of one metal but low grades of the other. The geology creates a choice set over which the producer must optimize their extraction. The heterogeneous grade distribution illustrated in Figure 3.1 occurs in many other mineral resource deposits and is not unique to the Pebble deposit.

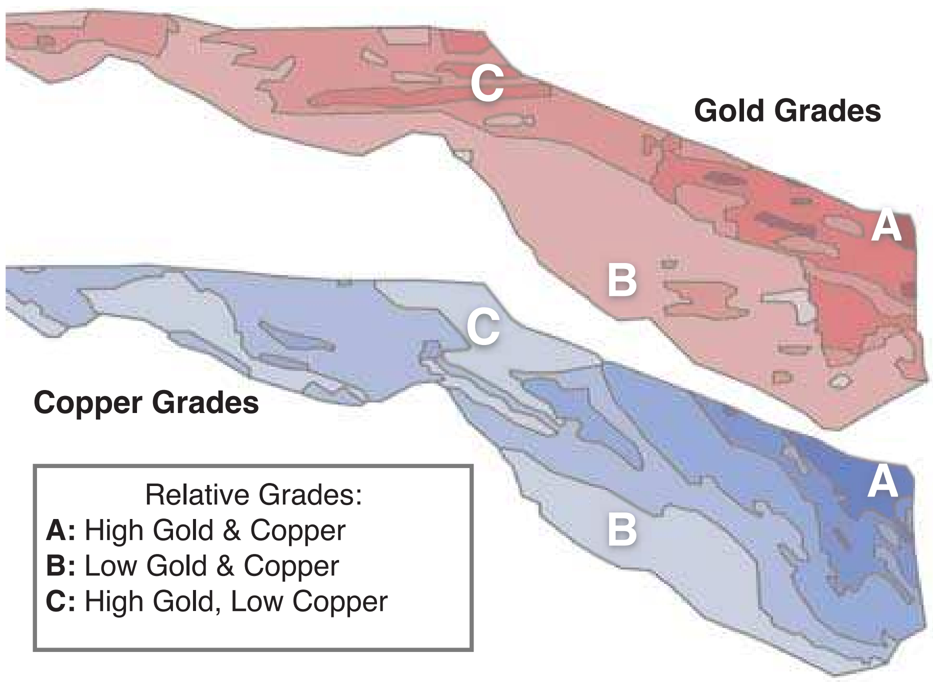


Figure 3.1: Heterogeneous Grade Distribution of Copper & Gold in the Pebble Deposit, Alaska USA

Source: Modified from figures in Lang *et al.* (2013). The figure shows a cross-section of the proposed Pebble mine. Heterogeneous grades for both gold and copper across the Pebble deposit create areas with high grades of gold and copper (A), areas with low grades for both metals (B), and areas with high gold grades but low copper grades (C).

3.5 Elasticity and Metal Revenue

Discussion of jointly produced metals is typically framed around the concept of main product, co-product, and by-product production relationships (Tilton & Guzmán, 2016). A main product is usually defined as a metal that is so important to the economic viability of a given mine that its price alone determines the production decisions at the operation. At the other end of the spectrum a by-product is a metal that is so unimportant to a mine that its price has no impact on the production decisions of a given mine. Co-products are two or more metals which jointly determine the production decisions at a given mine. These relationships can be roughly translated into own and cross-price elasticity magnitudes, at least in relative terms. Main products might be defined by a relatively high own-price elasticity but low cross-price elasticity, co-products by moderate own and cross-price elasticity, and by-products by low own-price but high cross-price elasticity of supply.[22]

For many metals, statistical elasticity estimation is not practical. Data on minor and specialty metals are particularly difficult to collect. The importance of own and cross-price responsiveness to making inferences about a metal's market dynamics has led many studies to infer what type of own and cross-price response a metal might have based on other observable characteristics. Most commonly, this classification is based on relative grades, revenues, or profits. For example, in what may be the most comprehensive recent study on the subject Nassar *et al.* (2015) classifies a large number of metals based on their relative revenue or relative profit shares. Many studies on the implications of metal by-product supply make similar assumptions about the link between grade, revenue, or profits and price responsiveness in metal supply. The following quotes are indicative of this assumed link:

"Due to its low concentrations in earths crust, cobalt usually is produced as a by-product element of other metals like copper or nickel" - Buchert *et al.* (2009)

[22] Afflerbach *et al.* (2014) defines by-products slightly differently than other works. In their framework, they use the term by-product to refer to metals with the properties of co-products as defined here.

“Even with very high prices for the by-products, the small size of the markets creates only a limited commercial incentive for refiners to pay strong attention to optimal by-product recovery” - Moss *et al.* (2013)

“In general, coproducts with lower revenue streams....are less likely to drive production than coproducts with higher revenue.” - Bauer *et al.* (2010)

While the link between grade, revenue, or profit and price responsiveness is intuitive, this is the first study test the link between these characteristics of metal supply and the metal’s actual supply responsiveness on the part of producers. Specifically I test whether metals with a large revenue share exhibit main product behavior, and low revenue share metals exhibit by-product behavior. It is possible to imagine a situation where these relationships would not hold. If a metal’s grade is uncorrelated with the grades of other metals in the deposit, then mines can more easily optimize their production levels separately. In this case a metal might have a small revenue share but be quite price responsive.

3.6 Estimation Strategy and Data

Previous studies which have empirically examined the behavior of multi-product mining firms have not utilized flexible functional form analysis[23] typical of production studies and well suited for the analysis of multi-product firms. The benefit of using a flexible functional forms over reduced form analysis in this application is the interpretability and consistency of estimated elasticity values. It also avoids equation-by-equation OLS estimation which has been shown by Vinod (1968) to be biased for jointly-produced products.

I utilize a revenue function approach to estimate own and cross-price elasticities of supply. A revenue function is chosen over a profit function for several reasons. First, this analysis is output oriented, and so the responsiveness of firms to input prices is not directly of interest. Second, mining firms face a strict capacity constraint (typically the quantity of ore that can be milled in a given period). Assuming that mines seek to produce at this capacity,

[23] Fizaine (2013) and Mudd *et al.* (2013) both utilize co-integration analysis. Afflerbach *et al.* (2014) use OLS regression on monthly price data. The study by Livernois & Ryan (1989) is an exception. They utilize a variable profit function approach with an application in oil and gas.

total input effort can be considered fixed. Additionally, if the transformation function is additively input-output separable then relative input prices have no effect on relative outputs and modeling them explicitly should have no theoretic impact on the result. Finally, a more practical consideration is the lack of public data on input costs for mining operations.

The empirical specification follows Kirkley & Strand (1988) who utilize a generalized Leontief revenue function for analysis of supply response in a fishery. The generalized Leontief function, first proposed by Diewert (1971), allows for estimation using levels rather than share data (as required by the translog function). The generalized Leontief form is also more conservative than the alternative translog and quadratic forms in estimating flexibility of the underlying technology (Williamson *et al.*, 2004). As in Kirkley & Strand (1988) the revenue function takes a non-homothetic form to account for changing production flexibility as varying quantities are extracted. Conceptually, if the annual quantity produced equaled the total size of the remaining resource, the mine would have no flexibility to target specific portions of the resource, they would simply mine whatever remained. As production relative to the total size of the remaining resource decreases, the flexibility to target certain portions of the resource increases. The revenue function for each mine, k, takes the explicit form[24] shown in Equation 3.1.

$$R_k(P, Z) = \sum_i \sum_j \beta_{ij}(P_i P_j)^{1/2} Z_k + \sum_i \beta_i(P_i Z_k^2 + a_k P_i) \tag{3.1}$$

where i, j are the indexes of metals produced from each mine k ($i, j \in M_k$, where M_k is the set of metals mine k produces), P_i is the price of the i^{th} metal product, Z_k is the composite input effort of the k^{th} mine. a_k is an individual mine fixed effect which could include effects such as smelter contracts which affect the prices the mine receives. β's are parameters to be estimated.

In the preferred specification, prices are assumed to be exogenous due to the low level of firm concentration in the five markets included for this study. Tilton & Guzmán (2016) argue that because of the large number of firms and distributed nature of production in

[24]The time index has been removed for presentation simplicity.

the gold, silver, copper, lead and zinc markets firms will lack the ability and incentive to manipulate prices and these markets likely function in a competitive way. Afflerbach *et al.* (2014) assumes producers of base metals like copper and zinc are price takers based on analysis by Lewis *et al.* (2011). Lewis *et al.* (2011) show lower levels of market concentration for gold, silver, and lead than for zinc or copper and note that all five metals are traded in major spot and futures exchanges. See Section 3.8 for a more complete discussion of potential issues with this assumption.

Applying Hotelling's Lemma to Equation 3.1 leads to the input compensated "in-situ" (Ore*Grade) supply functions for each metal, $Q_i(P, Z)$:

$$\frac{\partial R}{\partial P_i} = Q_{ik}(P, Z) = \beta_{ii} Z_k + \beta_i Z_k^2 + \sum_j \beta_{ij} (P_j/P_i)^{1/2} Z_k + a_k \tag{3.2}$$

where $i \neq j$.

Equation 3.2 is estimated as a seemingly unrelated regressions (SUR) model using the two step method. Coefficient symmetry, $\beta_{ij} = \beta_{ji}$, is imposed as a constraint on the estimation. Time effects must be omitted from the estimation because of co-linearity between time effects and prices. Coefficient stability over time is tested in Section 3.8.

The data for the analysis are an unbalanced panel of 113 mines operating in thirty countries from the period 1991 to 2005. The data come from two sources. Mine level production data were downloaded freely from minecost.com in February 2015. The dataset has since been purchased by SNL Financial and is no longer freely available. Variables from minecost.com are tonnes of ore mined, average grade of metal i in ore mined, and quantity of metal i in produced concentrate. Metal price data come from the USGS series 140. Series 140 prices are based on a weighted average price of US imports and provide a uniform basis of comparison between metals. These price data have been used previously as approximations of global prices by Lee *et al.* (2006), Mudd (2007) and Redlinger & Eggert (2016). Indexed prices are plotted over the relevant time period in Figure 3.2.

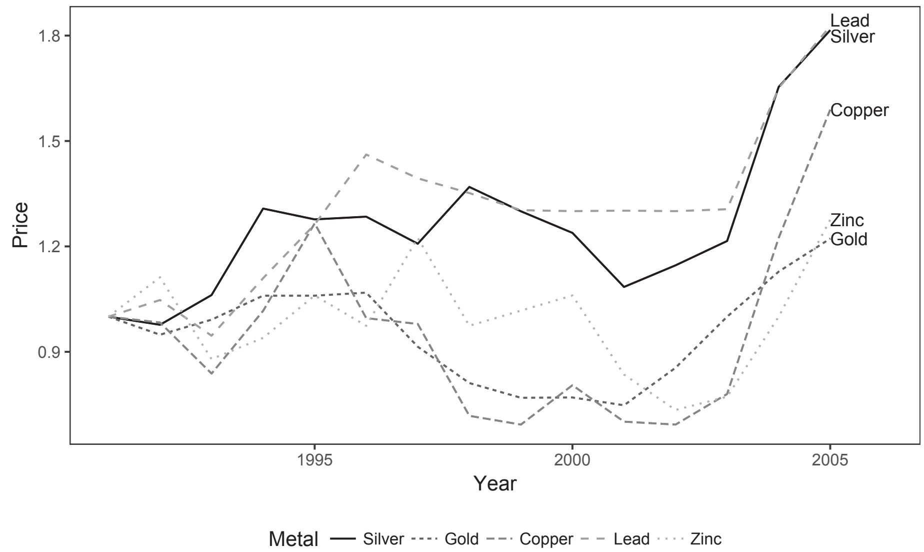


Figure 3.2: Selected Metal Prices from 1991-2005, Index 1991=1

Source: USGS series 140. Weighted Average US Import prices.

Five metal commodities: gold (Au), silver (Ag), copper (Cu), lead (Pb), and zinc (Zn), are selected from a larger sample for the analysis. This sub-setting was chosen to maximize the number of metals produced from the same mines. No mines are included that produced only one product over the period. Eleven mines in the sub-sample of 113 produce all five products, while 34 produce just two. To approximate the aggregate input effort, Z, I use tonnes of mined ore. Using ore mined as a measure of input effort is reasonable given that total material mined (ore+waste) will be some increasing function of the aggregated input effort Z, such that $ore + waste = f(Z)$. The approximation is stronger if the quantity of waste is small or if the proportion of ore to waste is constant with respect to input effort. Table 3.1 provides descriptive statistics for this and other variables used in the analysis over the sampled mines.

To test the relationship between revenue and price responsiveness, the five metals in the sample are characterized based on their contribution to mine revenue on average. Table 3.2 presents a summary of the estimated revenue share of each of the five metals. The overall average shares across all 113 mines in the sample varies from around 12% for silver (produced

Table 3.1: Descriptive Statistics

	N	Mean	St. Dev.	Min	Max
Ore Mined ('000 tonnes)	1,199	5,715	14,121	0	135,041
Gold Grade (%)	617	0.0004	0.001	0	0.008
Silver Grade (%)	1,056	0.011	0.030	0	0.365
Copper Grade (%)	649	0.968	1.082	0	10.000
Lead Grade (%)	702	2.793	2.420	0	13.000
Zinc Grade (%)	785	6.786	4.312	0	22.500
Gold Price (98 '000 $/tonne*)	1,695	11,230	2,056	8,060	14,000
Silver Price (98 $/tonne)	1,695	162,691	20,008	129,881	196,392
Copper Price (98 $/tonne)	1,695	2,297	603	1,513	3,271
Lead Price (98 $/tonne)	1,695	953	100	789	1,123
Zinc Price (98 $/tonne)	1,695	1,155	217	772	1,499

*1000 $/tonne for table presentation only. $/tonne used for analysis.

by 99 mines) to nearly 60% for zinc (produced by 73 mines). Gold and copper, which are produced by roughly half the mines in the sample, account for close to 40% of revenue each, on average. However, in mines that produce lead and/or zinc, gold and copper account for much smaller shares of revenue, between 8%-16%.

Table 3.2: Average Revenue Share of Metals, Overall and in Mines Producing Selected Metals

		In mines which produce at least:				
	All Mines	Silver	Gold	Copper	Lead	Zinc
Number of Mines (#)	113	99	60	60	62	73
Silver Revenue (%)	12	12	12	11	13	11
Gold Revenue (%)	37	39	39	18	13	12
Copper Revenue (%)	37	32	46	39	8	16
Lead Revenue (%)	20	20	14	14	21	20
Zinc Revenue (%)	59	57	45	54	61	60

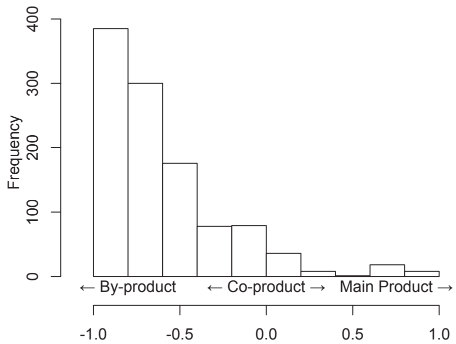
Note: Percentages should not necessary add to 100.

The average revenue shares shown in Table 3.2 are not sufficient to characterize the relationship between revenue and potential price responsiveness. More important than the average revenue of each metal is how large or small that contribution is relative to other metals at a mine. If silver, for instance, contributes 12% to revenue on average, but four other metals each contribute 22% to a mine's revenue, this situation is clearly different than if silver contributes 12% to revenue and just one other metal contributes 88%. To distinguish these two situations I calculate the relative revenue share by metal and plot the resulting frequency distribution of sample observations in Figure 3.3. Relative revenue share within each mine and is calculated for each metal as difference in revenue share for that metal and the single highest revenue share among the other metals. This calculation results in a value between -1 and 1. Values of 1 or near 1 corresponds to a metal being the primary driver of mine revenue, consistent with the definition of a main product as described in Section 3.5. Values near -1 correspond to the described by-product definition. Finally, values near 0 correspond to the co-product definition. The frequency distribution plots in Figure 3.3 are organized into three groups. Because the largest mass of observations for lead and silver falls close to -1, these metals might be considered by-products for the sampled mines. Zinc, on the other had, exhibits a pattern consistent with main product production. Lastly the bimodal distributions for gold and copper exhibit patterns consistent with main product production in some mines and by-product production in other mines.

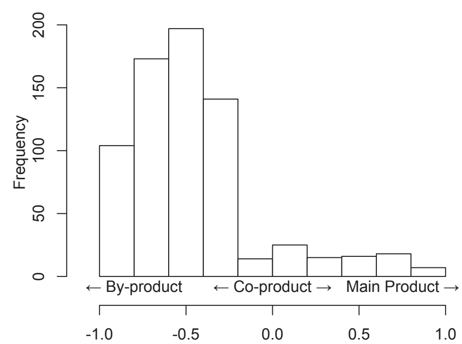
The patterns identified in Figure 3.3 are used to test the hypothesis that high revenue metals will be responsive to own-price, but not cross-price and low revenue metals are responsive to cross-price but not to own-price. Specifically, silver and lead are expected to exhibit by-product behavior and zinc is expected to exhibit main product behavior. With bimodal distributions, the expected response of gold and copper is unclear.

