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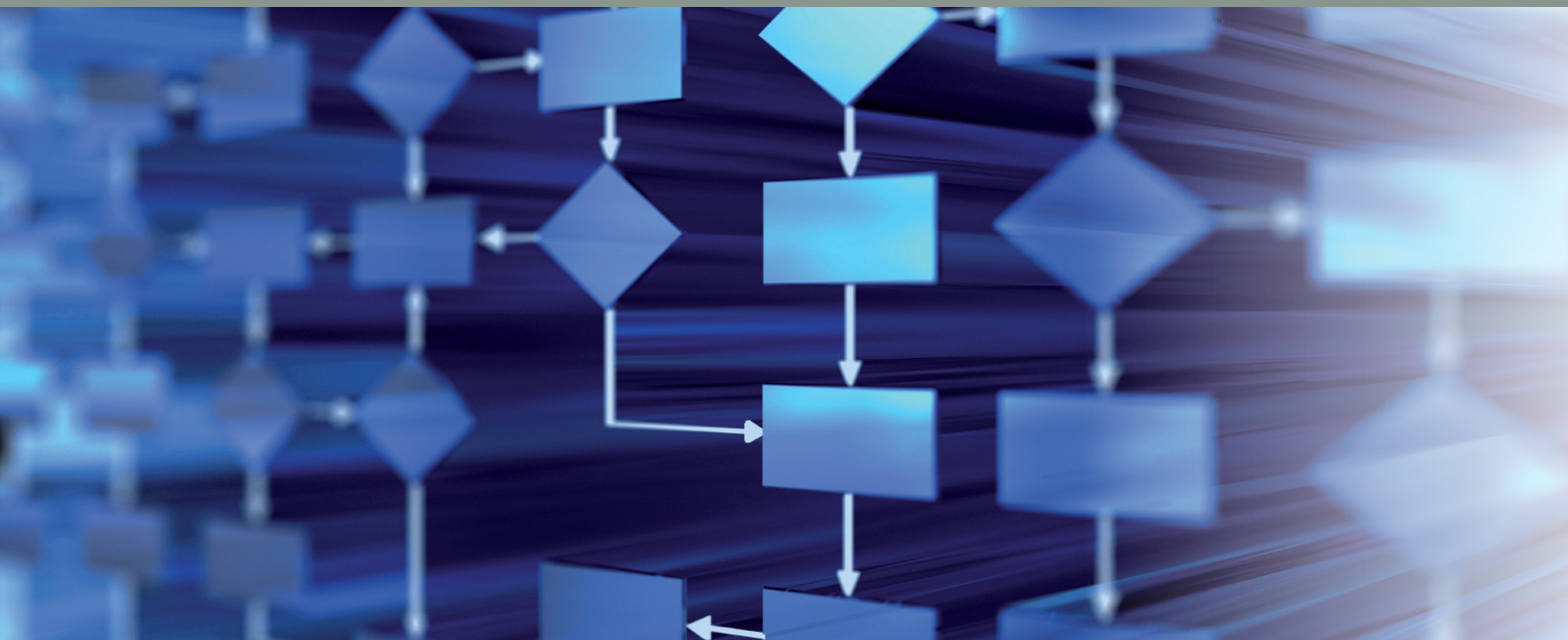

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Innovation in the mining sector and cycles in commodity prices

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Abstract

This paper analyses the evolution of innovation in the mining sector and how this innovation responds to the economic environment, in particular to changes in commodity prices. For this purpose, we combine commodity price data with innovation data as proxied by patent filings extracted from a novel unit record database containing comprehensive patent and firm level data for the mining sector from 1970 to 2015. We include patents registered both by mining companies and mining equipment, technology and service (METS) firms. With a multi-country panel analysis, we find that innovation in the mining sector is cyclical. Innovation increases in periods of high commodity prices while decreasing during commodity price recessions. Our results suggest that innovation increases mostly with long price cycle variations, while mostly unaffected by medium and short cycles. METS related innovation seem the driving force of this mechanism. In contrast, countries specializing in mining industries are found to be slower in reacting to price changes.

JEL codes: L72, L78, O31, E32, L16, Q02
Keywords: Mining, Innovation, Price cycles, Supercycles, Commodity prices

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1 Introduction

Mining and other associated activities are a significant part of the global economy. The value of global mine production has been estimated at around USD 1.3 trillion in 2014 (Lof and Ericsson, 2016). In 2015, mining related commodities represented approximately two percent of the world's total trade (UN COMTRADE, 2016). The mining industry provides non-replaceable products for our everyday needs. Products of the mining industry are used to build everything that surrounds us, from infrastructure to personal devices. The growing worldwide population, together with rising living standards, has increased the demand for minerals. Typically, the mining industry meets increasing demand in the short-term by optimizing operations in existing mining sites with decreasing returns. In the long-term, mining companies search for new mining sites that meet the demand requirements. In addition, the mining industry faces continuous operational challenges to fulfil the increasing sustainability and social requirements demanded by society. Innovation is a key instrument to address all these challenges.

Given the boom in demand, the decreasing returns of existing sites and the sustainability requirements, it is not surprising that mining related commodities have seen a remarkable increase in price over the past two decades. Equally predictable was the well-documented boom in mining production and exports that followed. What has happened to the rate of mining-related innovation during this period remains an understudied topic.

In this paper we study the effect of variation in commodity price on the innovation carried out within the mining industry. In particular, we look at whether the existence of cycles in commodity price, distinguishing between short- and long-term cycles – the so-called super-cycles – affects innovation levels. We identify the mining industry as the industry where the extraction of minerals takes place. We include coal in this definition but exclude oil and gas and quarrying.

Mining companies are increasingly sourcing innovation from specialized suppliers (Bartos, 2007). Therefore, we consider the mining industry in a broader technological sense. In addition to companies directly engaged in finding and developing mines, we include service providers which support the everyday activities of the mining firms by providing specialized equipment and technology, a sector commonly referred to as the Mining, Equipment, Technology and Services (METS) sector. Innovation is proxied by patent filing. Mining related patents filed by both mining firms and METS firms are part of the analysis.

This paper relies on mining patent data consolidated by WIPO for the period 1970-2015. We merge the patent data with a series of indicators related to the mining sector based on data from the World Bank, namely a mineral commodity price index, an estimation of effective demand of mining production and the country exposure to mining. We identify price cycles of different length using the Christian and Fitzgerald band-pass filter (Cuddington and Jerret, 2008). We conduct the analysis first using time series and then using panel data.

We find empirical evidence of pro-cyclicality between innovation and prices in the mining sector. We model innovation as response to changes in commodity prices and test for the effects of different cycle lengths. Our results suggest that innovation reacts more to long cycle changes rather than shorter ones. We also analyze the effect on mining innovation distinguishing between innovation generated by mining companies and by METS firms. METS companies appear the driving force of mining innovation response to price changes. When we move to the panel analysis, we find that mining specialized countries – as opposed to countries having little mineral production – only react to changes in the long cycle components of commodity price.

The rest of the paper is structured as follows. Section 2 reviews the literature and provides motivation for the paper's main research questions. Section 3 presents the data while providing a descriptive overview of the mining industry innovation; it also discusses our estimation method. Section 4 comments on the results and the main robustness checks performed and Section 5 concludes.

2 Literature review and hypotheses

External macroeconomic and financial shocks certainly affect mining production, but little is known on how they translate to the sector's technological change. Mining is considered a very cyclical sector. When prices are high, new mines are opened and existing mines are exploited more intensively. While when prices are low, production slows and mines are closed (Batterham, 2004). The way innovation and technology development react to these price cycles remain, to the best of our knowledge, an unexplored topic.

As part of the commodity super-cycle, mining related commodities have seen an outstanding increase in price over the past 15 years, which has been accompanied by a well-documented boom in mining production and exports. This period has not only been characterized by a high increase in prices but also a higher volatility (IMF, 2015). Recent work has shown that mining innovation – proxied by patent applications – in general has followed this boom, but it has also down trended after the global financial crisis (Daly et al., 2019).