3.7 Results

This section presents the coefficient estimates of Equation 3.2 and the resulting own and cross-price elasticities. The own-price estimates suggest that mines do engage in low-grading behavior. The positive and negative cross-price results paired with the negative own price results suggests that metals are both complements and substitutes in supply. Finally, By-Product Pattern

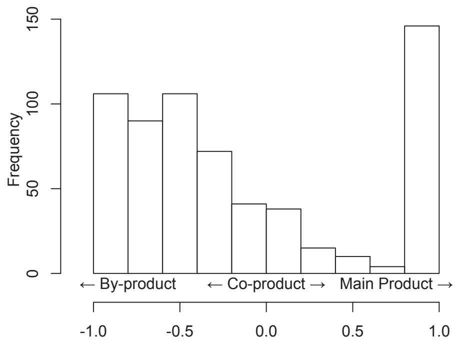


(a) Silver

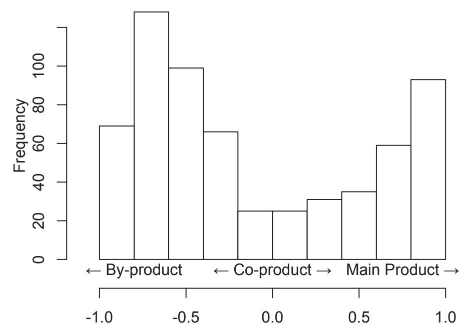


(b) Lead

Main Product *and* By-product Pattern

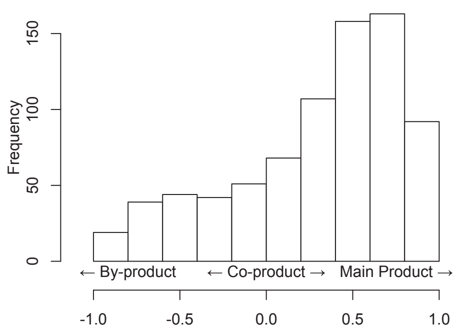


(c) Gold



(d) Copper

Main Product Pattern



(e) Zinc

Figure 3.3: Distribution of Mine Level Importance of Metals, Measured by Relative Revenue Share

Relative revenue share for a given metal-mine-year observation is calculated as the revenue share for that metal minus the single highest revenue share among the other metals at that mine in that year. A result of 1 indicates that metal contributes 100% of the revenue to a particular mine in a given year, indicative of a main-product. A score of 0 indicates that metal and at least one other metal contribute the same revenue to a mine - indicative of co-products. A score of -1 indicates a metal contributes 0% of a mine's revenue while one other metal contributes 100%, indicative of a by-product.

the large own and cross-price elasticity estimates for low revenue silver and lead suggests that inferring price responsiveness based on a metal's revenue share may be an incomplete characterization.

Own-price and cross-price elasticity values are calculated using Equations 3.3 and 3.4, respectively.

$$E_{ii} = \frac{\partial Q_i}{\partial P_i}\frac{P_i}{Q_i} = \frac{-Z}{2P_i^{1/2}Q_i}(\sum_j \beta_{ij} P_j^{1/2}) \tag{3.3}$$

$$E_{ij} = \frac{\partial Q_i}{\partial P_j}\frac{P_j}{Q_i} = \frac{\beta_{ij} Z P_j^{1/2}}{2Q_i P_i^{-1/2}} \tag{3.4}$$

The elasticity results, presented in Table 3.3, are evaluated at mean levels of Q, Z, P and represent average effects. Standard errors of the regression are bootstrapped and calculated using the delta method as described in (Greene, 2012, p. 1123) and implemented with the R package described in Jackson (2011).

Table 3.3: Input-Compensated Own and Cross-Price Elasticities

	P Gold	P Silver	P Copper	P Lead	P Zinc
Q Gold	0.096	-0.040*	0.507***	-0.182**	-0.381
	(0.247)	(0.017)	(0.021)	(0.055)	(0.240)
Q Silver	-0.118*	-6.958***	0.462***	0.465**	6.149***
	(0.050)	(0.307)	(0.035)	(0.170)	(0.238)
Q Copper	0.255***	0.078***	0.110	-0.404***	-0.038
	(0.010)	(0.006)	(0.111)	(0.056)	(0.095)
Q Lead	-0.515**	0.442**	-2.269***	-3.014***	5.356***
	(0.156)	(0.161)	(0.315)	(0.320)	(0.173)
Q Zinc	-0.322	1.749***	-0.064	1.604***	-2.967***
	(0.203)	(0.068)	(0.161)	(0.052)	(0.181)

P's are prices, Q's are quantities.
Elasticities are presented at their average values and calculated using Equations 3.3 and 3.4.
Bootstrapped standard errors are in parentheses and estimated using the delta method.
*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$

Own-price elasticities are represented along the main diagonal of Table 3.3, and cross-price elasticities on the off-diagonals. A statistically significant and negative own price-production relationship on the main diagonal in Table 3.3 is consistent with the hypothesized low-grading behavior. This is the case for three of the five metals assess, silver, lead, and zinc. Gold and copper are not found to have as statistical own-price relationship with produced grades. The low-grading result is consistent with past empirical findings in the work by Marsh (1983a) and Farrow & Krautkraemer (1989), and theoretical work by Shinkuma & Nishiyama (2000), Krautkraemer (1989), and Slade (1988).

The significant positive and negative results for the cross-price elasticities indicate a higher degree of interdependence in the supply of these metals than found by Farrow & Krautkraemer (1989). Of the ten possible cross-price effects, I find eight are statistically significant at the 95, 99 or 99.9% level. For example, a 1% increase in zinc prices is associated with a 6.1% increase in mined in-situ silver quantities and a 5.4% increase in mined lead. Copper prices have a divergent relationships with production. A 1% increase in copper prices is associated with a .5% increase in mined in-situ gold and silver, but a 2.3% decrease in mined lead. While the own-price results are consistent with the limited past empirical work, the cross-price results are generally reversed. Farrow & Krautkraemer (1989) find a price increase in zinc is associated with decreased grades of silver and lead; the results from the present paper show the opposite effect. Similarly, Marsh (1983b) finds a negative relationship between gold price and uranium grades in contrast to the present results. Marsh (1983b) does not include uranium prices in that analysis. If uranium exhibits a negative price-grade relationship and uranium prices are positively correlated with gold prices, the gold-uranium cross-elasticity estimate is negatively biased. Farrow & Krautkraemer (1989) include a full set of prices in their model which makes it harder to explain the discrepancy. It is possible that the results from Marsh (1983b) and Farrow & Krautkraemer (1989) are valid for a more limited sampling of mines. It is also possible that the flexible functional form analysis reveals a more complete, and complex, set of multi-product price responses.

The elasticity results do not generally conform to the expectations set based on revenue share and distribution. While zinc is own price responsive as its larger revenue share would suggest, so are low-revenue silver and lead. More surprisingly, changes in lead and silver prices are associated with changes in production of copper, gold, and zinc. These results suggest that inferring price responsiveness of metals based on revenue shares may be an incomplete framework.

The results point to a potential need for modified understanding of multi-product mineral supply. Only a handful of papers have considered the case of a multi-product mine producing from a heterogeneous resource, but this situation represents a significant share of metal supply. Considering that a heterogeneous resource (such as the Pebble deposit) and choice of grade can lead to a negative short-run supply response, it is potentially unsurprising that this more complex situation could also lead to equally complex response by multi-product firms beyond more simple frameworks of by-products and main-products.

The estimated cross-product relationships can be defined in terms of substitute and complement relationships. For metals with negative own price elasticity, a negative cross-price elasticity indicates a complement and a positive cross-price indicates a substitute (the reverse is true when a metal has a positive own-price relationship). For example, increases in lead prices are associated with mines shifting production toward lower in-situ quantities of lead and higher in-situ quantities of zinc. This makes lead and zinc substitutes in supply. The relationships for each of the ten metal pairs in the study are summarized in Table 3.4. Three pairs of metals have an unambiguous and symmetric substitute relationship, lead & silver, zinc & silver, and zinc & lead. The substitute relationship for silver & copper is not statistically symmetric because the copper own-price effect is not different from zero. Three of the complement relationships silver & gold, lead & gold, and lead & copper also do not have the statistically significant symmetry in response. The gold & copper complement relationship is symmetric but not significant. Finally, the zinc & gold and zinc & copper relationships are neither symmetric nor statistically different from zero.

3.8 Robustness of Findings

Coefficient Stability Over Time

Table 3.4: Estimated Metal Substitute and Complement Relationships

Substitutes in Output	Complements in Output
Lead & Silver	Silver & Gold[1]
Zinc & Silver	Lead & Gold[1]
Zinc & Lead	Lead & Copper[1]
Silver & Cooper[1]	Gold & Copper[2]

[1]Relationships do not have (statistical) symmetry.
[2]For an assumed significant and positive own-price response.
Ambiguous relationships Zinc & Gold, Zinc & Copper not shown.

As shown in Figure 3.2, prices for silver and gold began to rise sharply after 2001, and prices for lead, copper, and zinc begin rising together after 2003. These increases were largely driven by demand growth in China and other developing countries. The empirical model is identified based on the relative variation between prices, but it is useful to consider the possibility that the post-2001 period represented a structural change in the market. I test for the inter-temporal stability of the elasticity point estimates by running the model on the 1991-2001 portion of the sample; the results are presented in Table B.1. Comparing the 1991-2001 results to the results for the full sample (1991-2005) the conclusions do not change. Silver, lead and zinc exhibit low-grading behavior, the cross-price estimates indicate substitute and complement supply relationships, and the revenue shares of the metals do not appear to drive their elasticity. The estimation error of the model increases because of the reduced sample size which makes several of the estimates that are statistically significant in the full sample insignificant in the subsample.

Endogeneity in Prices

The empirical model has assumed that firms are price takers and that metal prices are exogenous. It is assumed that each firm is too small to impact global prices with their grade choice or that firms do not collectively act to move prices. If this assumption is invalid and prices are endogenous (i.e. grades do contemporaneously determine prices) then coefficient estimates will be biased by system simultaneity and price responses will be overestimated.

It is difficult to argue that aggregate production across all firms is inconsequential because the sample of mines includes a notable percentage of world production (around 30%) for each of the five metals. In alternative reduced-form specifications for the empirical model, a two-stage estimator is tested for the relationship between price and grade. Specifically, the effect of potentially endogenous own and cross-prices on grade is estimated for each of the five commodities, controlling for other metal grades, ore production, cumulative mine production and a mine fixed effect (see Equation B.1). The results of these models are compared to a set of 2-stage models using plausibly exogenous demand-side shifters (such as income, population, and automobile production) as first-stage instruments for metal prices. Similar coefficient estimates are found for prices in both sets of models, providing some confidence of an exogenous price-on-grade relationship. See Appendix B for a complete discussion.

Quantitative Test of Revenue Share and Price Responsiveness

The finding that revenue may be a poor predictor of elasticity is more formally tested using an alternative model specification in Appendix B. These quantitative tests align with the results in Section 3.7 that by-products and main products, as defined by revenue contribution, do not necessary differ in their own and cross-price responsiveness.

Distinguishing Mine Type

Different mine types (open pit and underground) may have varying flexibility to adjust to market conditions. This hypothesis is tested by regressing metal grade on prices interacted with a mine type dummy variable. The coefficient estimates of this regression are presented in Table B.9. The results show some differing flexibility between the two mine types. A t-test of the coefficients for the difference between the open pit price response and the underground price response indicates statistically different values for silver grades-copper prices, gold grades-silver prices, gold grades-copper prices, gold grades-lead prices and zinc grades-gold prices, or five of the twenty-five possible combinations.

3.9 Conclusions

This study finds significant cross-price elasticity estimates for many of the metal-pairs assessed. While the estimates themselves may be of interest to analysts of these particular markets, more generally they should call attention to the fact that metal supply should not be considered in isolation. The geologic processes which have concentrated these materials together into economically exploitable deposits have also critically linked their supply. The complexity of these geologic processes leads to equally complex responses when economic conditions change.

The metals assessed in this study are distinct from the minor and specialty metals that have been subject to recent concerns, but the central finding of this paper still has an important implication for assessing minor metal supply. Namely, that empirical studies of mining firms can reveal interesting and complex relationships in joint metal production. It is likely that producers of minor metals behave differently than producers of the base and precious metals addressed in this study, and so direct evidence of such behavior should be welcomed. In the meantime, presumptions of behavior for minor metal producers should be thoughtfully considered.

This paper has shown evidence for low-grading metals when prices rise and for metals behaving both as substitutes and complements in supply. The paper has also demonstrated that revenue share is not a strong indicator of how responsive a metal will be to price changes. These findings are all likely enabled by the heterogeneous nature of many mineral deposits. Producers with heterogeneous resources can re-optimize their production by mining different areas of the deposit when market conditions change. The more metals are decoupled from a fixed-proportions relationship, the easier it is for a producer to separately optimize each metal's production.

CHAPTER 4

CAN WE DIG IT? AN EMPIRICAL STUDY OF ENVIRONMENTAL ATTITUDES AND SOCIAL LICENSE TO OPERATE IN MINERAL EXTRACTION

A paper prepared for journal submission.

The benefits of mineral use are large and diffuse throughout the economy. However, mineral resource extraction typically involves environmental and social costs that are sizable but localized. Over the last three decades, local stakeholder opposition to mining has become more common (Davis & Franks, 2014).Despite some evidence that a majority of the global public still support the abstract idea of mining (GEI, 2014), public opposition to specific projects is frequently cited as a major concern among resource developers (Behre Dolbear (2014)). The contradiction between a general support or benefit but specific opposition is evidence for not-in-my-back-yard opposition or NIMBYism. NIMBYism has been studied in the siting of prisons, waste-disposal, windmills, and many other types of facilities which provide public good but local bads. NIMBY has also been documented in a mining context by Badera (2014); Bloodworth *et al.* (2009); Drew *et al.* (2002); He (2006); Martinez-Alier (2001); Menegaki & Kaliampakos (2014); Pelekasi *et al.* (2012); and Avcı *et al.* (2010), for example.

Growing NIMBY concerns on the part of mineral resource developers has led many to seek not only the formal permits and licenses required for their operations from local, state, and federal governments, but also an informal or "social license" to operate (SLO) from community stakeholders (Owen & Kemp, 2013). The SLO is an informal agreement between the resource development firm and the community which may include provisions on how the benefits and costs (internal and external) will be distributed. Because of their informal nature, a SLO is easily revocable and therefore must be modified as the preferences of the community and the nature of the mine change. Much of the past literature on social licensing in mining has focused on identifying the nature of the social license, as in Boutilier & Thomson (2011) or identifying the determinants of SLO using a limited number of case studies as in Campbell & Roberts (2010); Moffat & Zhang (2014); and Prno (2013). A related literature describes the consequences of an ignored or poorly managed SLO. Davis & Franks (2014) provide an informative study of 50 global cases of community tactics used against mining when the SLO is poorly managed. More extreme cases of violence resulting in injury and death are not unprecedented.

The purpose of this paper is to empirically estimate the impact of environmental preferences and SLO on mining firms and determine whether this impact varies by political jurisdictions. Specifically, I test whether mines close sooner in communities with stronger preferences for environmental quality. It is likely difficult or costly for mines to directly observe the preferences of their communities, therefore I assume that they can infer information about these preferences through the way their federal Congressional representatives vote on environmental legislation. The empirical methodology employs a survival model and an instrumental variable (IV) strategy to econometrically estimate the impact of environmental preferences inferred through voting on mine closure rates.

In this paper, I make several contributions to the literature on NIMBYism and SLO in the mining context. Past studies on SLO in mining tend to use case study methods and focus on the efficacy of various social licensing approaches that mines employ (Campbell & Roberts, 2010; Prno, 2013). This paper uses a large sample and empirical methods to ask a different question, how do community preferences affect mining firms' behavior? Both mining SLO and broader NIMBY literature emphasize the project development stage and facility siting. The welfare implications associated with NIMBYism and SLO are different for operating mines, given sunk fixed private and social costs. This paper focuses on operating mines and the decision to permanently close. Finally, I test whether community environmental preferences are channeled through state or federal policy; past literature tends to focus on protests and civil resistance.

The results of the empirical model show that mines shorten their life in response to increases in their representative's environmental voting record, with the magnitude of response depending on the state's political control. Generally, the effect of statewide environmental preferences has a larger impact than local preferences. Specifically, a standard deviation increase about the mean of statewide green voting (about a 30 percentage point increase in green voting) leads mines to close between 1.1 to 1.3 times faster, whereas the local preference effect is smaller and not robust to model specification. The model is extended by assessing how environmental preferences are channeled to mine closure through federal or state policy. While federal policy is found to be a weak channel for preferences, mines are responsive to statewide preferences channeled through state policy. Finally, mines are also responsive to more local preferences which might be channeled through civil resistance or procedural action. These results confirm the importance of environmental preferences and social license to operate in mining, and also highlights the role of state governments in providing a channel for legislative action. When this channel becomes less effective due to split party control of the state legislature, local preferences become particularly important.

The remainder of the paper is divided into five subsections. subsection 4.1 presents a theoretical framework that illustrates how increased costs from SLO activities result in faster mine closure. subsection 4.2 presents the empirical model, the IV strategy to address endogeneity, and the data used in the analysis. In subsection 4.3, the empirical results are discussed and checked for robustness to model specification. subsection 4.4 discusses the implications for welfare of the empirical results and potential for future work. subsection 4.5 contains concluding remarks.

4.1 Theoretical Framework: The Impact of Environmental Preferences on Firm Behavior

In this subsection, I present a simple model to illustrate the impact of environmental preferences on extractive firms. The framework and notation is drawn from a model of non-renewable firm optimization with reserve-dependent costs described in Conrad (2010). I extend the model to the case of additional costs incurred from social licensing activities. The model illustrates how increased costs from social licensing activities shorten mine lives.