There have been many studies about trends and cycles in commodity prices (Tilton, 2006; Radetzky, 2006). A few of these have focused on the mining commodities, such as Labys, Achouch and Terraza (1999), by analyzing the relationship between metal prices and business cycles. But in general, there has been less attention on the economic effects of the longer cycles of these prices. Traditionally, economic scholars have been very skeptical about the presence of these commodities "supercycles" (Howrey, 1968; Cogley and Nason, 1995). However, a number of relatively recent studies have begun to shed some light on the topic (Solow, 2000; Comin and Gertler, 2006; Cuddington and Jerret, 2008). They find empirical evidence of substantially more volatile and persistent fluctuations in the medium- and long-term of business cycles and commodity prices, respectively.

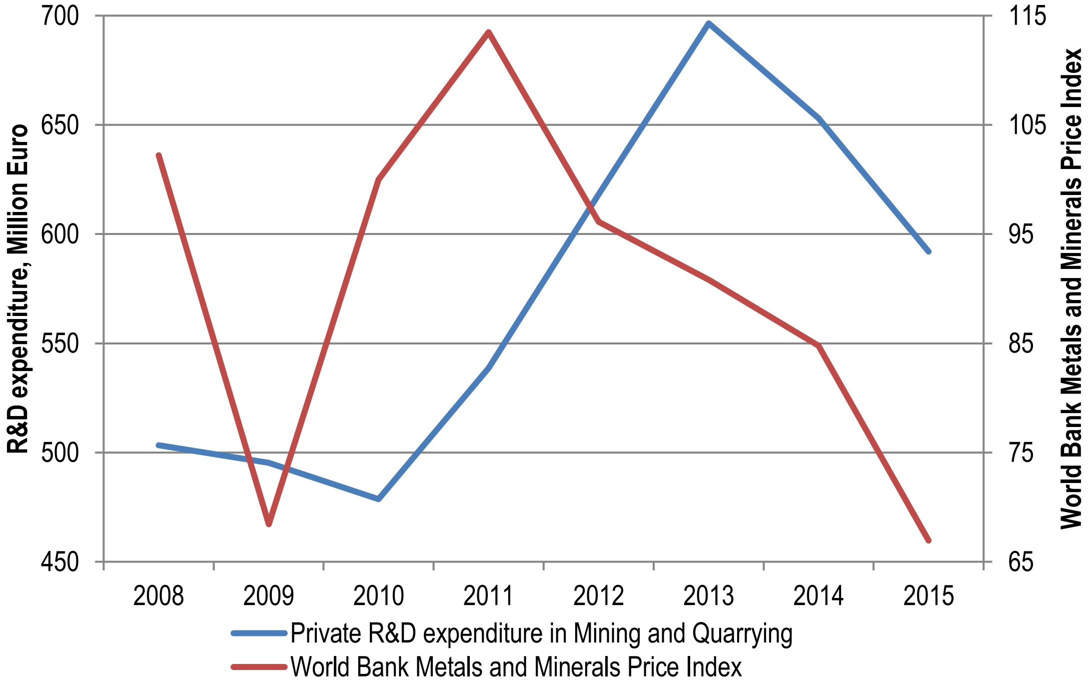
What happened to the innovation rate of mining-related technologies during the recent period? Given the stiffness that characterizes mining sector investment, it seems plausible that R&D decisions will be based more on expectations about long-term variation of price rather than short-term ones. The existing literature has focused on how R&D expenditures varies over business cycles, although never focusing on mining or other commodity sectors. The traditional view is that recessions should promote various activities that contribute to long-run productivity and thus to growth, such as technical change (Canton and Uhlig, 1999), job turnover (Gomes et. al. 2001) and human capital accumulation (Barlevy and Tsiddon, 2006). Many studies have found innovation to be pro-cyclical, measured by R&D activities (Fatas, 2000; Rafferty and Funk, 2004; Barlevy, 2007) or patents (Geroski and Walters, 1995). According to Geroski and Walters (1995), the direction of the causality seems statistically stronger for business cycles causing innovation than the opposite, although innovation is largely explained by other factors than demand. In what concerns the length of cycles, Barlevy (2007) argues that macroeconomic shocks are likely to have overly persistent effects due to such the pro-cyclicality of R&D activities.

The mining industry is often considered a slow innovator (Scherer, 1984). Nevertheless, Bartos (2007) shows that its rate of innovation is comparable with general manufacturing, even if it is still lower than so-called high-tech manufacturing (Dunbara et. al. 2016).
The total amount of money spent on R&D by the sector is significant, particularly in mining specialized countries such as Australia (Balaguer et al., Forthcoming). According to

EUROSTAT figures (2018), the mining sector spent 592 million euro in 2015, which is below the amount spent by the pharmaceutical (9,791 million euro) or chemical manufacturing (6,681 million euro) sectors but higher than agriculture (589 million euro) or consumer electronics (313 million euro).