Consider a competitive mining firm operating in a particular community. The mine owns a stock of resource[25] R which they will extract from in each discrete period t. The firm's profit maximization problem is described by

$$\begin{gathered} \text{Maximize} \sum_{t=0}^{T} \pi_t = \sum_{t=0}^{T} \rho^t [P q_t - \frac{c q_t}{R_t}] \\ \text{Subject to } R_{t+1} - R_t = -q_t \quad \forall\ t \end{gathered} \tag{4.1}$$

where $P > 0$ is the exogenous market price, q_t is contemporaneous extraction, $c > 0$ is variable production cost, $1 > \rho > 0$ is a discount factor, and T is the mine's endogenous terminal time. In addition to the standard costs of wages, rents, and consumables, the variable production cost c also includes "protest" from the community. Protest is a generic term referring to any activity a community engages in to express their preferences that is also costly to the mine. Protest might include vandalism, blockade, or violence, appeals to regulators or policy makers, litigation, or public relations campaigns. The nature and frequency of these actions are studied more completely by Davis & Franks (2014). Protests are a response to the environmental damages of mining. Environmental damages and externalities include noise, dust, aesthetic losses, large truck traffic, acid mine drainage and other water pollution, for example. Communities with stronger preferences for higher environmental quality may engage in protests that are more costly to a mine. For simplicity, I assume environmental preferences have a proportional relationship with protest cost such that $\alpha Prefs = Protest$, where $Prefs$ is some measure of community preferences of environmental quality, α is a cost scaling term, and $Protests$ represent the cost inured by the mine from community protests. A mine's variable costs, c, is the sum of wages, rents, and consumables (generically w here),

[25]The term resource here is used in the non-technical sense, i.e. they are not necessarily compliant with financial reporting standards.

and protest costs.

$$c = w + Protest = w + \alpha Prefs \tag{4.2}$$

The producer's Lagrangian function is

$$L = \sum_{t=0}^{T} \rho^t [Pq_t - \frac{cq_t}{R_t} + \rho\lambda_{t+1}(R_t - q_t - R_{t+1})] \tag{4.3}$$

Because the Lagrangian is linear in q_t, the optimal solution will take an "all or nothing" outcome. The level of production either equals some level of fixed capacity or the mine extracts nothing. As mines are typically characterized by notable economies of scale, but a fixed capacity constraint, the linear profit function and Lagrangian are reasonable approximations of real firm behavior. From the Lagranian, a switching function can be defined to determine which level of output the mine should extract. Assuming $q_{capacity} > q_t > 0$, the mine's switching function can be derived from the first order conditions $\partial L/\partial q_t = 0$

$$\sigma_t \equiv P - \frac{c}{R_t} - \rho\lambda_{t+1} \tag{4.4}$$

From the switching function, a mine's optimal production quantity, q_t^*, is

$$q_t^* = \begin{cases} = 0, & \text{if } \sigma_t \leq 0 \\ = q_{capacity}, & \text{if } \sigma_t > 0 \end{cases} \tag{4.5}$$

At the terminal time, T, some portion of the resources may be un-profitable to extract in period $T+1$. This quantity of resources left un-extracted, R_T, can be solved by Equation 4.4, assuming that the producer is indifferent between operating and shutting down in the final period $\sigma_T = 0$ and the user cost (shadow price) of the resource is zero, $\lambda_{T+1} = 0$. These assumptions lead to

$$R_T = \frac{c}{P} \tag{4.6}$$

R_T represents quantity of resource that is left un-extracted (abandoned) in the ground when the mine closes.

From the switching function in Equation 4.4, a mine will operate at capacity unless the marginal extraction cost plus the discounted user cost exceeds the price. The discrete nature of optimal production means that mines will not respond to marginal changes in $Prefs$ through marginal changes in annual output q_t. However, the terminal time T will be impacted at the margin by changes in $Prefs$, making this effect more empirically identifiable. To solve for the optimal terminal time, T, assume that it is profitable to extract in every period such that $\sigma_t > 0 \; \forall \; t < T$ for levels of the resource greater than the abandoned quantities ($R_t > R_T$).

$$T = \frac{R_0 - c/P}{q_{capacity}} - 1 = \frac{R_0 - (w + \alpha Pref)/P}{q_{capacity}} - 1 \tag{4.7}$$

From Equation 4.7, a mine's life T is increasing in initial resources $\partial T/\partial R_0 > 0$, decreasing in costs $\partial T/\partial c < 0$, increasing in price $\partial T/\partial P > 0$, and deceasing in capacity $\partial T/\partial q_{capacity} < 0$. Most importantly, an increase in community preferences for environmental quality will lead to a reduction in the mine's life.

A complication for mining firms, and important motivation for the empirical strategy, is that direct observation of $Prefs$ is likely impractical. Instead, mines might instead make inferences about $Prefs$ by observation the voting behavior of an elected government representative, $GreenVote$. While it is unlikely that $Prefs$ and $GreenVote$ are exactly equal, I will assume that there is some positive relationship between them such that $f(\text{Prefs,GreenVote}) = 0, \delta\text{GreenVote}/\delta\text{Prefs} > 0$.

4.2 Empirical Strategy and Data

This subsection describes the empirical model used to test the effect of inferred environmental preferences on mine closures. First, the Cox Proportional Hazard model and assumptions are described. Second, subsection 4.2.2 discusses the instrumental variable strategy that is used to address endogeneity. subsection 4.2.3 argues for the use of the chosen instrument. The forth subsubsubsection, 4.2.4, identifies the sources of data used in the analysis and provides summary statistics and figures.

4.2.1 Description of Empirical Model

The impact of the inferred environmental preferences is tested using a Cox proportional hazard (Cox PH) model. The time-to-event nature of a mine closure decision makes the survival class of models an appropriate framework for the analysis. The Cox PH model offers the specific benefit of readily incorporating covariates, allowing the baseline hazard function to be flexibly estimated, and the inclusion of censored observations. The Cox PH model takes the general form shown in Equation 4.8.

$$h(t, X) = h_0(t)exp(\sum_i \beta_i X_i) \tag{4.8}$$

where $h(t, X)$ represents the hazard rate, the probability that a mine will close after a given number of years t, $h_0(t)$ is the unspecified baseline hazard function, and X_i are the covariates which explain shifts in the baseline hazard rate. Covariates are assumed independent of the baseline hazard function, $E(h_0(t)|X) = h_0(t)$. The model is estimated using maximum likelihood. A more explicit model representation is shown in Equation 4.9.

$$h_i(t, X) = h_0(t)exp(\beta_1 \widetilde{Pref}_i^{Local} + \beta_2 \widetilde{Pref}_i^{State} + \beta_3 \frac{Price_i^{Close}}{Price_i^{Open}} + \beta_4 X_i) \tag{4.9}$$

where $\widetilde{Pref}_i^{Local}$ is a mine's inference about local preferences $Pref_i^{Local}$ of the local environmental preferences of an area surrounding mine i in the year mine i closes or is censored[26], $\widetilde{Pref}_i^{State}$ is inferred statewide environmental preferences in the year of closure or censor, and $\frac{Price_i^{Close}}{Price_i^{Open}}$ is a ratio measuring the relative price of the primary commodity extracted by mine i in closing year to the price of the commodity in the mine's opening year. X_i represents a vector of additional mine, county, state, and time control variables.

Of interest are the coefficients β_1 and β_2, the effect local and state environmental preferences have on mine closure rates. As described in subsection 4.1, mines are unlikely to be able to directly observe $Pref_i$, and instead use the voting behavior of community representatives to make inferences about $Pref_i$. I use US Congress roll-call votes on environmental legislation, which has been used as proxy for environmental preferences in many past stud-

[26]Censoring in the study occurs in at the end of 2014.

ies (Ferraro *et al.*, 2007; Gray & Shadbegian, 2004; Kahn, 2007; Sigman, 2005; Simcoe & Toffel, 2014). $Pref_i^{State}$, measures state level voting by using an average of a state's two US Senator's green votes, while more local preferences, $Pref_i^{Local}$, measures the votes cast by members of the US House of Representatives.[27] Roll-call voting data come from the League of Conservation Voters (LCV). LCV identifies not only which votes are relevant for the organization's stakeholders, but also what constitutes a pro-environmental "green" vote, or anti-environmental "brown" vote. For a given vote, legislators can receive a LCV score of 1, NA, or 0. A score of 1 reflects a green vote, an NA score reflects an excused absence (e.g. legislator was sick), and a score of 0 is given for a brown anti-environmental vote or unexcused missed vote.

4.2.2 Identification Strategy

The estimated effects of inferred environmental preferences, β_1 and β_2, on mine closures may be biased by important unobservables correlated with environmental preferences or the effect of reverse causality. Three important unobservables are the size of the deposit, the quality of the deposit, and the size of the mine, all of which are plausibly correlated with community environmental preferences. For example, if exceptional resource quality in a particular region allows mines to remain open longer, this resource quality may also shape the environmental preferences of the area.[28] Communities may also strengthen or weaken their environmental preferences when mines begins to consider shutdown, blurring the causal direction of the effect. For these reasons, I will employ a two-stage, instrumental variables approach to exploit a unique feature of the environmental preference proxy; federal

[27] In 2014, the last year of the sample period, 7 US states had only one US House Representative. For these states, local and statewide preferences are equivalent. However, many of these same states near the beginning of the sample time period had more than one Representative (See North and South Dakota, and Montana in Figure 4.1 panel (a).) While other sub-state measures environmental preferences were considered, either data are not available for the entire US or available for the entire sample period. Finally, subsection 4.2.2 describes how federal environmental voting has a unique set of characteristics that are exploited to identify a causal effect.

[28] The omitted and unobservable effect of resource quality may be time invariant, but it cannot be accounted for with a fixed effect. Mines are only observed to permanently close once, therefore the analysis is of a repeated cross-subsection. Further, resource discovery and characterization is time time dependent, and a fixed effect will not capture this.

green voting takes place far away from the mine. I instrument a given legislator's green voting behavior using the leave-out mean of the green voting behavior of the legislator's congressional office-mates. In other words, how do other legislators who work nearby vote on a given piece of legislation? The first-stage regression, estimated using ordinary least squares, is shown in Equation 4.10.

$$GreenVote_{r,v} = \beta_0 + \beta_1 \frac{\sum_q GreenVote_{q \neq r,v}}{R_r - 1} + State_r + Year_v + \epsilon_{r,v} \tag{4.10}$$

where $GreenVote_{r,v}$ is a binary variable which equals 1 if legislator r votes green on roll-call vote v and 0 if they vote "brown". $\frac{\sum_q GreenVote_{q \neq r,v}}{R_r - 1}$ is the leave-out mean term. The numerator is the sum over all other votes casts on roll call vote v by the legislators q which share office space with legislator r. I define shared office space to be an office floor in a given congressional office building. In the denominator, R_r is the total number of legislators that share office space with legislator r, subtracting 1 because r is left out of the mean calculation. $State_r$ is a state fixed effect, to account for general voting tendencies. $Year_v$ is a year fixed effect for the vote. This variable is only included when a year fixed effect is included in the second stage regression.

Because two-stage least squares is biased when the second stage is non-linear, two-stage residual inclusion is preferred for estimation of the Cox PH model (Terza *et al.*, 2008). Additionally, the first stage is estimated at the vote level to exploit high resolution data, with between 10-50 votes per year, while the second stage mine closure equation is estimated on an annual basis. To correct the discrepancy, the raw first stage levels values are aggregated from the vote level measure $GreenVote_{r,v}$ to the annual measure, $\widetilde{Pref}_i$, using a simple average. The first stage residuals, $\epsilon_{r,v}$, are averaged in a similar fashion to become $\widehat{\epsilon_i}$. The averaging makes the analysis a mixed two-stage model, similar to the linear model described in Dhrymes & Lleras-Muney (2006). Equation 4.11 shows the second stage model to be estimated, with the noted corrections.

$$h_i(t,X) = h_0(t) exp(\beta_1 \widetilde{Pref}_i^{Local} + \beta_2 \widetilde{Pref}_i^{State} + \beta_3 \frac{Price_i^{Close}}{Price_i^{Open}} + \beta_4 X_i + \hat{\epsilon}_i^{Local} + \hat{\epsilon}_i^{State}) \quad (4.11)$$

where $\widetilde{Pref}_i^{Local}$, and $\widetilde{Pref}_i^{State}$ are the averaged levels values of $GreenVote$ at the local and state levels, respectively. $\hat{\epsilon}_i^{Local}$ are the residuals for the US House votes from Equation 4.10, aggregated annually at the year mine i closes, and $\hat{\epsilon}_i^{State}$ are the US Senate vote residuals aggregated by state and year.

4.2.3 Justification for Instrument

The leave-out mean instrument has many advantages over potential alternatives. Because most federal legislators work hundreds of miles away from the mines they represent, many variables specific to conditions in Washington DC should be independent from mine operations, except through the effect of interest (preferences). These variables include measures of the external environmental (e.g. weather, air pollution), and characteristics of particular pieces of legislation (e.g. sweeping bi-partisan support). While spurious common shocks to voting behavior provide a plausibly exogenous source of time variation, they do not allow for differentiating an effect cross-subsectionally among congressional districts. For cross-subsectional variation, the instrument must be legislator-specific, but in order to satisfy excludability, also unrelated to conditions in the legislator's district. The excludability condition makes legislator characteristics like party affiliation, age, or gender arguably unsuitable. A variable that satisfies excludability and varies cross-subsectionally (and over time) by legislator is the location of a legislator's office in Washington DC.

In addition to capturing spurious common shocks in voting, the leave-out mean instrument potentially captures peer effects. Through their interactions, legislators might intentionally or unintentionally sway their colleagues' opinions. While peer effects are not a requirement for valid identification of the environmental preference effect on mine closures, they offer a more causal and intuitive justification for the instrument than spurious common shocks. Legislative peer effects on voting are debated in the political science literature. Kingdon (1989) argues for the importance of interpersonal ties in voting behavior, and more applicable to my application, Caldeira & Patterson (1987); Young (1966); and Fowler (2006) argue for legislative peer effects and relationships based on spatial proximity. Masket (2008) finds empirical evidence for legislative peer effects when legislators share nearby desks, but Rogowski & Sinclair (2012) using an IV strategy to account for endogenous selection finds no meaningful casual effect. Therefore, peer effects are a possible explanation for first stage correlation, but the only (unverifiable) requirement in the present case is that the voting behavior of other legislators on a particular legislator's floor be otherwise uncorrelated with mine closures in that legislator's jurisdiction.

One potential issue with the shared office-space strategy is that legislators may choose to cluster themselves into particular groups because they tend to vote in a similar way. While this selection issue would need to hold for environmental votes specifically in addition to voting tendencies more generally to pose a threat to identification, it is worth describing the congressional office selection process to alleviate this as a concern. Today six congressional office buildings host members and their staff.[29] Three buildings on the north side of the US Capital are reserved for members of the US Senate, and three on the south side for members of the US House. Each of these buildings has between 3 to 5 office floors (not including basement space, which under normal circumstances is not occupied by legislators). In turn, each of these floors houses approximately 10 to 20 legislators (depending on the building).

The congressional office selection process works differently for returning and junior members, and for the US House and US Senate. First term members of the US House enter a lottery which determines the order in which office selection occurs. House members then have several hours to tour their prospective choices before making a selection. The system for first term Senators is based more in tradition and gives selection priority to some states over others. Returning legislators in either chamber are given selection based seniority.

[29]Prior to 1982, their were only two US Senate office buildings, but this historical fact is readily handled by the identification design.

According to Nocera (2012), Miller (2014), and Fahrenthold (2010), legislators have simple objectives in choosing offices. Members are looking to maximize space for themselves and staffers, for views of the Capital, to be near elevators, for quick access to the Capital, and to have access to public transit. Generally speaking, most members have similar notions about which are the most, and least, desirable options. The implication of this pre-established ranking is that seniority or lottery number matter more than variables which could introduce selection issues, most importantly party affiliation or the legislator's state. Rogowski & Sinclair (2012), studying legislative peer effects on voting based on office proximity, find that party affiliation and home state are not predictive of first-term office selection. Instead, in office lottery number order, members tend to "follow" one another. This behavior is consistent with the pre-established ranking based on fixed office characteristics. Apart from the discussed selection issues, identification is potentially threatened by three factors. First, macro-economic forces my drive overall congressional voting behavior and mine closures. All legislators may vote greener when unemployment is low or financial markets are performing well.[30] In many model specifications, control variables are added to the model to account for this potential issue. County unemployment, metal prices, time trends, and time fixed effects are used in the second stage of the model to account for the potential economic component of correlated green voting behavior. Second, mines may respond to overall congressional voting behavior in addition to the behavior of their particular legislators. However, as shown in subsection 4.3.1, mines do not appear to respond to voting differently when those votes lead to federal policy that passes versus when it fails. The test suggests that mines are responding primarily to the voting behavior of their representative, and not the behavior of Congress at large. Third and finally, if constituents (for example, mine representatives) from a legislator's district come to Washington DC to advocate for or against particular environmental issues and capitalize on the visit by also visiting other legislators' nearby offices, this spill-over will re-introduce simultaneity and violate the excludability of instrument. While the bias from

[30]The data are not necessarily consistent with macro-economic drivers of overall voting behavior. Instead there is a clear trend of increasing partisanship in environmental voting, producing a flat trend overall.

office visit spillovers is likely the smallest of the three identified threats, there is no direct test for it given available data. Instead, an alternative set of exogenous instruments is tested. These alternative IV results are shown in Table 4.6 of subsection 4.3.

4.2.4 Data

Tables Table 4.1 and Table 4.2 present summary statistics for the data. Table 4.1 reflects the statistics for the full sample, while Table 4.2 breaks out the mean and standard deviation for the lowest and highest 25% of US House districts based on green voting scores. As shown in Table 4.1, the average mine in the sample opens in 1988 and closes 1996, having an average life of 8.65 years. The variance of mine life is notable, with some mines as short-lived as 1 year, and others remaining open for several decades. Table 4.2 provides a stylized preview of main result. The mines located in US House congressional districts with highest rates of green voting close, on average, after 8.72 years, where the mines located in the districts with the lowest rates of green voting close, on average, after 11.57.

These data come from a variety of sources. The primary dataset is drawn from the Mine Safety and Health Administration (MSHA). These data provide information to construct the dependent variable: the mine's opening year, closing year, and current status. Opening year is the first year a mine enters the MSHA system. Closing year is the year the mine's status was entered as "Abandoned" or "Abandoned and Sealed." Mines with a currently operating status are censored in 2014. Mines with any other status are dropped from the sample. The MSHA data also includes information on a mine's commodity (used to match commodity specific pricing data), and mine type (surface, underground). Where information on a mine's opening year or geospatial information was missing, and when possible, data from the US Geological Survey's Mineral Resource Data System was supplemented. For non-coal materials, commodity prices come from the USGS Series 140, which measures average import prices by year. For coal, price data come from the Energy Information Administration. The analysis uses a ratio of commodity price in the closing year to prices in the opening year, which provides a convenient normalization to a single price variable across various commodities and captures intertemporal effects in a time-invariant measure. For commodities with no USGS match, an average of all price ratios was used to construct an index measure.

The independent variable of interest, green voting behavior, is drawn from data prepared by the League of Conservation Voters. County level unemployment comes from the US Bureau of Labor Statistics (BLS) Local Area Unemployment Statistics. County population data come from the US Census Bureau. Variables are added to control for the effect location near a stream or lake. Water is an important input to many mining operations, but also a frequent source of environmental concern. To better account for the ambiguous direction of this effect, a mine's distance to water is interacted with a long-run measure of drought conditions, measured with the Palmer Drought Z Index. A mine close to a temporarily low water body may be subject to the same environmental scrutiny as a mine located near a higher water body, while being unable to enjoy the same surface water access. Palmer Drought Z Index data come from the National Oceanic and Atmospheric Administration. Distance to Water, calculated using the standard Haversine method, measures the distance (in kilometers) from a mine to the nearest stream or lake. Stream and lake shapefiles come from the USGS. While omitted from Table 4.1, a categorical variable indicating the conservation status of the land is also included in some regression specifications as a control. These spatial data come from the Conservation Biology Institute's Protected Areas Database of the US.

Figure 4.1 shows the spatial and temporal variation of environmental preferences as measured by US House environmental votes overlayed with the location of the mines operating in a given congressional session. Across space, variation is visible in the locations mines are sited, with coal mines prominent in the Appalachian region of the United States. Mines located in the same state can be subject to considerable heterogeneity in local preferences, as visible in the figures for New Mexico and Oregon. Two important trends are notable over time: a decline in the number of operating mines, and an increase in the polarization of preferences, with a particularly stark difference between the country's interior and coasts.

Table 4.1: Summary Statistics

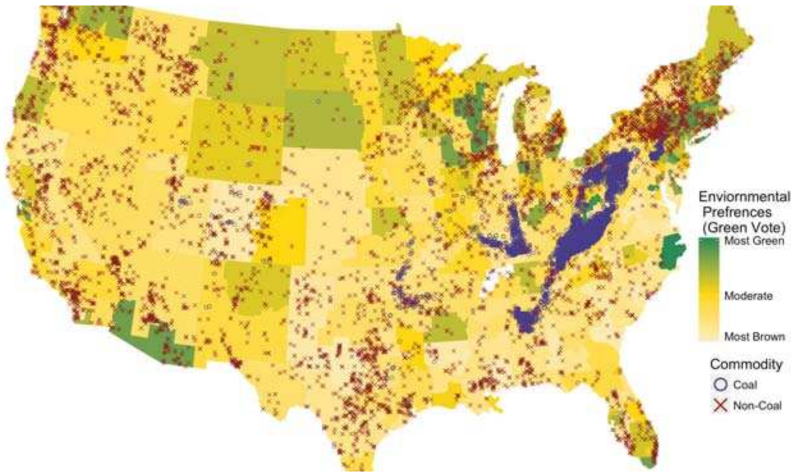
Variable	N	Mean	St. Dev.	Min	Max
Mine Open Year	18,650	1988	10.514	1966	2013
TimMine Close Year	18,650	1996	11.702	1975	2014
Mine Life (year)	18,650	8.653	7.886	1	44
Coal Mine (1=Yes)	18,650	0.592	0.492	0	1
Underground Mine (1=Yes)	18,650	0.266	0.442	0	1
ln Price Ratio (Close Yr/Open Yr)	18,629	0.280	1.888	-13.1	15.53
House Green Voting (0-100% Green)	18,650	36.216	29.571	0	100
Senate Green Voting (0-100% Green)	18,650	39.225	28.669	0	100
County Unemployment rate (%)	18,391	9.57	4.539	1.1	39.1
County Population (000's)	18,650	161.8	538.3	0.262	10,117
Palmer Drought Index	18,539	0.077	1.843	-7.31	7.32
Distance to Water (km)	18,538	16.22	14.38	0.001	99.4

Time-dependent variables (voting, unemployment, population, and drought index) are measured in the year of mine closure.

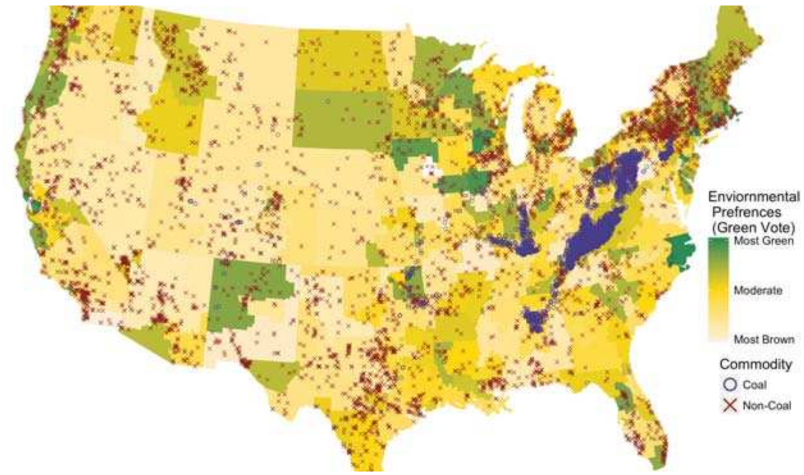
Table 4.2: Summary Statistics by House Green Voting

	House Green Voting Percentile					
	Full Sample		Bottom 25%		Top 25%	
	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.
Mine Open Year	1987.7	(10.51)	1993.7	(10.4)	1988.0	(10.31)
Mine Close Year	1996.3	(11.7)	2005.3	(8.47)	1996.8	(11.22)
Mine Life (years)	8.65	(7.89)	11.57	(9.3)	8.72	(7.6)
Coal Mine (1=Yes)	0.59	(0.49)	0.42	(0.49)	0.55	(0.5)
Underground Mine (1=Yes)	0.27	(0.44)	0.18	(0.38)	0.26	(0.44)
ln Price Ratio (Close/Open)	0.28	(1.89)	0.85	(2.96)	0.14	(1.5)
House Voting	36.22	(29.57)	3.12	(2.84)	76.68	(13.2)
Senate Voting	39.23	(28.67)	25.41	(30.88)	52.74	(27.61)
County Unemployment rate (%)	9.57	(4.54)	7.35	(2.98)	9.86	(5.22)
County Population (000's)	161.80	(538.33)	182.31	(563.91)	223.42	(727.02)
Palmer Drought Index	0.08	(1.84)	-0.50	(2.04)	0.29	(1.86)
Distance to Water (km)	16.22	(14.38)	16.61	(15.56)	16.70	(13.94)

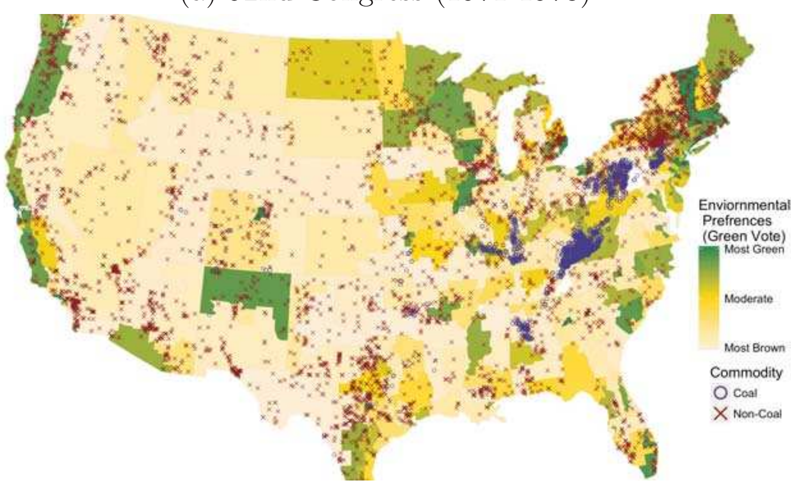
Time-dependent variables (voting, unemployment, population, and drought index) are measured in the year of mine closure.



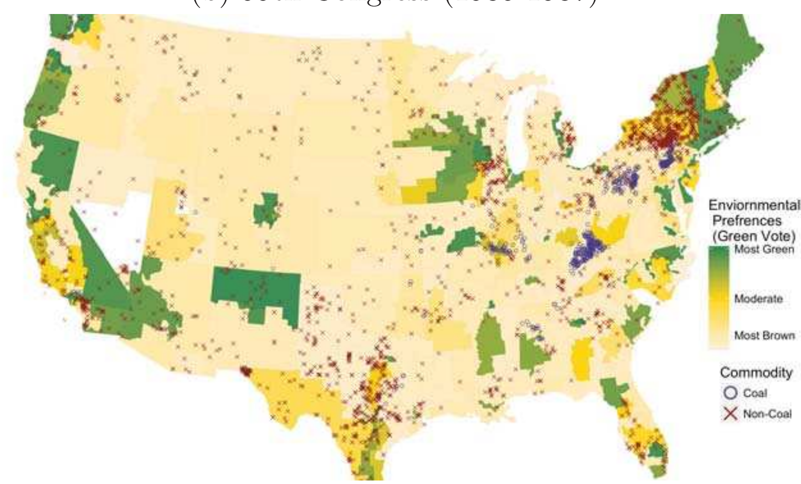
(a) 92nd Congress (1971-1973)



(b) 99th Congress (1985-1987)



(c) 106th Congress (1999-2001)



(d) 112th and 113th Congresses (2011-2015)

Figure 4.1: Local Environmental Preferences (US House Green Voting) & Operating Mines (by commodity)

Source: Author's representation using data from the US Mine Safety and Health Administration, the League of Conservation Voters and congressional district shapefiles from Lewis *et al.* (2013). Areas with missing vote data are shown in white.

While partisanship in environmental voting has increased notably over the study period for both chambers of the US Congress, party affiliation alone is not completely predictive of environmental voting behavior.[31] This trend is highlighted in Figure 4.2. Figure 4.2 also shows a close, but imperfect, relationship between US House and US Senate voting behavior.

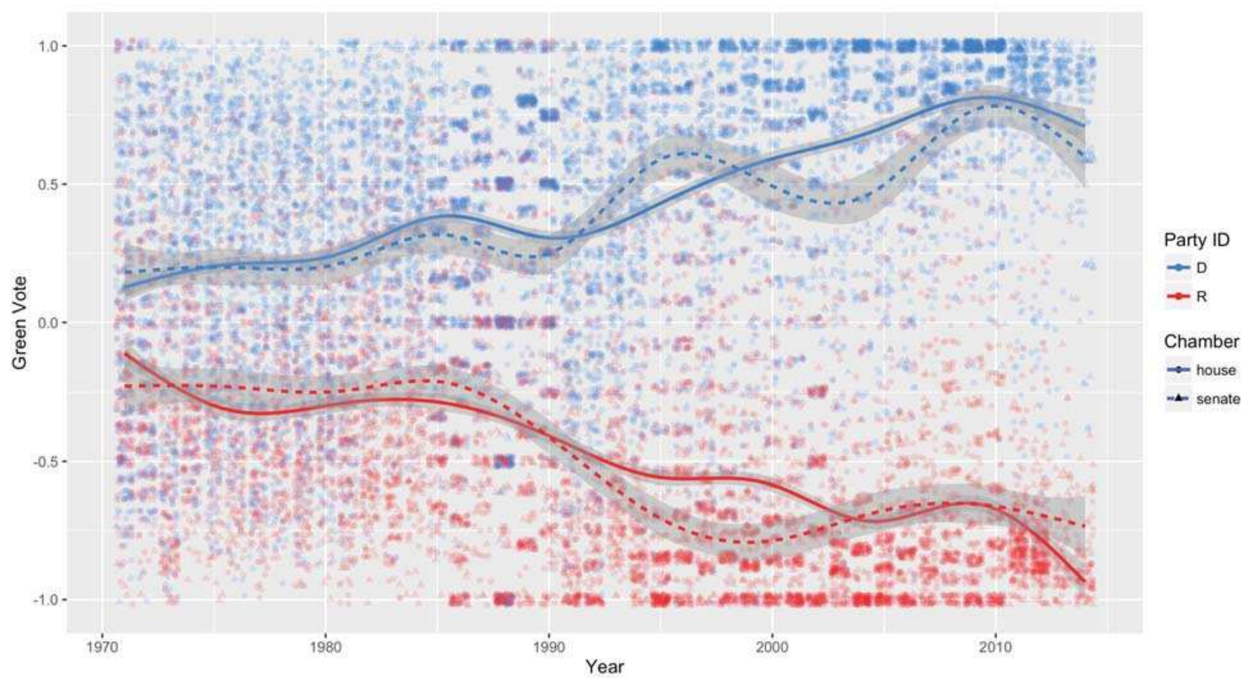


Figure 4.2: Annual Legislator Green Voting Scores, by Chamber and Party, 1971 - 2014

Source: Author's representation using data from the League of Conservation Voters. Solid and dashed lines are smoothed values for the US House and US Senate, respectively, and are estimated using a generalized additive model. Grey bands indicate 95% confidence intervals.

4.3 Results

This subsection presents estimates on the effect of inferred environmental preferences on mine closure rates and presents evidence of the importance of state policy in channeling

[31] The relationship between party affiliation and environmental voting exhibits an R^2 value of approximately 0.2. Even when interacted with a time trend to account for increasing partisanship, the R^2 only improves to 0.3.

environmental preferences into outcomes for the mine.

Table 4.3 presents the regression results for 2SRI Cox PH model across seven model specifications. Results are shown as exponentiated Cox PH coefficients, interpreted as hazard ratios, the ratio of closure rates of two mines that differ by one unit of the independent variable. Coefficients greater than 1 indicate mines close at a faster rate, while coefficients less than 1 indicate minces close at a slower rate given a one unit increase in the right-hand side variable.

The expected result for both state and local preferences is an effect greater than 1. Across the seven model specifications in Table 4.3 the statewide effect varies between 1.002 to 1.016 and is significantly greater than 1. Conversely, the coefficient on the local preference effect is inconsistent in significance and magnitude (in difference from unity) across specifications. As the model is extended in subsection 4.3.1, the result for the local preference effect is more consistent with expectations.

Standard errors are bootstrapped using 1,000 replications. To account for spatial error clustering, three stratas were tested at progressively higher levels of aggregation: county, congressional district, and state. The state clustering produced the largest standard errors, so this stratification was chosen.

Results for the naive model with no first-stage residuals are shown in specification (1) in Table 4.3, and the simplest model with residuals added is shown in specification (2). The difference in these results shows a divergent bias between the local and state preferences effects, where local effects are biased upward and statewide effects are biased downward. Specification (3) adds a state dummy variable, a variable that is co-linear with the cross-subsectional component of statewide preferences. Including the state dummy increases the local and statewide effect, making the local effect not statistically different from unity. Specifications (4) and (5) add a time of open year fixed effect or time of closure year fixed effect, respectively.[32] Including the closure year effect has a much larger (attenuating) impact on

[32] I omit a specification that includes opening and closure time fixed effects. The optimization does not converge when both effects are included in the same model as they jointly define the baseline hazard

the estimates than opening year effect, and causes the coefficient for commodity price to take a counter-intuitive >1 effect, indicating that increasing prices leads to faster mine closure (which would be consistent with a model of mine production with no output capacity constraint). The attenuation from including closure year effects is intuitive as the voting effect is also measured in the year of mine closure. Finally, the addition of mine, county, and regional control variables in specifications (6) and (7) has little impact on the estimated green voting effect.

The extended time scope of the analysis introduces the possibility of changing policy and macroeconomic conditions confounding the results. While the open and closure time fixed effects should mitigate these effects to some degree, as an additional check, I also estimate the model for time-subsets of the data, dropping mines that open in earlier years decade-wise. These results are presented in Table 4.4. To simplify presentation, mine and county controls are omitted from these tables (and following tables). The decade-wise subsets show mines becoming more responsive to the statewide vote effect as they open more recently, while again the response to local preferences is not robust to these subsets. I also estimate models for state by open-year and state by closure-year time trends in order to account for broader movements in state attitudes and policy over time. These results are presented in Table 4.5, and are generally consistent with the previous results discussed, with statewide preferences being positive and significantly related to closures, but local effects being (counter-intuitively) negative and significantly related to closures. In both trend specifications, the state preference effect is approximately double the magnitude of the local prefrence effect.

Another concern for the analysis are the threats to identification noted in subsection 4.2.3, particularly the concern of spillovers from an office visit from a constituent. An alternative set of first stage instruments was tested to address these issues. The alternative instrument set does not involve a spurious regression, instead using Washington DC weather

function.