Figure 1 shows the private R&D expenditure in EU countries together with the metals and minerals price index from the World Bank. We can see a positive correlation between the two indicators with some delay of the R&D expenditure in reacting to price changes.

Figure 1. Private R&D expenditure in mining and quarrying in EU countries, and World Bank metals and minerals price index

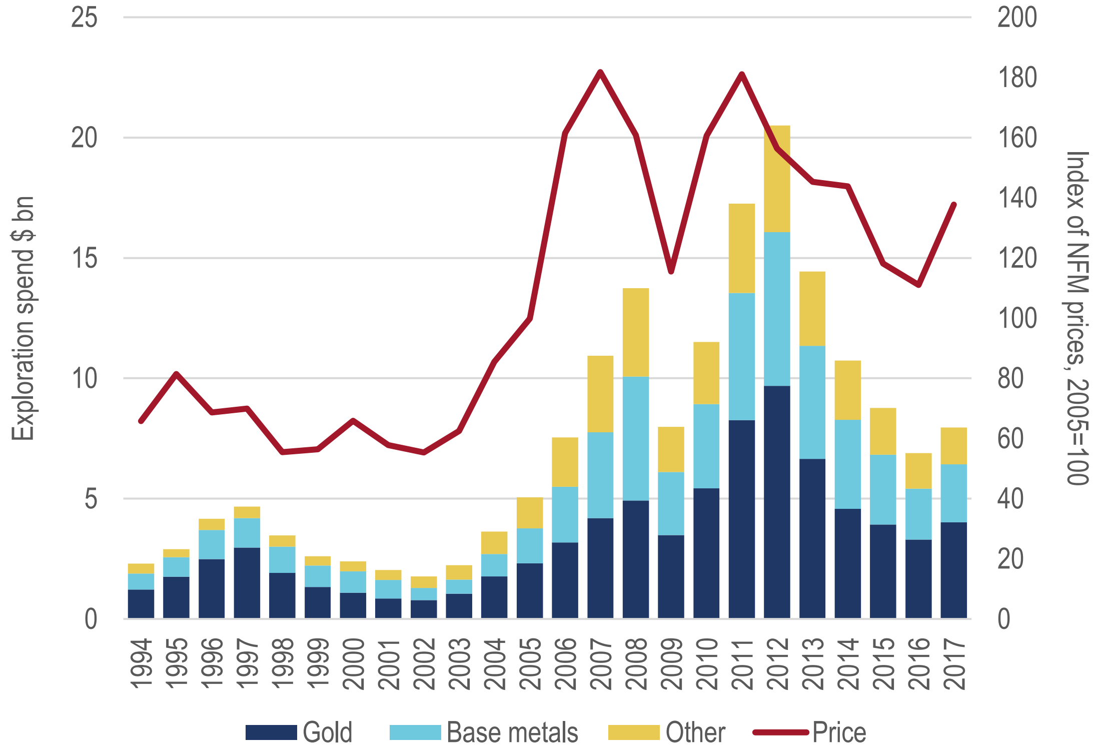


Source: Eurostat (2018), BERD by NACE Rev. 25 activity. Note: EU includes Belgium, Bulgaria, Czech Republic, Denmark, Germany, Ireland, Greece, Spain, France, Croatia, Italy, Lithuania, Hungary, Netherlands, Austria, Portugal, Romania, Slovakia, Finland, UK, Iceland and Norway.

In addition to R&D expenditure, the discovery of new commercially viable mining deposits through exploration is an important part of the economics of the industry. In fact, there is a case to be made that it is the deposit or the mine that is really the new 'product' rather than the mineral recovered therein. Viewed in this way, a company's expenditure on exploration becomes a part of its R&D expenditure, in the sense that it is expenditure aimed at finding new, commercially-exploitable sources of a mineral, even though exploration may not be not recognized formally as R&D.