Table 4.3: Regression Results for Cox Proportional Hazard Model of Mine Closure Response to Environmental Preferences

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				Hazard Rate			
Local (US House) Green Vote	1.001***	0.984***	0.999	0.997*	1.001	0.995***	1.001
	(0.000)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)
Statewide (US Senate) Green Vote	1.002***	1.006***	1.013***	1.016***	1.003**	1.011***	1.003**
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
ln Commodity Price Ratio			0.867***	0.862***	1.237***	0.858***	1.215***
			(0.008)	(0.009)	(0.024)	(0.010)	(0.023)
Commodity: Coal						1	1
						(0.000)	(0.000)
Commodity: Non-Coal						0.717***	1.657***
						(0.027)	(0.061)
Type: Facility						1	1
						(0.000)	(0.000)
Type: Surface						1.230***	1.218***
						(0.039)	(0.034)
Type: Underground						1.124***	0.990
						(0.036)	(0.028)
lnDistance to Water (m)						0.977***	1.004
						(0.006)	(0.006)
Palmer Drought Index						1.040	0.994
						(0.029)	(0.028)
lnDistance to Water x Palmer Drought						1.000	1.001
						(0.003)	(0.003)
Unemployment Rate (%)						1.062***	1.000
						(0.002)	(0.002)
lnPopulation						1.155	1.081
						(0.099)	(0.084)
$(\text{lnPopulation})^2$						0.993	0.996
						(0.004)	(0.003)
Land: Federal Land						1	1
						(0.000)	(0.000)
Land: Joint Ownership						0.229	1.010
						(2.517)	(10.854)
Land: Local Land						0.811	0.959
						(0.192)	(0.211)
Land: Native American Land						0.645***	0.843
						(0.082)	(0.127)
Land: Private Conservation Land						0.848	0.897
						(0.373)	(0.239)
Land: Private Land						0.808***	0.954
						(0.041)	(0.043)
Land: State Land						0.841*	1.034
						(0.061)	(0.069)
State Effects	No	No	Yes	Yes	Yes	Yes	Yes
Closing Time Fixed Effects	No	No	No	Open Yr	Close Yr	Open Yr	Close Yr
First Stage Residuals	No	Yes	Yes	Yes	Yes	Yes	Yes
N	18650	18650	18629	18629	18629	18222	18222
First Stage IV F-stat		15659	15659	15659	386	15659	386

Exponentiated coefficients; Bootstrapped standard errors in parentheses (State level stratification)

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4.4: Regression Results for Cox Proportional Hazard Model of Mine Closure Response to Environmental Preferences, Decade-wise Subset

	(1)	(2)	(3)	(4)
Open Year	$\geq$ 1970	$\geq$ 1980	$\geq$ 1990	$\geq$ 2000
	Hazard Rate			
Local (US House) Green Vote	0.996**	0.999	0.989***	0.995
	(0.001)	(0.001)	(0.002)	(0.003)
Statewide (US Senate) Green Vote	1.009***	1.012***	1.021***	1.030***
	(0.001)	(0.001)	(0.002)	(0.002)
ln Commodity Price Ratio	0.861***	0.850***	0.850***	0.822***
	(0.009)	(0.011)	(0.014)	(0.016)
State Effects	Yes	Yes	Yes	Yes
Mine & County Controls	Yes	Yes	Yes	Yes
First Stage Residuals	Yes	Yes	Yes	Yes
N	18220	13323	6429	3447
First Stage IV F-stat	433	399	419	350

Exponentiated coefficients
Bootstrapped standard errors in parentheses (State level stratification)
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4.5: Regression Results for Cox Proportional Hazard Model of Mine Closure Response to Environmental Preferences, State-time Trends

	(1)	(2)
	Hazard Rate	
Local (US House) Green Vote	0.994***	0.996**
	(0.001)	(0.001)
Statewide (US Senate) Green Vote	1.012***	1.009***
	(0.001)	(0.001)
ln Commodity Price Ratio	0.843***	0.921***
	(0.011)	(0.007)
State Effects	Yes	Yes
Time Trend	Open Yr	Close Yr
State-Time Trend	Open Yr	Close Yr
Mine & County Controls	Yes	Yes
First Stage Residuals	Yes	Yes
N	18222	18222
First Stage IV F-stat	15659	15659

Exponentiated coefficients; Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

(precipitation, average daily temperature, and high-low temperature spread) on the day of the vote (data from NOAA's National Centers for Environmental Information), the margin of the vote (from GovTrack),[33] an office-floor fixed effect, and office wing fixed effect.[34] The intuition behind using weather as an instrument is similar to the motivation of studies on weather and stock market behavior, as in (Saunders, 1993). Weather influences mood and optimism which in turn informs expectations about the future. These instruments were not used in the preferred model specification because, while they are not technically weak by conventional standards, the leave-out mean instrument is much stronger.

Table 4.6 presents the results of the alternative IVs strategy across four specifications of time effects. In this alternative specification, the local green voting effect becomes positive, but only significant in specification (2) with state-by-year of closure time trends. Both the local and statewide effect becomes insignificant in this alternative IV specification when closure year fixed effects are included.

Across all of the estimated models, the statewide preference hazard ratios are found to have the expected >1 effect, while the local effect hazard ratios do not. The magnitude (difference from 1) of the statewide hazard ratio is generally found to be larger than the magnitude of the local effect, implying mines are more responsive to state preferences. However, both the state and local hazard ratios are small relative to the impact of commodity prices. Looking at the hazard ratio alone under-represents the importance of inferred environmental preferences, as the variance in preferences is large. Another measure of the effect is to look at mine response to a standard deviation change in voting behavior around the mean. As shown in Table 4.1, statewide green voting and local green voting both have large standard deviations, 28.67 and 29.57, respectively. A standard deviation increase around the mean for statewide preferences is a change from voting green on 21% of roll-calls to 51% of roll-calls, and 25% to 54% for local preferences. Table 4.7 presents the relative marginal

[33] Vote margin is distinct from the peer effect because it measures the yes-no percent spread of the measure, regardless of whether the yes position is also the pro-environmental position or not.

[34] An office wing is defined as the cardinal direction side of the building the office is located on. For the H-shaped Rayburn building, intercardnal directions are used.

Table 4.6: Regression Results for Cox Proportional Hazard Model of Mine Closure Response to Environmental Preferences, Alternative IVs

	(1)	(2)	(3)	(4)
	Hazard Rate			
Local (US House) Green Vote	1.001	1.004***	1.000	1.001
	(0.001)	(0.001)	(0.001)	(0.001)
Statewide (US Senate) Green Vote	1.009***	1.004***	1.000	1.010***
	(0.001)	(0.001)	(0.001)	(0.001)
ln Commodity Price Ratio	0.841***	0.915***	1.207***	0.856***
	(0.011)	(0.008)	(0.023)	(0.010)
Mine & County Controls	Yes	Yes	Yes	Yes
State Effects	Yes	Yes	Yes	Yes
Opening Time Trend	Yes	No	No	No
Closure Time Trend	No	Yes	No	No
State Effects by Time Trend	Open Yr	Close Yr	No	No
Time Fixed Effects	No	No	Close	Open
First Stage Residuals (No Leave-Out-Mean IV)	Yes	Yes	Yes	Yes
N	18007	18007	18007	18007
First Stage IV F-stat	109	109	109	109

Exponentiated coefficients

Bootstrapped standard errors in parentheses (State level stratification)

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

effects for three specifications of time effects. The interpretation of these values is that for a one standard deviation increase about the mean, mines close X-times faster. So, for specification (3), with closure time fixed effects, a mine in a state with a green voting score of 51% will close 1.1 times faster than a mine in a state with a green voting score of 25%.

Table 4.7: Relative Mine Closure Rates for a Standard Deviation Increase Around the Mean of Green Voting

Time Fixed Effects	(1) No	(2) Open	(3) Close
Local (US House) Green Vote	0.84	1.24	1.02
Statewide (US Senate) Green Vote	1.27	1.34	1.1
Mine & County Controls	Yes	Yes	Yes
State Effects	Yes	Yes	Yes
Time Fixed Effects	No	Open	Close
First Stage Residuals	Yes	Yes	Yes

Because the social license to operate literature tends to focus on more local impacts and attitudes, these differentiated state and local effects are important for placing this paper into the context of the broader literature. subsection 4.3.1 tests mines' response to state policy and federal policy as a potential channel for state and local preferences.

4.3.1 Testing Federal & State Policy Mechanisms

While the general mean effects help to tell some of the story of mine response to community environmental preferences, uncovering the mechanisms through which firms are responding will add to a greater understanding of the social licensing effect. In this subsection, I test the hypotheses that mines respond to environmental preferences that are written into federal or state policy.

First, I test the for the possibility that mines are responding to federal policy created when their legislators vote on green or brown on environmental issues. Mines likely need a national social license, and federal policy is one way citizens modify their requirements for that license. However, past work on the the nature of a social license tends to describes SLO as manifesting in more informal ways. Regardless of this distinction, it is informative to determine if mines respond to preferences enacted in federal policy or by some other means. To this end, I conduct two falsification tests by modifying the first-stage voting sample. In the first test, federal votes which do not directly target mining are removed. Votes are considered "mining votes" and removed if the shorthand name used by the League of Conservation Voters to describe the vote includes "mine", or "mining". These names include "strip mining," "mine safety," "mining give-away," or "hardrock mining," to name a few. The second test removes those federal roll-calls from the first stage which did not achieve the necessary votes to pass the particular motion. The pass/failed threshold varies by the congressional chamber and the nature of the roll-call, but takes values of either 1/2, 2/3, or 3/5. Threshold data come from the website GovTrack.us. Where the required threshold data are unavailable, 1/2 is assumed for the US House. In the US Senate, higher thresholds are more common (2/3 or 3/5), and the midpoint threshold value of 55/100 is assumed where GovTrack data unavailable.

The results for the federal policy tests, with mining votes or passed votes removed, are presented in Table 4.8 and Table 4.9, respectively. These tables include reference specifications (Ref) with all first stage votes included for comparison. Results that show significant attenuation toward one when the mining votes are dropped or when passed votes are dropped indicate that mines are responding primary to federal policy. The results in Table 4.8 show no statistically significant difference between any one of the pairs of time specifications when mining votes are dropped from the sample. However mines may respond to other, more general, federal environmental policy, and so any votes that passed are dropped from the first stage sample to test for this more general response. For the results in Table 4.9, attenuation is present in only one test pair, the statewide green vote coefficient when closing year fixed effects are included in the model in specifications (5) and (6). In (6) the statewide effect becomes small and statistically not different from one at the 95% level (but is significantly different at the 90% level).

Table 4.8: Test for Federal Policy Effect, No Mining Votes in First Stage

Time Effects	Open Trend		Close Trend		Close Fixed		Open Fixed	
	Ref	No Mine	Ref	No Mine	Ref	No Mine	Ref	No Mine
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Local (US House) Green Vote	0.994***	0.995***	0.996**	0.996**	1.001	1.001	0.995***	0.995***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
Statewide (US Senate) Green Vote	1.012***	1.012***	1.009***	1.009***	1.003**	1.003**	1.011***	1.011***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
ln Commodity Price Ratio	0.843***	0.843***	0.921***	0.921***	1.215***	1.215***	0.858***	0.858***
	(0.011)	(0.011)	(0.007)	(0.008)	(0.023)	(0.023)	(0.010)	(0.010)
Mine & County Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Trend	Open Yr	Open Yr	Close Yr	Close Yr	No	No	No	No
State Effects by Time Trend	Open Yr	Open Yr	Close Yr	Close Yr	No	No	No	No
Time Fixed Effects	No	No	No	No	Close Yr	Close Yr	Open Yr	Open Yr
First Stage Mine Votes	Yes	No	Yes	No	Yes	No	Yes	No
N	18222	18222	18222	18222	18222	18222	18222	18222

Exponentiated coefficients

Bootstrapped standard errors in parentheses (State level stratification)

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Taken as a whole, the results in Table 4.8 and Table 4.9 provide evidence that mines are not responding only to federal environmental policy when closing. This leaves open the possibility that mines respond to local and state environmental preferences enacted through state policy, or that mines are responding to more conventional and direct SLO protests.

In the United States, states play an important role in permitting and regulating resource extraction. Mines may use *federal* voting behavior to make inference about how their communities may advocate for changes in *state* policy. This type of inference is likely to change based on the political composition of a mine's state legislature. Mines in communities with a Democratic state legislature may interpret green voting behavior on the part of federal legislators differently that those in states controlled by Republicans. I will exploit a particular situation where Republicans control one chamber in the state legislature and Democrats control the other to test for mine responsiveness to a state policy mechanism for environmental preferences. Specifically, I test the hypothesis that in states with split legislative control, mines will not be responsive to environmental preferences. If the legislature is split and

Table 4.9: Test for Federal Policy Effect, Only Failed Votes in First Stage

Time Effects	Open Trend		Close Trend		Close Fixed		Open Fixed	
	Ref	Fail	Ref	Fail	Ref	Fail	Ref	Fail
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Local (US House) Green Vote	0.994***	0.974***	0.996**	0.990***	1.001	1.001	0.995***	0.974***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
Statewide (US Senate) Green Vote	1.012***	1.016***	1.009***	1.006***	1.003**	1.002	1.011***	1.014***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
ln Commodity Price Ratio	0.843***	0.843***	0.921***	0.920***	1.215***	1.215***	0.858***	0.858***
	(0.011)	(0.011)	(0.007)	(0.007)	(0.023)	(0.023)	(0.010)	(0.010)
Mine & County Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Trend	Open Yr	Open Yr	Close Yr	Close Yr	No	No	No	No
State Effects by Time Trend	Open Yr	Open Yr	Close Yr	Close Yr	No	No	No	No
Time Fixed Effects	No	No	No	No	Close Yr	Close Yr	Open Yr	Open Yr
First Stage Incl. Passed Votes	Yes	No	Yes	No	Yes	No	Yes	No
N	18222	18221	18222	18221	18222	18221	18222	18221

Exponentiated coefficients
Bootstrapped standard errors in parentheses (State level stratification)
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

policy making is more difficult, mines may infer a low chance of state policy being passed. The split legislature has the effect of blocking the state policy channel for environmental preferences to be expressed. This hypothesis follows from a strain of political science literature which argues that the policy making process is less effective in legislatures with split party control. For empirical studies of this effect, see Bowling & Ferguson (2001) for the case of divided state legislatures, and Howell *et al.* (2000) for the federal Congress.[35]

The test specification for a state policy mechanism is shown in Equation 4.12.

$$\begin{aligned} h_i(t, X) &= h_0(t) exp(a + \beta_9 X_i + \beta_{10}\hat{\epsilon}_i^{Local} + \beta_{11}\hat{\epsilon}_i^{State}) \\ a =& \beta_1 \widetilde{Pref}_i^{Local} + \beta_2 \widetilde{Pref}_i^{State} + StateCont(\beta_3 + \beta_4 \widetilde{Pref}_i^{Local} + \beta_5 \widetilde{Pref}_i^{State} + \\ &\beta_7\hat{\epsilon}_i^{Local} + \beta_8\hat{\epsilon}_i^{State}) \end{aligned} \tag{4.12}$$

[35] Bowling & Ferguson (2001) expect, but do not find a significant impact of divided legislature on environmental legislation in US state houses. Bowling & Ferguson (2001) do find the split control effect significantly decreases legislative productivity for most other types of conflict-prone policy. Howell *et al.* (2000) find the largest effect in the case of "landmark" (important or controversial) legislation. From these papers, the empirical evidence on the effect is mixed. However, the results I present are consistent with their hypotheses and theoretic arguments, if not their (statistically insignificant) findings.

where $StateCont$ is a dummy variable indicating if a state legislature is united under Democratic control, Republican control, or if control is divided, and X_i is a vector of mine and county level controls, and a state fixed effect. Data for $StateCont$ come from the National Conference of State Legislatures (Warnock, 2016). The hypothesis described implies that $\beta_1 + \beta_3(StateCont = Split) + \beta_4(StateCont = Split) \approx 0$ for local preferences and $\beta_2 + \beta_3(StateCont = Split) + \beta_5(StateCont = Split) \approx 0$ for state preferences. The results of these regression models are most easily conveyed with a margins plot. Figure 4.3 presents the results for the statewide prefrence effect in states under a united Democratic legislature, united Republican legislature, or legislature under split control. While the results are somewhat under-powered, they suggest that the in states with Republican controlled legislatures with green voting US Senators, mines close at a much faster rate than in Republican controlled states with brown voting US Senators. However, in states united under a Democratic legislature, mines are not necessarily responsive to green voting behavior on the part of their state's US Senators. Most importantly, and in confirmation of the tested hypothesis, mines do not appear responsive to statewide preferences in states with a split controlled legislature.

To highlight which states have Republican controlled legislatures but have US Senators that vote green, and which states have Democratic controlled legislatures and US Senators that vote brown, Figure 4.5 presents the average statewide environmental preference effect by state and under the three control regimes. The average green vote when mines close for split controlled legislatures, shown in Figure 4.5 panel (c), varies from very green for states like Oregon, Vermont, New Jersey, and Iowa to very brown for states like Texas, Georgia, and Kentucky. States legislatures united under Republican control, presented in Figure 4.5 panel (b), vary from the very green states of Minnesota, New Jersey, and Oregon to brown states such as Illinois, Georgia, Idaho, Alaska, Texas, and Oklahoma. Figure 4.5 panel (a) - Democratic legislative control - is suggestive of why mines might be less responsive in these state. Across Democratic states, green voting is more homogeneous than in the Republican states shown in panel (b).

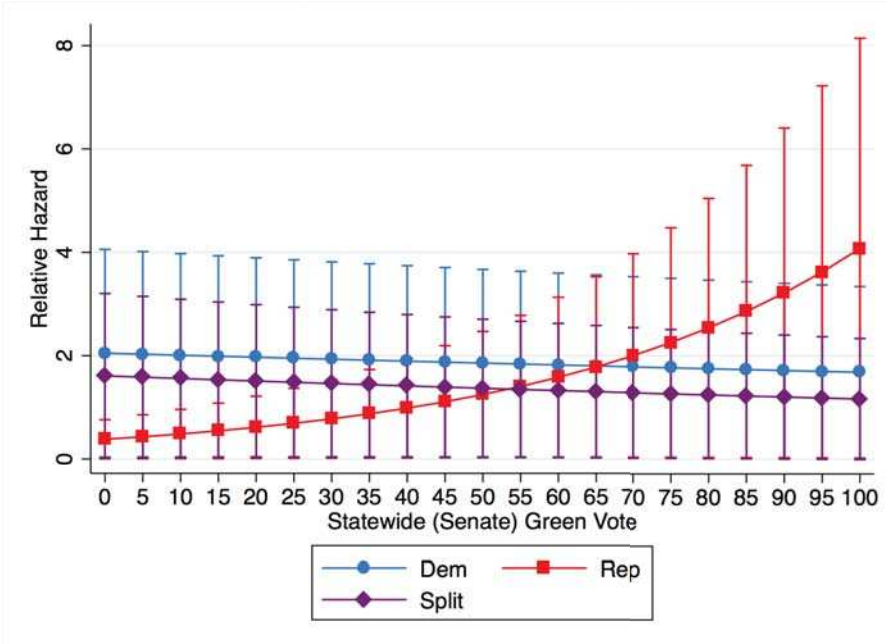


Figure 4.3: Impact of Statewide Environmental Preferences on Mine Closures, by State Legislative Control

With respect to the local prefrence effect, Figure 4.4 presents the margins plot for the three legislature control statuses. The results show an interesting reversal in the expect effect. In states with split control, mines are comparatively much more responsive to the local preferences of the community than in states where the legislature is under unified control. In this case, where policy is slower to be enacted, communities may "take matters into their own hands." This result is more consistent with the standard picture that is painted of social license to operate, with pickets and protesters, than of politicians crafting legislation. Figure 4.6, panel (c) shows the average (when mines close) of the local prefrence effect in states with split legislative control. This result adds a new layer to the literature on SLO. In states where policy is slow to respond, it appears that the importance of other mechanisms, perhaps those more conventionally associated with SLO, increases. This result can illuminate an interesting development in the discussion taking place in another extractive industry, oil and gas, and the current debate over hydraulic fracturing. In the "fracking" debate, federal regulation of the process has little chance of enactment given the currently split federal government. Therefore, states with strong environmental preferences and a united Democratic legislature may ban the process outright, as Vermont did in 2012 (Etnier, 2012), while states such as Oklahoma (a major oil/gas producer) or Virginia (a minor producer), may choose comparatively weaker restrictions (Richardson *et al.*, 2013) based on their preferences and legislature control. In Colorado, where control of the state legislature has been split in three of the last five legislative sessions (Warnock, 2016), the debate around fracking has centered on city and county regulation (Bunch, 2016). While state regulation in Colorado is moderately stringent (Richardson *et al.*, 2013), there is little chance of an outright ban. As shown in Figure 4.1 panel (d), the state contains large areas represented by both very green and very brown US House members. The stark difference suggests why local bans may be desired in some parts of the state, but why a consensus at the state level is likely to be difficult.