There are interesting parallels here with other industrial sectors. Mines, open up, operate and close down, very much in the way that manufactured products are invented and produced before moving through to obsolescence. Just as industries like pharmaceuticals spend large amounts of money on trying to discover new marketable drugs, despite the long odds against them, so the mining industry has to battle equally long odds in its search for commercially viable 'greenfield' (new) sources of a mineral commodity. Very broadly it has been estimated that for every thousand mineral occurrences identified, only one will be subject to exploration and of every thousand deposits explored, only one is likely to become a mine (Kreuzer and Etheridge, 2010). In any case, existing series of worldwide exploration expenditures show a high degree of correlation with the evolution of the price index for non-ferrous metals (see Figure 2).

Figure 2. Mineral exploration expenditure by commodity and non-ferrous metals price index



Source: SNL Mining & Metals, The Economist.

Understanding the innovation activity in the mining sector is important, and challenging. Innovation can take place at different stages of production: (1) exploration and discovery of new deposits, (2) organization and site construction, (3) exploitation of the site, and (4) decommissioning and final closure of the site. In addition to companies directly engaged in finding and developing mines, there is a large number of METS companies supplying the mining industry with equipment and technology.

METS companies contribute a substantial share of the innovation in the mining sector. These companies work very closely with mining companies to understand their requirements and to develop innovative solutions. METS firms invest, on average, more on R&D compared to mining firms (Daly et al, 2019). They also have lower capital expenditures than mining companies, which are required to have big initial investments both for the exploration phase and for the establishment of mining operations. Mining firms often prefer to outsource services to METS firms rather than making it in a less efficient way. For instance, transport innovation in the mining sector is often produced METS companies (Dionori and Zehtabchi, forthcoming). METS firms are therefore an essential part of the mining innovation ecosystem.

Table 1 summarizes the differences between mining and METS firms along crucial dimensions of their activity. In general, mining firms are large and they operate at different stages of the mining value chain. METS firms range from big multinationals – e.g. Caterpillar or Siemens – which not only provide specialized services for the mining sector, but also serve other industries as well; to SMEs, which are typically specialized in the production of one product or service specially developed for the mining activity.

On average mining firms have larger sunk costs compared to METS firms. When opening a mine, the initial investment is very big and it can only be recovered after many years of operation. Therefore, their activity is not very flexible. METS firms are more flexible. They could also have large fixed costs but this applies more to large multinationals which therefore spread them across the different industries they serve reducing the risk associate with their activity. Finally, mining firms produce mostly process innovation, while METS firms produce both new process and new products which then are sold to the mining companies which use them to improve their performance.

Table 1. Characteristics of mining and METS firms

Characteristic	Mining firm	METS firms (Large)	METS firms (SMEs)
Size	Large	Large (horizontally diversified)	Micro, small & medium
Diversification	Vertical (within the mining supply chain)	Horizontal (across several industries)	Horizontal (if any)
Sunk costs	Large (within the supply chain)	Large (across different industries)	Low
Innovation type	Process	Product & process	Product & process

Existing studies have shown several channels through which a price change could affect the decision to invest in innovation for other industries. Canton and Uhlig (1999), Gomes et al. (2001) and Barlevy and Tsiddon (2006) find evidence of pro-cyclicality channels between prices and innovation in other industries. These studies suggest that the pro-cyclicality can be direct or indirect, where the latter is typically through the access to finance for the firm. Conversely, Fatas (2000), Rafferty and Funk (2004), Barlevy (2007) and Geroski and Walters (1995) suggest that a counter-cyclical effect can arise from cost-reducing innovative effort.

How would the pro-cyclical effect apply to the mining sector? An increase in mineral prices could directly stimulate innovation for the mining firms, which have more disposable income to invest in innovation. A price increase also affects METS firms indirectly, as they experience a higher demand for their products/services from mining firms. Moreover, diversified METS firms may have stronger incentives to adapt technologies developed for other business.

At the same time, an increase in price also increases the access to external finance of both types of firms, if financial markets discount future income will also be related to the new price. Similarly, the increased access to finance could boost investment in innovation. Therefore, both direct and indirect effects point toward pro-cyclicality of innovation with respect to price.