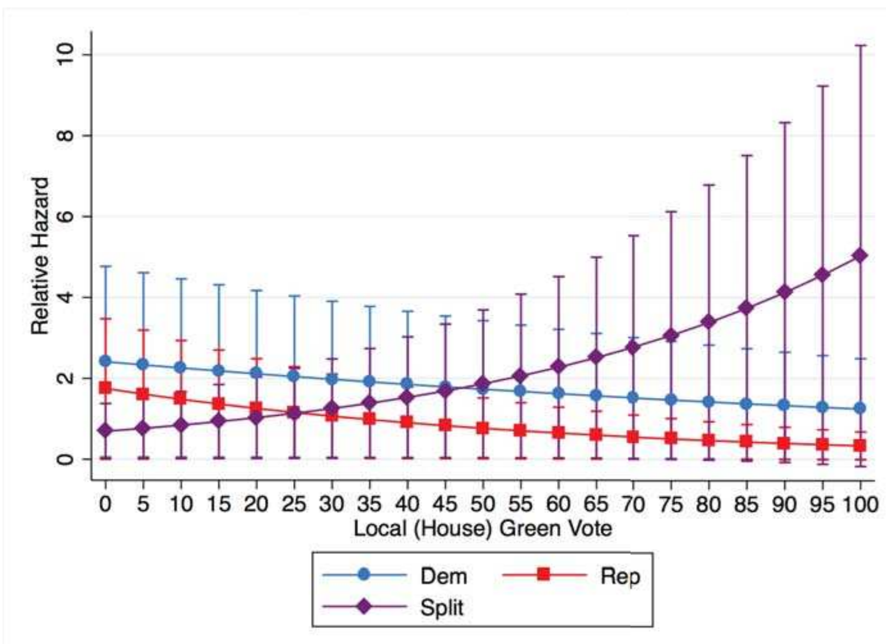


Figure 4.4: Impact of Local Environmental Preferences on Mine Closures, by State Legislative Control

(a) When State Legislature United Under Democrats

(b) When State Legislature United Under Republicans

(c) When State Legislature is Split

Figure 4.5: Average Statewide Environmental Preferences (US Senate Green Voting) Under Varying State Legislative Control At Time of Mine Closure

(a) When State Legislature United Under Democrats

(b) When State Legislature United Under Republicans

(a) When State Legislature is Split

Figure 4.6: Average Local Environmental Preferences (US House Green Voting) Under Varying State Legislative Control At Time of Mine Closure

Source: Author's representation using data from the US Mine Safety and Health Administration and the League of Conservation Voters. States that do not have mine closure observations under particular legislative control are shown in gray.

4.4 Implications for Welfare

While a definitive estimate of welfare effects from the social licensing process would be useful for policy makers, mine developers and other stakeholders, a properly constructed estimate is outside the scope of this study. Further, providing a back-of-the-envelope calculation would be misleading given the available data. However, drawing from past work on SLO and NIMBY, and the econometric estimates of this paper, it appears that the total effect of SLO on welfare is ambiguous. From the results in this paper, SLO provides a mechanism to spatially distribute resource extraction according to environmental preferences. Communities with strong green environmental preferences see mines close faster, while those with weaker preferences have longer lived mines. This distribution should, in theory, be welfare improving. However, welfare decreases may result if the fixed costs of mining (both internal and external) are large and persistent relative to the variable costs.

Social licensing could be welfare improving by providing (as shown in this paper) an effective mechanism for communities to make their preferences known. Even when these preferences are otherwise difficult for firms to directly observe, mines may infer them through the voting behavior of elected community representatives. Provided that environmental damages are confined to a given community (i.e., there is no leakage), SLO may provide for efficient spatial allocation of mining. Mines will close in communities with very green preferences, replaced by mines in communities with brown preferences. However, leakage across community boundaries is possible. The 2015 waste water spill from the abandoned Gold King mine in Silverton, Colorado is a potent illustration of multi-jurisdiction damage. Inspectors accidentally destroyed the mine's containment plug, allowing three million gallons of mine tailings to spill into the Animas River. Contamination impacted not only water in Southwestern Colorado, but also New Mexico, and Utah. Clearly, mine waste can not always be confined to a single community jurisdiction. When leakage of environmental damage is possible, SLO may be an insufficient mechanism on its own for efficient spatial distribution of mining activity. Regional or national regulation of mining may be required.

Social licensing may also have welfare reducing effects. A motivation for some literature on the NIMBY issue is that for high fixed cost projects, concentrating production to a single large facility will allow for fixed costs to be spread over a large volume of production. However, NIMBY push-back tends to be particularly prominent as the scale of the project increases. This pressure may lead to more decentralization in capital and production than is optimal. Additionally, the environmental cost of mining has a variable and a fixed cost component. The externalities of noise and dust are variable costs and depend on the mine currently operating. Once it closes, these costs fade, but mining also leaves fixed "legacy" environmental costs which remain after a mine has closed. This is the type of damage illustrated in the example of the Gold King Mine spill, but also with other aesthetic losses that may be irreversible in the short and long term. When these fixed environmental costs are large relative to the variable damages, there is little benefit from a social perspective of closing an already open mine sooner or later. In fact, if these fixed costs are large, it is likely to be more efficient to keep a mine open longer than to replace its production with a new mine that must incur these large fixed environmental costs again.

The ambiguity of welfare impacts certainty calls for further investigation. Past work on valuing the non-market impacts of mining has tended to have specific contextual scope, making benefit transfer to broader contexts (such as this national level study with many commodity and mine types), virtually impossible. In addition to a broader valuation study, another important contribution would be to differentiate the value of the variable and fixed environmental costs of mining. Particularly, what is the willingness to pay to avoid mining of any scale (the fixed cost of mining)? What is the willingness to pay to avoid a one unit increase in mined material? How do the non-market impacts of mining change before, during and after the mine is open? Answering these questions would have important implications for whether policy should intervene in SLO-type protest or free-ride on it. It would have implications for government land leasing activities. Namely, should government lease un-exploited federal lands to new mining development, or should it instead try to encourage existing operations to remain open longer?

4.5 Conclusion

Over the last three decades, the way communities interact with local mining has become a growing topic of investigation. Today, concerns over the ability to secure and maintain a social license to operate are often cited as a primary reason a resource developer may choose to abandon a project. Social licensing may lead to efficient distribution of mining, or may cause perverse impacts if there is significant leakage of environmental damages between communities, if capital is miss-allocated, or if the fixed costs of mining (both private and social) are large and lasting.

The results of this paper provide new insights into the nature of the social license to operate in mining. While the importance of SLO has been studied using more focused case studies in the past, the estimates this paper provide the first identified attempt to measure the impact of social licensing across a large and diverse sample of mines and community contexts. This paper has shown how stronger local and state environmental preferences can speed mine closures by as much as one third. These preferences impact mining primarily through state policy, in addition to local action.

Determining the channels mines are most responsive to provides insight into how mining firms may choose to direct their social licensing efforts. The insight is furthered by understanding how policy channels might close when federal and state governments come under divided political control. The oil and gas industry provides a recent example in the debate over which level of government should have the authority to regulate or ban fracking activity. The results of this paper highlight the important role state legislative unity can play in determining which political jurisdiction has the authority to issue a social license to operate.

Future mineral demand is likely to continue growing as developing countries industrialize. To meet demand, the extractive industry will need to replace currently exploited resources with new mines, which if current trends persist, may be met with violent and costly conflict over the distribution of mining's costs and benefits. As this paper has shown, when a community's environmental preferences are strong, costs associated with SLO have a tangible effect on firm behavior. Despite SLO becoming increasingly recognized as a key piece to any resource development project, many projects still fail to secure or maintain their SLOs. The results of a failed SLO do not just have costs to the firms in terms of productivity and property. Conflict over resource development has resulted in serious injury and death as stakeholders clash with law enforcement and mine employees.

CHAPTER 5
CONCLUDING REMARKS

Mineral resources are critical inputs in societys modern standard of living but many aspects of their supply are still poorly understood. This dissertation has explored three specific issues related to the availability of these minerals for societys use: geologic availability, the joint production of metals, and the social availability of minerals.

Chapter 2 explored geologic abundance and mineral joint production using engineering economic models to construct hypothetical short and long run supply curves. The findings of this chapter point to the important role of mineral joint production in sourcing low cost supply of minerals which have low concentrations in the earth. For these low-concentration minerals, joint production presents a double-edged sword. Dividing costs of extraction to several outputs allows otherwise un-exploitable resources to be profitably extracted and used for society. However, it also makes their supply dependent (or interdependent) on the market for other materials. To further understand the dynamics of joint production, Chapter 3 analyzed how multi-product mining firms respond to changes in relative prices. As the results showed, the supply relationships between metals linked through joint extraction is potential more complicated and geologically dependent than is conventionally understood.

Chapter 4 assessed the implications of social and environmental constraints to resource availability by estimating the impact of stronger local preferences for environmental quality on nearby mine closure. This analysis found that preferences are likely channeled through state policy or through directed local action such as civil resistance or publicity campaigns against mining operations. These results add empirical evidence to the growing literature on the importance of understanding local community activities as they relate to resource availability and mining.

Despite addressing several emerging issues in the study of mineral supply, there are still many more unanswered questions related to how society will secure the mineral resources it needs in the future. Over the last century, new technology has outpaced of cost increasing effects of resource depletion even as humans continue to use mineral resources at a growing pace. Meeting challenges of growing demand will require more research into how society interacts with vital non-renewable resources and the environment.

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APPENDIX A - SUPPLEMENTARY INFORMATION FOR CHAPTER 2

This appendix contains cost estiamtion data that was used to construct supply curves in Chapter 2 as well as the assumptions used to create the demand scenario in Chapter 2.

A.1 Cost Estimation

Table Table A.1 presents the escalation factors (and their sources) that were used in this study to convert Young *et al.* (1980) estimates', which are in 1978 dollars, to 2013 dollars which are the basis of this study. Cost items for the hypothetical thorium recovery plant are grouped by their corresponding escalation factors.

Table Table A.2 presents each cost item for the estimated Bear Lodge by-product thorium recovery facility and the scale factor used to scale the cost item from the escalated hypothetical plant cost. Interested readers should refer to Jordan & Eggert (2014) for complete documentation on the cost estimation for all deposits.

The scaling factor used in all Table Table A.2 is calculated using:

$$(DailyCapacity_{New}/DailyCapacity_{Old})^{0.7} = (111/272)^{0.7} = 0.53 \tag{A.1}$$

Where $Capacity_{New}$ is the required capacity of the Bear Lodge facility, and $Capacity_{Old}$ is the capacity of the hypothetical Palmer recovery facility estimated by Young *et al.* (1980). The parameter 0.7 is term related to economies of scale, and is the same one used by Young *et al.* (1980) and described in (Green & Perry, 2008, p. 9-13:14). For costs that scale linearly with plant size, the factor .41 was used (the ratio of "new" and "old" capacity). Finally, some costs are assumed to be fixed regardless of plant size.

The values marked with an asterisk (*) in Table Table A.2, Total Depreciable Capital Investment, Working Capital, and Total Annual Operating Costs are used as inputs into Table Table A.3. Total Depreciable Capital Investment is multiplied by the fixed charge rate of 0.2338 and Working Capital is annualized linearly over 10 years.

Table A.1: Escalation Factors and Sources by Cost Item

Cost Item	Factor	Source
Equipment	3.12	Marshal and Swift Mining and Milling Equipment Cost Index, Equipment
Buildings and Equipment Effluent Control Buildings & Equipment Exploration Mine Equipment Replacement Mill Equipment Replacement Mine/Mill Effluent Control Sulfuric Acid Plant Buildings & Equipment Spare Parts Inventory Contingency		
Construction	2.96	Bureau of Labor & Statistics (BLS)-Stage of processing-Construction
Mine Tailings Pond Development Mill Tailings Pond Access Road Tailings Pond Waste Sludge Landfill		
Professional Services Environmental Impact Exploration Feasibility Study Laboratory Charges	3.87	BLS- ECI-Professional and Related
Miscellaneous	3.43	Federal Reserve Economic Data (FRED) Consumer Price Index for All Urban Consumers: All Items
Land Development Working Capital Maintenance and Repairs Sulfuric Acid Plant Op Costs Water		
Labor-Mining	3.54	FRED Average Hourly Earnings of Production and Nonsupervisory Employees: Mining and Logging
Mine Labor Costs Mill Labor Operating Labor		
Supplies Materials and Supplies Mill Materials and Supplies	2.51	BLS-Stage of processing-Supplies
Chemical Supervision & Engineering	1.97	Chemical Engineering Magazine, Plant Cost Index, Engineering and Supervision
Mill/Refinery Supervision Mill/Refinery Overhead Mill/Refinery Administrative Costs		
Chemicals	2.97	Marshal and Swift Mining and Milling Equipment Cost, Chemicals
Refinery/Mill Operating Supplies Refinery/Mill Reagents		
Diesel Fuel Fuel Oil Diesel Fuel	4.64	BLS-Fuels and related products and power
Electricity	2.82	BLS- Commercial electric power

Table A.2: Scaled Hypothetical Thorium Recovery Plant to Bear Lodge Capacity

	Hypth. Plant $000s	Resize Factor	Bear Lodge $000s
Capital Expenditures			
Refinery Or Mill Capital Cost			
Building and Equipment	10,949	0.53	5,847
Effluent Control Buildings & Equipment	456	0.53	243
Feasibility Study	387	1	387
Environmental Impact	387	1	387
Contingency	1,564	0.53	835
Tailings Pond	1,383	0.53	739
Total Depreciable Capital Investment	15,126		8,438*
Working Capital	1,716	0.41	700*
Total Capital Investment	16,842		9,138
Operating Expenditures			
Operating Labor	2,488	0.53	1,329
Supervision	207	0.53	111
Maintenance and Repairs	1,503	0.53	803
Operating Supplies	507	0.41	207
Laboratory Charges	406	1	406
Total Direct Costs	5,112		2,856
Indirect Costs			
Plant Overhead	2,304	0.53	1,230
Administrative Costs	576	0.53	308
Total Indirect Costs	2,880		1,538
Total Fixed Operating Costs	7,992		4,393
Variable Operating Costs			
Reagents	7,401	0.41	3,021
Utilities	2,858	0.53	1,526
Transportation	2,549	0	
Total Annual Operating Costs	20,800		10,302*

Table A.3: Bear Lodge Scaled Production Costs

Depreciable Assets ($000s)	1,973
Non-Depreciable Assets ($000s)	70
Annual Operating Costs ($000s)	10,302
Annual Production Cotsts ($000s)	12,345
Annual Production ('000 kgs)	134
Levelized Production Cost ($/kg)	92

A.2 Context for Sample Deposits

Because the medium term supply estimates presented in this paper are for a limited number of selected resources, they do not capture the full extent of estimated global resources. Table Table A.4 presents the resources that have been estimated as part of NEA/IAEAs Red Book alongside the life of mine (LOM) production included in this study. The LOM production is calculated by multiplying the assumed annual production of a given resource by its anticipated mine life. The table shows that less than 6% of global thorium resources are included in the cost analysis.

Table A.4: Selected and Total Estimated Thorium Resources by Country

	Low-Range Estimate[1] (Tonnes)	LOM Production Included in this Study[2] (Tonnes)	% of Total Estimated Resources
India	846,500	12,632	1.50%
Turkey	744,000		
Brazil	606,000	15,713	2.60%
Australia	521,000	18,622	3.60%
United States	434,000	180,384	41.60%
Egypt	380,000		
Norway	320,000		
Venezuela	300,000		
Canada	172,000		
Russia	155,000		
South Africa	148,000	90,306	61.00%
China	100,000		
Rest of World	581,300		
Total	5,307,800	317,657	<6.0%

[1] Data from (NEA and IAEA, 2012)
[2] This study

Measuring thorium in terms of known and estimated resources has limitations in putting included resources into context. Demand for titanium and rare earth elements may continue to drive the discovery of thorium bearing deposits. This would imply that 6.0% should be considered an upper bound of included resources. However, it is uncertain how costly and therefore how available these other resources may be.

Table Table A.4 also does not distinguish potential main product sources of production from potential by-product and twice by-product sources. This distinction is important as by-product thorium recovery would be derived from titanium and rare earth markets and, in the medium term, supply of these products would be limited by installed capacity. On the other hand, by-product supply could likely come online more quickly than main product sources due to smaller capital requirements. To assess these medium term effects, we calculate the potential quantities that have been excluded from the industry cost curve. Table Table A.5 below shows the quantity of main product supply accounted for in this analysis compared to the global supply of these main products recorded by the USGS.

Ilmenite and rutile are titanium bearing minerals that are frequently recovered together from heavy mineral sand operations and so by-product thorium cannot be attributed to one or the other. Rare earth mines are also broken into two categories, REO Current Production and REO Unutilized Capacity at Operating Mines. This distinction accounts for the fact that the included potential thorium production in the analysis is estimated based on the installed capacity of the Mt. Weld and Mountain Pass mines rather than their actual 2011 production. The percent of main product supply included in the analysis is calculated from USGS estimates, and this number implies a certain amount of potential thorium supply that has been excluded from the analysis, approximately 7,968 tonnes per year or 246,805 tonnes over the life of the excluded mines. These figures rely on the assumption that titanium and rare earth mines that have been excluded from the cost and availability curve analysis are similar in thorium grade, thorium tonnage and mine life to mines that have been included. In reality, mines included in the curves were chosen specifically for their potential to produce thorium and not for their being representative of other main product mines.