How would the counter-cyclical effect apply to the mining sector? A price decrease imposes cost reduction pressure on mining firms, which already operate with tight operating margins in many mining sites. Cost-reducing technologies could be an effective way to avoid the closure of mines. Similarly, mining companies may invest in exploration aiming to discover new deposits with higher grade, hence more cost-effective. Either the cost-reducing or exploration related technologies can be produced in-house or sourced from METS firms. This implies a counter-cyclical effect, where innovation is boosted, for both mining and METS firms, in periods of low prices.

The effect of a price decrease on the access to finance for firms is instead ambiguous. In the one hand, it definitely implies a reduced access to external private finance as the risk profile of these firms is now higher. In the other hand, the bigger and more diversified firms could still rely on internal resources (for the case of big vertical integrated mining firms) or on revenues from other industries that they supply (for the case of big horizontally integrated METS). Moreover, in mining specialized countries – e.g. Chile, Australia or South Africa – the large mining companies and the sector as whole might be, arguably, too big to fail.

Policy-makers may have strong incentives to aid the sector troubled by decreasing prices and innovation financing is one valid option.

We don't know which of these effects will prevail. Still, we can argue that the counter-cyclical effect is more likely to occur for shorter term price variations. Typically, a mining company can cross-subsidize activities in the short-term to iron out a price fluctuation expected to be temporary. If the price variation is expected to be structural – i.e. of a longer term – companies may be limited to the counter-cyclical innovative actions they can undertake. A similar logic applies to public financial support, although likely with a longer horizon. In any case, we can expect the ambiguous effect is less likely in the longer cycles.

Table 2 summarizes the channels just through which a commodity price change could affect the decision of both types of mining sector stakeholders to invest in innovation.

Table 2. Effect on innovation and access to finance of price change

	Mining firms	**METS firms**
Price increase	**+ Innovation** (+) more disposable income to invest in innovation (+) more access to external finance	**+ Innovation** (+) more demand from mining industry (+) more incentives to adapt other technologies to mining (+) more access to external finance
Price decrease	**? Innovation** (–) less disposable income to invest in innovation (–) less access to external private finance (+) cost reduction and exploration pressure (+) more access to external public finance	**? Innovation** (?) depends on mining industry demand (–) less incentives to adapt existing technologies

We can formulate the main conclusions from the existing literature as four distinct hypotheses which we are going to test in this paper:

H1a: Higher prices generate higher disposable income (direct or indirect) that is invested to generate more (pro-cyclical) innovation;

H1b: Lower prices generate higher cost reduction and exploration pressure generating (counter-cyclical) innovation;

H2: Price shocks do not affect innovation unless they are perceived as structural (i.e. long lasting);

H3: As METS firms can adapt other sectors' technologies to mining, they are more likely to innovate more and faster due to price variation than mining firms; and,

H4: Mining specialized countries have stronger incentives to have counter-cyclical innovation policies.

3 Data and methodology

In this section, we present and discuss the data used in our analysis. We then give an overview at the estimation methods used to study the relationship between commodity prices and innovation in the mining sector.

We use the World Bank Metals and Minerals Price Index as a proxy for an average global commodity price. This index weights the price of seven commodities – aluminum, copper, iron ore, lead, nickel, tin and zinc – traded in the London Metals Exchange, based on their world production shares. All the prices are reported in 2010 USD. The index is available from 1960 to 2017.