Rare earth production from India (2,800 tonnes REO), Brazil (250 tonnes REO), and Malaysia (280 tonnes REO) has been subtracted from total mine production to prevent

Table A.5: Thorium Contained in Current REO and Titanium Mine Production

Main Product	Tonnes Thorium/y[1]	Life of Mine (LOM) Thorium Production[1]	Main Product Mine Supply Included in Analysis[2]	Total Main Product Supply in 2011[2,3]	% Main Product Supply Included in Analysis[1]	Implied Thorium Excluded (Tonnes/y)[1]	Implied Thorium Excluded (LOM)[1]
Ilmenite	See Titanium Total	See Titanium Total	674,100	5,870,000	10.50%		
Rutile			468,600	764,000	59.40%		
Titanium Slag	598	50,495	970,000	2,210,000	43.90%		
Titanium Total	2,242	67,265	2,112,700	8,844,000	23.90%	7,143	214,315
REO Current Production	280	13,008	13,800	106,670	12.90%		
REO Unutilized Capacity at Operating Mines	121	2,784	31,599		100.00%		
REE Total	401	15,792	45,399	138,269	32.80%	820	32,305
Grand Total						7,964	246,621

[1] This study
[2] USGS Mineral Commodity Summaries and Mineral Yearbook
[3] Total 2011 Rare Earth Supply (less India, Brazil, Malaysia) + Mt. Weld, Mountain Pass Capacity

double counting as all of these countries produce rare earth from heavy mineral sands, but this small correction does not materially affect the results. As shown in Table Table A.5, 4-5 times more thorium (nearly 7,143 tonnes per year) might be producible annually as a twice by-product from heavy mineral sand operations that are mining titanium today. Approximately three times more thorium (820 tonnes per year) might me available from other rare earth operations not included in the cost curves.

Table Table A.5 has not included some of the potential rare earth mines that were included in the cost and availability curves because Table Table A.5 only includes operating mines. To capture the thorium that could be produced from potential rare earth mines, these mines capacity is simply added to the 138,269 tonnes of rare earth production per year from Table Table A.5 . Total REO main product supply has increased over 57% with the inclusion of these mines. When this potential REO mine supply is added, Main Product Supply Included in Analysis increases by approximately 14 percentage points. Total rare earth supply in this scenario is 173,563 tonnes per year.

A.3 Hypothetical Thorium Demand Scenarios

Not only is there a great deal of uncertainly about how a potential thorium fuel cycle might develop, but it is still unclear if thorium will be commercialized. Nevertheless, assessing potential demand for thorium provides context to the quantities of thorium potentially available. So while any demand scenario will be highly speculative, such scenarios are important to understanding potential supply. This appendix develops a simple scenario for demand, and outlines the assumptions used.

A convenient way to characterize the potential total global quantity of thorium demanded annually by a thorium-based fuel cycle is as follows:

$$Demand_{ThO_2}/year = \frac{TheoreticalMinimumConsumption}{FuelUtilizationRate} * OperationalCapacity \quad (A.2)$$

Where theoretical minimum consumption is the quantity of thorium (in tonnes of 99.99% ThO_2) required to generate 1 GWe (1,000 MWe) per year if Fuel Utilization Rate was 100%. Operational capacity measures the total operating capacity of "thorium reactors[36]" in GWe per year.

Assuming a thermal efficiency of 40%, theoretical minimum consumption is calculated to be 1 tonne (rounded to the nearest whole tonne) of 99.99% ThO_2 per GWe per year. Fuel utilization may range from approximately 1%, corresponding with the current uranium fuel cycle, to 100% corresponding with a continuous recycle with no losses. We will assume a value of 10% because it is an order of magnitude higher than the 1% case and one order of magnitude lower than the 100% case. A value of 10% for fuel utilization corresponds to a once-through and limited recycle case (Wigeland *et al.*, 2014). This results in a thorium requirement of 10 tonnes per GWe per year. Note that changing the assumption of fuel utilization would scale this requirement linearly. For instance, if a full recycle fuel cycle is employed, bringing fuel utilization to nearly 100%, then the required thorium per GWe of capacity would fall to 1 tonne per year. Readers interested in estimates of thorium requirements for a variety of fuel cycles should refer to Wigeland *et al.* (2014).

[36]Most conceptualizations of a thorium fuel cycle propose reactors that convert fertile thorium-232 to fissile uranium-233. U-233 can then be used as a "fuel." The term "thorium reactor" is used here for simplicity to refer to a reactor that could consume thorium.

For operational capacity, we assume that the 435 operating reactors around the world are replaced by thorium-consuming reactors after a 60-years life. For simplicity, we further assume that no other reactor construction occurs and thorium-consuming reactors remain operating in perpetuity. These 435 reactors represent 373 GWe of installed capacity, which is the second term in Equation A.2. For simplicity, we assume a capacity factor[37] of 100%. See Appendix A of Jordan & Eggert (2014) for a more complete detailing of these assumptions. This scenario is depicted in Figure Figure A.1.

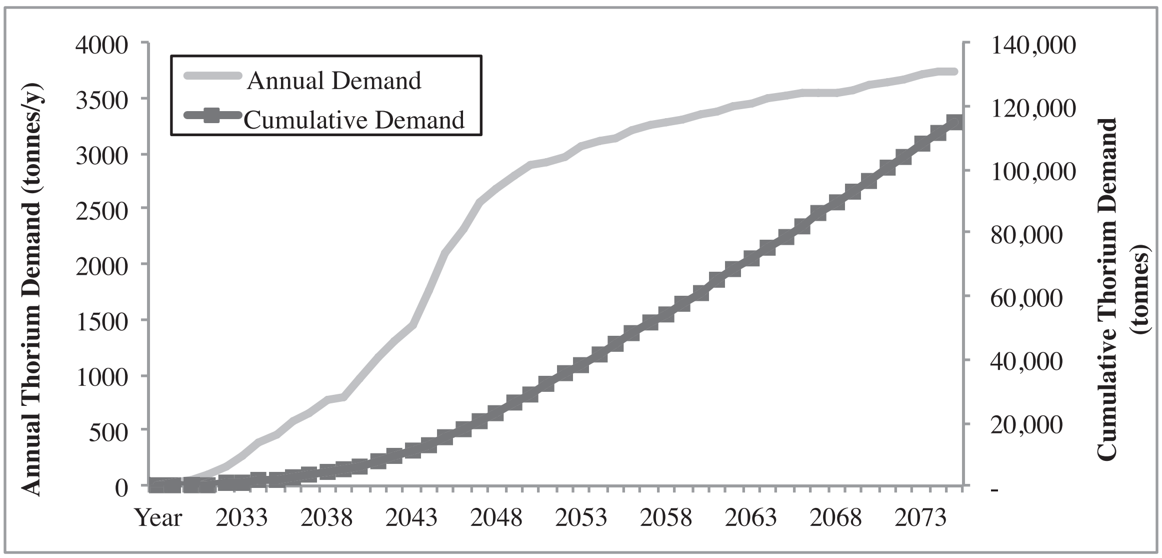

Figure A.1: Assumed Global Thorium Demand Scenario

Figure Figure A.1 plots annual demand in this scenario on the left axis and cumulative demand on the right axis. In this scenario, the first thorium-consuming reactor comes online in 2029.[38] While specific dates are given for this scenario, one could also think of them generically, with year 2029 being year 0. Demand rises slowly at first before growth accelerates as a number of reactors retire before finally leveling off. In the year 2074 (or 45 years after the first reactor is converted), the scenario assumes the last reactor converts to thorium and total annual consumption reaches its peak of 3,730 tonnes per year. While one

[37]Annual generation divided by capacity

[38]China has recently made commitments to develop thorium reactor technology within a decade, so this a timeline is not unreasonable.

could analyze the thorium requirements at any given level of demand, the peak is particularly relevant in addressing availability because it will dictate the highest level of production needed and in turn require the highest cost resources to be recovered. It is this peak level of demand that we will use in our assessment of the mining-industry cost curve.

Annual demand is not a relevant measure in the context of the cumulative availability curve. For the cumulative availability curve, cumulative demand is needed. Figure Figure A.1 plots cumulative demand through 2074. As with annual demand, there are several ways that one could approach constructing a cumulative demand scenario. We will take a simplified approach and measure cumulative demand at the arbitrary points of 45, 100, 250, 500 years after thorium consumption begins. These later timeframes, 250 and 500 years, are s ufficiently far into the future, considering electricity has only in the last century been demanded on a large, commercial scale. The first 45 years in this scenario involves the ramp-up in demand shown in FigureFigure A.1. After 45 years, we will assume annual demand remains constant, as existing thorium-consuming reactors are operated in perpetuity and no addition construction or capacity expansion occurs. Our cumulative demand scenario is shown in Table Table A.6. Our scenario has cumulative demand reaching over 312,960 tonnes by 2129, or 100 years after the first reactor is converted. By 2529, or 500 years after the first "thorium reactor," cumulative demand reaches 1,804,960 by the assumptions used in this study.

Table A.6: Cumulative Demand 45, 100, 250, and 500 Years After First "Thorium Reactor"

Scenario Year	Years From First "Thorium Reactor"	Cumulative Demand (tonnes)
2074	45	107,810
2129	100	312,960
2279	250	872,460
2529	500	1,804,960

APPENDIX B - SUPPLEMENTARY INFORMATION FOR CHAPTER 3

This appendix will detail several extensions that are used in order to validate results and test hypotheses.

B.1 Robustness of Findings and Alternative Models

An alternative model was used in the cases where the primary model did not have necessary flexibility in order to add extensions. These alternative models are based on the empirical model in Equation B.1.

$$Grade_{itm} = (\sum_{j \neq i} Grade_{jtm} + \sum_{i} Price_{it}) * PDum_{im} + Ore_{tm} + \sum^{t} Ore_{mt} + \alpha_m \tag{B.1}$$

where i and j are the set of metals, silver, gold, copper, lead, and zinc. $Grade_{itm}$ measures the percent of metal i in ore mined in year t by producer m. $PDum_{im}$ indicates if a particular metal is produced at a given mine, m. $PDum_i$ takes a value of 1 if a metal i is produced at any time in the sample period and 0 otherwise. Ore_{mt} measures annual ore production from mine m at year t. The sum of Ore to the current period represents cumulative production. α is a mine individual fixed effect. The estimates from Equation B.1 are presented in Table B.2. In this "base case" model lead's own-price result is significant and negative. Additionally, three cross-price effects Ag-Au, Pb-Au, and Zn-Pb are significant at the 95, 95, and 99.9% levels, respectively. This model will form the basis for comparison of the alternative specifications.

B.1.1 Price Endogeneity and Instrumental Variables

As discussed in Section 3.8 one potential concern about the primary model's specification is that prices are assumed exogenous. While this is the same assumption of all past studies on the price/grade relationship, the potential for prices to be simultaneously determined with grades warrants testings. To test for and correct the potential effect of price endogeneity I employ an instrumental variables approach, a common method for consistently estimating price/quantity relationships (Angrist & Krueger, 2001; Goldberger, 1972). The SUR model does not lend itself to an instrumental variable correction, even through three stage least-squares, because not all prices are relevant to all mines. Because the set of instruments (via dummying) will be different for each metal's price, the standard 2-stage least squares regression is invalid. Instead the first and second stage models are fitted separately resulting in an unbiased estimate of the prices' coefficients. The standard errors are corrected via bootstrapping. The instruments selected for the analysis are a set of demand-side shifters that should otherwise be unrelated to the supply of silver, gold, copper, lead and zinc. These instruments include world GDP (to measure income), population density of East Asia (to account for demand from industrialization and construction), global steel demand (zinc is used as a steel alloy), production and stock of vehicles (lead's primary use is in batteries), the US urban consumer price index, US inflation, US inflation volatility (gold and silver are sometimes used as inflation hedges), and a trade-weighted measure of the US foreign exchange rate (also related to precious metal demand). The results of the IV estimation are presented in Table B.3.

After instrumenting, lead maintains a significant and negative own price-grade effect. Copper's own-price response also becomes significant (although the point estimate is not substantially different). Also, the three cross-price effects that were significant in the base case model retain their significance and signs. The magnitude of the coefficient estimates is also similar between the two models. The similarity provides some confidence that endogeneity is not introducing major bias into the results of the primary or alternative models.

B.1.2 Formal Tests of Revenue Effects

In this section, the finding in the primary model that a metal's revenue contribution is a poor indicator of its own and cross-price responsiveness is formally test. Utilizing the alternative model in Equation B.1 and adding time fixed effects (η_t) and milling recovery rate ($Recov_{it}$) control variables, the model in Equation B.2 is estimated.

$$
\begin{aligned}
Grade_{itm} &= (\sum_{j\neq i} Grade_{jtm} + \sum_{i} Price_{it} * RevDum_{itm}) * PDum_{im} \\
&\quad + Recov_{it} + Ore_{tm} + \sum^{t} Ore_{mt} + \eta_t + \alpha_m
\end{aligned} \tag{B.2}
$$

The variable of interest in Equation B.2 is $RevDum_{itm}$, an indicator dummy variable which measures a metal's revenue contribution. The indicator variable can take a value of "Zero", "by-product", "co-product", or "main product," each measured as a 0-1 dummy variable. The zero dummy is 1 if a metal contributes 0% revenue to the mine, and 0 otherwise. The by-product dummy take a value of 1 if a metal contributes >0% and <10%, and 0 otherwise. The co-product dummy is 1 if a metal contributes ≥10% and <75%, and 0 otherwise. And the main product dummy is 1 if a metal contributes more than ≥ 75% revenue, and 0 otherwise These bounds are arbitrary, but a useful starting place for the analysis. Choosing different percentage revenue cut-offs, even defining a by-product using a 1% revenue cutoff, does not meaningfully change the results. The estimated coefficients of Equation B.2 are presented in Tables Table B.4 and Table B.5.

If revenue share does impact price response, main products classified as such by revenue should have large impacts on their own and other-metal supply, while by-product prices should have no effect on their own supply or the supply of other materials. This is examined using F-tests of the estimates in Tables Table B.4 and its continuation in Table B.5 with the test specifications and expectations in Table B.6. The by-product dummy interacted with price should not have a statistically significant effect on the grade of the by-product or other metals. Further, it is expected that the main product dummy interacted with price will have a statistically significant effect on the grade mined both of the main product and other metals. Finally, a Wald test is used to determine if the main product effect is statistically different than the by-product effect. The results of the three tests are summarized for each of the 5 metals in Tables Table B.7 and Table B.8.

Comparing the test outcomes in Table B.7 to the expectations in Table B.6, the results are mixed. When produced as by-products, silver, gold, copper, and lead are not own-price responsive (as expected), but zinc is. Contrary to revenue-based expectations gold, copper, and lead are not own-price responsive when produced as main products. The main product effect should also be statistically different than the by-product effect, but the results show this is only the case for silver and lead. Of the 15 own-price tests, roughly half (8) conform to our expectations about behavior. The results for gold and copper are notable because they echo the findings of the primary model despite cutting the revenue distribution using the dummy variables.

The cross-price effect tests results are shown in Table B.8. Gold grades are responsive to the price of by-product lead (Pb), and copper grades are responsive to the prices of by-product lead (Pb) and zinc (Zn). Lead grades are responsive to prices of all other metals when they are produced as by-products. In total, there only two significant main product effects, far fewer than the seven significant by-product effects. A price increase in main-product silver drives an increase in mined copper grades, and a price increase in main-product gold results in an increase of mined grades of zinc. Of the 40 total cross-price tests, only 15 conform to the defined exceptions about behavior.

These tests of the the revenue interaction terms provides quantitative confirmation of the qualitative conclusion in Section 2.3 that the revenue share is an incomplete way to form expectations on price responsiveness.

B.1.3 Placebo Test of the Cross-Price Effect

To test the robustness of the cross-price effect, a series of placebo regressions are estimated. These regressions are estimated using the model in Equation B.3:

$$Grade_{itm} = \sum_{i} Price_{it} + Ore_{tm} + \sum^{t} Ore_{mt} + \alpha_m \tag{B.3}$$

where i and j are in the set of metals, silver, gold, copper, lead, and zinc. $Grade_{itm}$ measures the percent of metal i in ore mined in year t by mine m. $Price_{it}$ is the price of metal i in year t. Ore_{mt} measures annual ore production from mine m at year t. The sum of Ore to the current period represents cumulative production. α is a mine individual fixed effect. Equation B.3 is estimated for each of the five metals on a full sample of every mine producing each metal. Equation B.3 is then estimated for each metal pair, dropping mines producing producing one of the metals. In this way, silver's grade response to price is tested across all mines producing silver, then in those mines that produce silver but not gold, then in those mines that produce silver but not copper, then in those mines that produce silver but not lead, and so on for each metal. The results of these models are presented in Table B.10. In mines that produce a given metal i, but not metal j, i's grade should not respond to j's price. The placebo-specific effects from Table B.10 are presented in Table B.11. A significant coefficient estimate in Table B.11 indicates a grade change from a placebo price change. Of the 19 metal pairs for which there was sufficient data to fit a model, only 2 exhibit a placebo response, gold's price on zinc grade and copper price on zinc grade. This is contrasted to the 11 "true" grade-price responses found in Table B.10. These placebo tests provide some confidence that grade-price relationships found in this paper are not a spurious result.

B.2 Tables and Figures

Table B.1: Input-Compensated Own and Cross-Price Elasticities, Subsample 1991-2001

	P Gold	P Silver	P Copper	P Lead	P Zinc
Q Gold	0.329	-0.006	0.438***	-0.072	-0.689
	(0.562)	(0.044)	(0.11)	(0.089)	(0.568)
Q Silver	-0.019	-5.76***	0.253	0.16	5.366***
	(0.137)	(1.108)	(0.189)	(0.359)	(1.114)
Q Copper	0.231***	0.043	-0.355	-0.236*	0.318
	(0.058)	(0.032)	(0.235)	(0.12)	(0.186)
Q Lead	-0.188	0.133	-1.172*	-3.274***	4.501***
	(0.234)	(0.299)	(0.594)	(0.601)	(0.597)
Q Zinc	-0.578	1.434***	0.505	1.443***	-2.803***
	(0.477)	(0.298)	(0.296)	(0.191)	(0.468)

P's are prices, Q's are quantities.
Elasticities are presented at their average values and calculated using Equations 3.3 and 3.4.
Bootstrapped standard errors are in parentheses and estimated using the delta method.
$*p < 0.05$, $**p < 0.01$, $***p < 0.001$

Table B.2: Base Case for Alternative Specification

	(1) Silver Grade	(2) Gold Grade	(3) Copper Grade	(4) Lead Grade	(5) Zinc Grade
Silver Price	0.050	-0.931*	0.108	-0.007	0.047
	(0.196)	(0.431)	(0.199)	(0.131)	(0.080)
Gold Price	-0.242	0.367	-0.156	-0.170	0.027
	(0.344)	(0.323)	(0.215)	(0.150)	(0.082)
Copper Price	0.004	0.189	-0.152	0.062	-0.022
	(0.130)	(0.159)	(0.112)	(0.088)	(0.054)
Lead Price	-0.173	0.730*	-0.066	-0.985***	-0.070
	(0.172)	(0.310)	(0.247)	(0.213)	(0.125)
Zinc Price	-0.083	0.143	-0.030	0.532***	-0.025
	(0.099)	(0.103)	(0.149)	(0.151)	(0.092)
No. of obs.	1122	1122	1122	1122	1122
R^2	0.369	0.376	0.217	0.202	0.285

Bootstrapped standard errors in parentheses

Variables are mean-normalized

Control variables: grades of other metals, cumulative production, and current production.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table B.3: Alternative Specification - 2nd Stage Estimates with Instrumented (Inst) Prices

	(1) Silver Grade	(2) Gold Grade	(3) Copper Grade	(4) Lead Grade	(5) Zinc Grade
Silver Price (Inst)	0.076	-1.045*	0.199	-0.087	0.077
	(0.243)	(0.433)	(0.221)	(0.144)	(0.083)
Gold Price (Inst)	-0.256	0.440	-0.091	-0.158	0.034
	(0.380)	(0.338)	(0.197)	(0.161)	(0.085)
Copper Price (Inst)	-0.001	0.181	-0.197*	0.065	-0.029
	(0.157)	(0.162)	(0.095)	(0.103)	(0.053)
Lead Price (Inst)	-0.188	0.814*	-0.051	-0.988***	-0.080
	(0.195)	(0.321)	(0.242)	(0.217)	(0.133)
Zinc Price (Inst)	-0.096	0.216	-0.172	0.643***	-0.058
	(0.106)	(0.120)	(0.116)	(0.158)	(0.096)
First Stage F-Stat	30503	NA	24932	NA	32666
No. of obs.	1122	1122	1122	1122	1122
R^2	0.369	0.376	0.218	0.205	0.285

Bootstrapped standard errors in parentheses

Variables are mean-normalized

Control variables: grades of other metals, cumulative production, and current production.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Instrumental variables are: world GDP, population density of East Asia, global steel production, production and stock of vehicles, the US CPI-U, US inflation, US inflation volatility, and a trade-weighted measure of the US foreign exchange rate.

Table B.4: Alternative Specification - Revenue Interactions

	(1) Silver Grade	(2) Gold Grade	(3) Copper Grade	(4) Lead Grade	(5) Zinc Grade
Silver By-ProductDUM	-0.018	0.594	-3.993	-0.748	-1.555
	(0.664)	(16.932)	(230.121)	(1.388)	(0.950)
Silver Co-ProductDUM	1.135	-1.349	-4.192	0.345	-1.859
	(0.852)	(16.816)	(230.098)	(1.373)	(0.962)
Silver Main ProductDUM	3.807*	-3.995	-14.454*	-1.823	-3.316*
	(1.695)	(30.592)	(6.788)	(2.101)	(1.359)
Silver Price	-0.317	0.047	-8.366	-2.726	-1.474
	(0.730)	(9.203)	(4.637)	(1.529)	(1.007)
Silver By-ProductDUM*Silver Price	0.259	-0.482	8.633	1.600	1.514
	(0.621)	(9.242)	(4.630)	(1.190)	(0.932)
Silver Co-ProductDUM*Silver Price	-0.666	1.087	8.763	0.687	1.761
	(0.777)	(9.191)	(4.645)	(1.176)	(0.937)
Silver Main ProductDUM*Silver Price	-1.576	1.976	10.163*	1.855	1.951*
	(1.562)	(21.494)	(4.677)	(1.732)	(0.977)
Gold By-ProductDUM	-2.384	3.033	1.071	0.865	-1.024
	(1.765)	(12.048)	(4.008)	(1.841)	(1.544)
Gold Co-ProductDUM	-2.569	3.645	-0.142	-0.623	-1.496
	(2.056)	(12.073)	(4.014)	(1.893)	(1.523)
Gold Main ProductDUM	-2.173	0.432	-0.124	Insufficient Obs.	-6.904
	(2.031)	(12.126)	(4.278)		(10.774)
Gold Price	-2.157	4.151	1.348	0.260	-1.475
	(1.596)	(11.260)	(3.629)	(1.722)	(1.434)
Gold By-ProductDUM*Gold Price	2.147	-2.911	-0.956	-1.506	1.484
	(1.621)	(11.052)	(3.630)	(1.718)	(1.461)
Gold Co-ProductDUM*Gold Price	2.381	-3.635	0.102	-0.060	1.687
	(1.932)	(11.077)	(3.624)	(1.753)	(1.439)
Gold Main ProductDUM*Gold Price	1.129	-0.265	-0.883	Insufficient Obs.	7.178
	(1.719)	(11.056)	(3.730)		(11.359)
Copper By-ProductDUM	0.530*	-0.608	0.313	0.133	-0.391
	(0.266)	(22.821)	(0.466)	(0.388)	(0.303)
Copper Co-ProductDUM	0.298	-1.196	1.550**	0.233	-0.699*
	(0.379)	(22.806)	(0.601)	(0.423)	(0.331)
Copper Main ProductDUM	0.394	-1.677	1.159	-2.073	-0.408
	(0.425)	(22.801)	(0.611)	(6.790)	(2.728)
Copper Price	0.589	-0.826	-0.924	0.413	-0.336
	(0.344)	(22.648)	(0.631)	(0.366)	(0.252)
Copper By-ProductDUM*Copper Price	-0.555	0.321	0.595	-0.059	0.251
	(0.285)	(22.666)	(0.464)	(0.376)	(0.265)
Copper Co-ProductDUM*Copper Price	-0.605	1.790	-0.213	-0.402	0.452
	(0.374)	(22.627)	(0.423)	(0.369)	(0.272)
Copper Main ProductDUM*Copper Price	-0.647	1.865	0.345	2.224	0.112
	(0.418)	(22.625)	(0.443)	(5.470)	(2.550)
No. of obs.	1015	574	605	692	770
R^2	0.241	0.291	0.676	0.438	0.501

Bootstrapped standard errors in parentheses
Variables are mean normalized
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Control variables: time fixed effects, mill recovery, grades of other metals, cumulative production, and current production. By-ProductDum =1 if Metal Revenue >0% and <10%, Co-ProductDum =1 if Metal Revenue ≥10% and <75%, Main ProductDum =1 if Metal Revenue ≥75%

Table B.5: Alternative Specification - Revenue Interactions (Continued)

	Silver Grade	Gold Grade	Copper Grade	Lead Grade	Zinc Grade
Lead By-ProductDUM	0.903	-8.040	-22.250	-4.529	-1.296
	(48.520)	(108.048)	(1088.436)	(18.356)	(32.985)
Lead Co-ProductDUM	0.954	-8.235	-21.328	-3.553	-1.042
	(48.525)	(108.068)	(1088.395)	(18.325)	(32.985)
Lead Main ProductDUM	1.390	Insufficient Obs.	Insufficient Obs.	-1.730	-2.013
	(48.489)			(18.417)	(32.979)
Lead Price	0.673	-1.744	-16.126	-3.421	-1.637
	(48.443)	(103.085)	(859.102)	(14.685)	(31.880)
Lead By-ProductDUM*Lead Price	-1.119	6.608	17.277	3.776	1.539
	(48.437)	(103.089)	(859.111)	(14.673)	(31.887)
Lead Co-ProductDUM*Lead Price	-1.104	6.901	16.399	3.284	1.305
	(48.446)	(103.119)	(859.080)	(14.648)	(31.894)
Lead Main ProductDUM*Lead Price	-1.710	Insufficient Obs.	Insufficient Obs.	2.139	2.220
	(48.406)			(14.765)	(31.889)
Zinc By-ProductDUM	0.502	-0.761	9.838	-2.417	3.650
	(2.476)	(9.634)	(18.541)	(1.466)	(3.639)
Zinc Co-ProductDUM	-0.278	-0.851	7.831	0.000	3.658
	(2.372)	(7.084)	(18.443)	(0.000)	(3.605)
Zinc Main ProductDUM	-0.398	-4.099	8.364	-0.302	3.886
	(2.383)	(7.301)	(18.427)	(0.317)	(3.594)
Zinc Price	0.021	-1.116	6.679	0.000	0.000
	(2.296)	(4.505)	(17.112)	(0.000)	(0.000)
Zinc By-ProductDUM*Zinc Price	0.549	-1.192	-9.308	3.323	-1.917
	(2.356)	(7.871)	(17.218)	(5.246)	(1.969)
Zinc Co-ProductDUM*Zinc Price	0.315	-0.862	-6.562	1.646	-1.790
	(2.251)	(4.453)	(17.130)	(5.043)	(1.935)
Zinc Main ProductDUM*Zinc Price	0.267	0.938	-7.272	1.231	-1.582
	(2.251)	(4.533)	(17.100)	(5.036)	(1.932)
No. of obs.	1015	574	605	692	770
R^2	0.241	0.291	0.676	0.438	0.501

Bootstrapped standard errors in parentheses
Variables are mean normalized
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Control variables: time fixed effects, mill recovery, grades of other metals, cumulative production, and current production. By-ProductDum =1 if Metal Revenue >0% and <10%, Co-ProductDum =1 if Metal Revenue ≥10% and <75%, Main ProductDum =1 if Metal Revenue ≥75%

Table B.6: Revenue Interaction Tests and Expectations

Test Name	Specification	Expectation
By-product	H_0: $(ByProduct\_RevDum_{itm} + 1) * Price_{it} = 0$	Not Reject
Main Product	H_0: $(MainProduct\_RevDum_{itm} + 1) * Price_{it} = 0$	Reject
Differnce	H_0: $(MainProduct\_RevDum_{itm} + 1) * Price_{it} = (ByProduct\_RevDum_{itm} + 1) * Price_{it}$	Reject

Table B.7: Test Results for Revenue Interactions, Own Grade-Price Results

Revenue Effect	Silver Grade	Gold Grade	Copper Grade	Lead Grade	Zinc Grade
By-product Effect	0	0	0	0	-
Main product Effect	-	0	0	0	-
Effects Different	Yes	No	No	Yes	No

Result of 0 indicates no significant ($\alpha = 90\%$) effect.
+/- denote direction of significant effect.
Yes/No indicates whether main product effect is statistically different than by-product effect.

Table B.8: Test Results for Revenue Interactions, Cross Grade-Price Results

	Silver Grade	Gold Grade	Copper Grade	Lead Grade	Zinc Grade
By-product Price Effect of	0	Pb	Pb, Zn	Ag, Au, Cu, Zn	0
Main product Price Effect of	0	0	Ag	0	Au

Result of 0 indicates no significant ($\alpha = 90\%$) effects.
Chemical symbols denote the relevant cross-prices.

Table B.9: Alternative Specification - Mine Type Interaction

	(1) Silver Grade	(2) Gold Grade	(3) Copper Grade	(4) Lead Grade	(5) Zinc Grade
Silver Price	-0.102	0.003	0.102	0.039	-0.002
	(0.118)	(0.096)	(0.163)	(0.058)	(0.065)
Gold Price	-0.447**	0.403**	0.050	-0.121*	0.147*
	(0.163)	(0.131)	(0.229)	(0.057)	(0.066)
Copper Price	0.232**	-0.165*	0.079	0.074	0.006
	(0.078)	(0.068)	(0.258)	(0.048)	(0.047)
Lead Price	0.105	-0.123	0.021	-0.457**	0.276
	(0.133)	(0.108)	(0.221)	(0.164)	(0.196)
Zinc Price	0.087	0.027	-0.074	0.365	-0.133
	(0.121)	(0.106)	(0.253)	(0.188)	(0.196)
UGDUM*Silver Price	0.411	-1.069**	-0.368	-0.150	0.209
	(0.368)	(0.397)	(0.206)	(0.252)	(0.139)
UGDUM*Gold Price	0.281	-0.306	0.110	-0.083	-0.465***
	(0.678)	(0.576)	(0.251)	(0.321)	(0.141)
UGDUM*Copper Price	-0.317	0.439	-0.298	-0.024	0.088
	(0.208)	(0.236)	(0.272)	(0.172)	(0.086)
UGDUM*Lead Price	-0.526	1.049**	0.218	-0.459	-0.334
	(0.333)	(0.324)	(0.252)	(0.333)	(0.247)
UGDUM*Zinc Price	-0.242	0.162	0.241	0.152	-0.101
	(0.201)	(0.179)	(0.264)	(0.288)	(0.226)
No. of obs.	933	933	933	933	933
R^2	0.554	0.560	0.101	0.116	0.121

Bootstrapped standard errors in parentheses

Variables are mean normalized

Control variables: grades of other metals, cumulative production, and current production.

UGDUM=1 if the mine is underground.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table B.10: Multi-product Placebo Regressions

Grade	Sample	Silver Price	Gold Price	Copper Price	Lead Price	Zinc Price	No. of Obs.
Silver	All Mines	-0.796	0.438	-0.314	0.500	0.365	1018
		(0.552)	(0.456)	(0.325)	(0.382)	(0.402)	
	No Gold	-0.236*	0.071	0.027	0.180	-0.133	500
		(0.117)	(0.089)	(0.083)	(0.232)	(0.228)	
	No Copper	-1.312	1.138	-0.908	0.822	1.068	491
		(1.132)	(0.982)	(0.623)	(0.709)	(0.836)	
	No Lead	-1.252	0.957	-0.354	0.448	0.556	412
		(1.196)	(0.964)	(0.416)	(0.358)	(0.898)	
	No Zinc	-1.523	1.136	-0.474	0.461	0.739	330
		(1.434)	(1.184)	(0.557)	(0.427)	(1.136)	
Gold	All Mines	-0.762	0.880	-0.213	-0.872	0.951	728
		(0.457)	(0.506)	(0.340)	(0.644)	(0.526)	
	No Silver	0.408	-0.258	-0.466	0.273	0.348	197
		(0.335)	(0.216)	(0.542)	(0.446)	(0.466)	
	No Copper	-1.252	1.597	-0.561	-1.355	1.698	391
		(0.788)	(0.925)	(0.611)	(1.061)	(0.961)	
	No Lead	-0.877	1.255	-0.295	-1.629	1.445	557
		(0.576)	(0.673)	(0.446)	(0.930)	(0.724)	
	No Zinc	-0.951	1.342	-0.396	-1.758	1.603	489
		(0.655)	(0.748)	(0.503)	(1.011)	(0.837)	
Copper	All Mines	0.144	-0.536	0.119	0.074	-0.129	647
		(0.163)	(0.433)	(0.188)	(0.256)	(0.271)	
	No Silver	0.223	0.010	-0.418	-0.345	0.673	105
		(0.327)	(0.277)	(0.245)	(0.259)	(0.321)	
	No Gold	0.077	-0.426	0.108	-0.130	0.005	288
		(0.149)	(0.350)	(0.342)	(0.259)	(0.257)	
	No Lead	0.149	0.157	-0.254*	-0.453	0.486*	376
		(0.123)	(0.177)	(0.110)	(0.271)	(0.187)	
	No Zinc	0.067	0.005	-0.107	0.099	0.095	277
		(0.105)	(0.149)	(0.104)	(0.151)	(0.162)	
Lead	All Mines	-0.001	0.171	-0.056	-0.420	0.278	672
		(0.110)	(0.157)	(0.118)	(0.250)	(0.189)	
	No Silver	0.370	-0.086	0.171	-0.162	0.193	63
		(0.238)	(0.271)	(0.400)	(0.203)	(0.078)	
	No Gold	0.186	0.024	0.039	-0.282	0.047	505
		(0.108)	(0.138)	(0.087)	(0.212)	(0.163)	
	No Copper	0.002	0.207	-0.168	-0.316	0.384	401
		(0.161)	(0.194)	(0.165)	(0.357)	(0.261)	
	No Zinc						NA
Zinc	All Mines	-0.158	0.312	-0.177	-0.156	0.295*	800
		(0.099)	(0.158)	(0.110)	(0.182)	(0.142)	
	No Silver	-0.247	0.953*	-0.636**	0.034	0.647*	89
		(0.243)	(0.308)	(0.161)	(0.439)	(0.205)	
	No Gold	-0.054	0.324**	-0.195*	-0.244	0.294**	553
		(0.079)	(0.100)	(0.076)	(0.128)	(0.101)	
	No Copper	-0.111	0.371**	-0.308*	-0.041	0.299**	430
		(0.109)	(0.121)	(0.121)	(0.225)	(0.097)	
	No Lead	0.064	0.065	-0.142	-0.314	0.230	128
		(0.163)	(0.500)	(0.369)	(0.614)	(0.622)	

Cluster-robust standard errors in parentheses. Clusters at mine level.
Variables are mean normalized
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Controls variables: Cumulative production and current production.

Table B.11: Placebo Regression Summary Table

	Placebo Prices of:				
	Silver	Gold	Copper	Lead	Zinc
Silver Grade		0.071	-0.908	0.448	0.739
		(0.089)	(0.623)	(0.358)	(1.136)
Gold Grade	0.408		-0.561	-1.629	1.603
	(0.335)		(0.611)	(0.930)	(0.837)
Copper Grade	0.223	-0.426		-0.453	0.095
	(0.327)	(0.350)		(0.271)	(0.162)
Lead Grade	0.370	0.024	-0.316		NA
	(0.238)	(0.138)	(0.357)		NA
Zinc Grade	-0.247	0.324**	-0.308*	-0.314	
	(0.243)	(0.100)	(0.121)	(0.614)	

Cluster-robust standard errors in parentheses. Clusters at mine level.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$