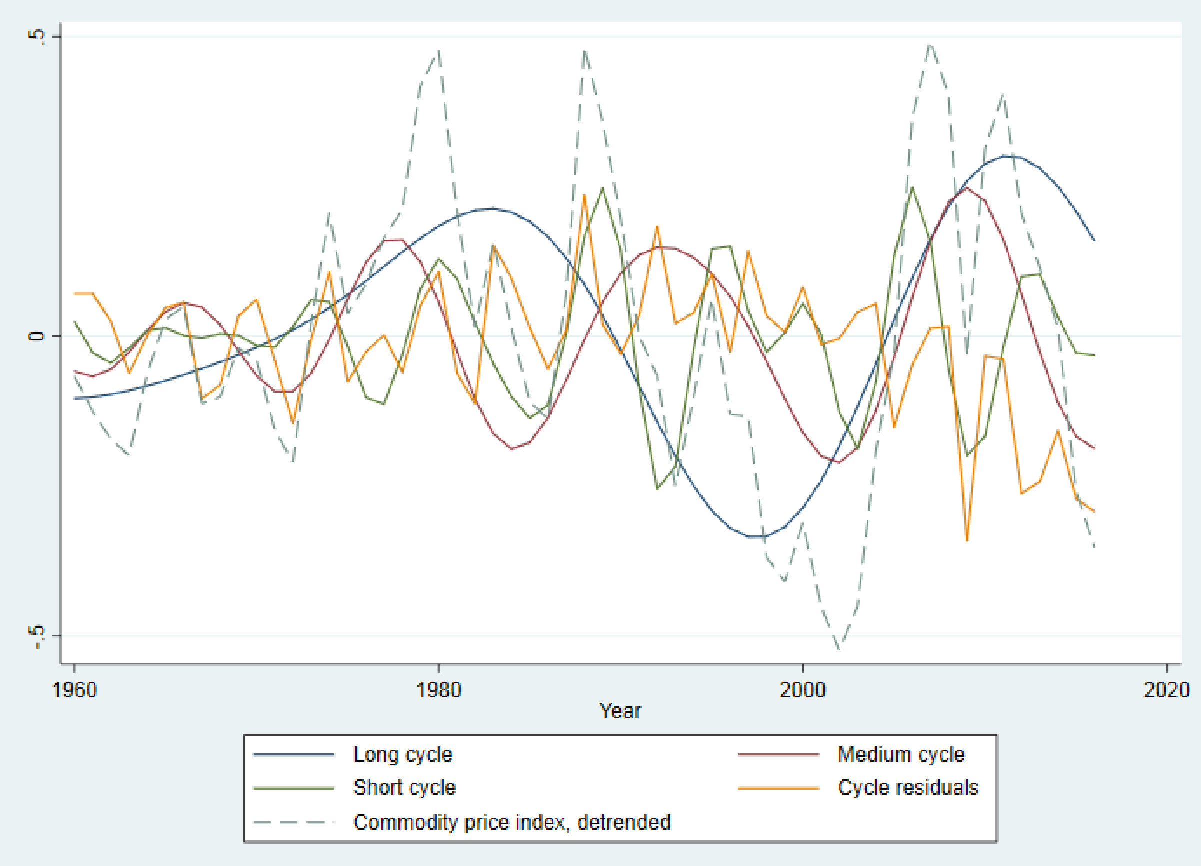
One limitation of such an index is that countries differ in their mining activities. Countries producing other mineral commodities than the seven minerals covered by the index or having a different weight of them, may react to other price variations than those captured by the index. In order to partially address this issue, we rely on an alternative measure of metal commodities price as a robustness check. In particular, we build a country-specific index using disaggregated commodity prices from the World Bank database[3] and weighting them based on export shares for each country. We extract data on commodity trade by country of origin from Feenstra et al. (2005). These data are classified by SITC codes. We were able to match SITC codes of export flows with products' prices from the World Bank. To see in details how we built the country-specific prices read Appendix A.

Following Cuddington and Jerret (2008), we decompose the natural logarithm of the de-trended commodity price in cycles of different lengths: long cycle[4] (from 20 to 70 years), medium cycle (from 10 to 20 years), short cycle (from 5 to 10 years) and a residual component (less than 5 years). Figure 3 plots the de-trended price index across and the different component cycles of the price index. The long and medium cycles show a relatively smooth variation over time. The short cycles exhibit more sharp fluctuation around the mean value. The residual component exhibits the sharpest fluctuations and captures the short-term variation of the price. All these components sum to the value of the de-trended price index (the dash line).

Being mineral output commodities, we can expect that an excess of demand to be transferred to prices only if there is no idle supply capacity. In the short run, mineral supply will follow those demand fluctuations with the installed capacity limiting the effect on prices. In the long run, mining companies can also vary capacity by opening and closing mining sites without necessarily changing technology. So, it is important to understand how the volume of supply behaves in order to fully capture how prices may affect the innovation decision. For this purpose, we also collect information on mineral rents for each country from the World Bank Development Indicators. Given that we want to include in each specification a general measure of mineral products volume, we deflate the mineral rents with the metals and mineral price index and create a mining quantity index based on the 2010's artificial volume.

[3] We use prices of aluminum, copper, lead, nickel, tin, zinc, coal, iron ore and precious metals.
[4] Often referred to, in the literature, as supercycle.

Figure 3. De-trended metals and minerals price index, and different cycles components



Source: World Bank Metals and Minerals Price Index

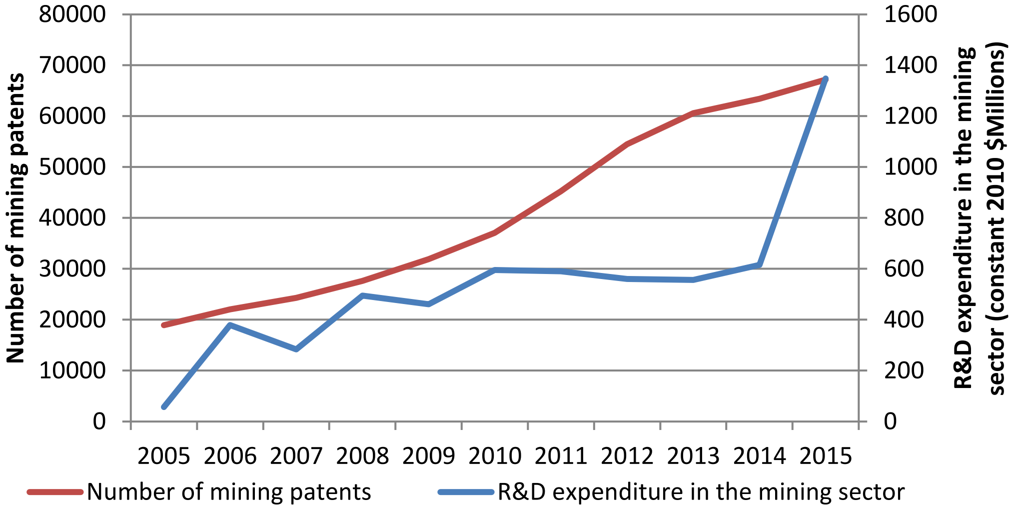
In this paper we use patents as a proxy for innovation. A patent is a legal right that is granted for any device, substance, method or process that is new, inventive, and useful. Patents give the owner exclusive rights to commercially exploit the invention for a limited period of time. In return for exclusive rights, patent applications must be published and must fully disclose the claimed invention. As a result of this requirement, the body of patent literature reflects developments in science and technology. Furthermore, patent data is rich in information adjacent to technology information, such as temporal, geographic and bibliographic data. Through the extraction and analysis of data associated with patent applications, it is possible to measure aspects of invention and economic researchers have long used patent applications as a measure of inventive activity.

Some recent studies have highlighted the rising importance for mining enterprises to use IP instruments – particularly patents – when they pursue an internationalization strategy (Francis, 2015; Daly et al, 2019; Blundi et al., 2019; Bravo-Ortega and Price, 2019). They are often multinational companies operating in different countries and patents may help them secure their intellectual property across states and appropriate the knowledge embedded in new discoveries. Outside the mining sector, using patents as a proxy for innovation is an established practice in the literature (Acs et al, 2002; Griliches, 1998; Jaffe and Trajtenberg, 1999). In doing so, we need to acknowledge all the limitations about this approach that several studies in the existing literature have extensively raised and addressed (Lerner and Seru, 2017). In particular, we acknowledge that the innovation captured through patents is a fraction of the wider range of innovative activity that is happening in the field.

Even if not all inventions are patented, it is largely agreed that a patent embodies an original result of an R&D activity undertaken by an entity. As a result, patent data are highly correlated with R&D expenditures in the mining sector (Figure 4). In addition, patents offer full coverage of both application countries and years. Therefore, they are more suitable for a global study of mining innovation as this is intended to be. The rest of the paper uses patent data as a direct measure of innovation activity in the mining sector.

Another challenge when using patent data is the lag between this variable and R&D activities. The real lag between R&D expenditures and patents has been the subject of multiple studies (Hall et al., 1984, Gurmu and Pérez-Sebastián, 2008). These studies find relatively contemporaneous effects between the two variables, which justifies the use of patent as a proxy for the R&D expenditures at the firm level. We follow this approach by using a minimum lag between these two.

Figure 4. Number of patent families and R&D expenditure in the mining sector



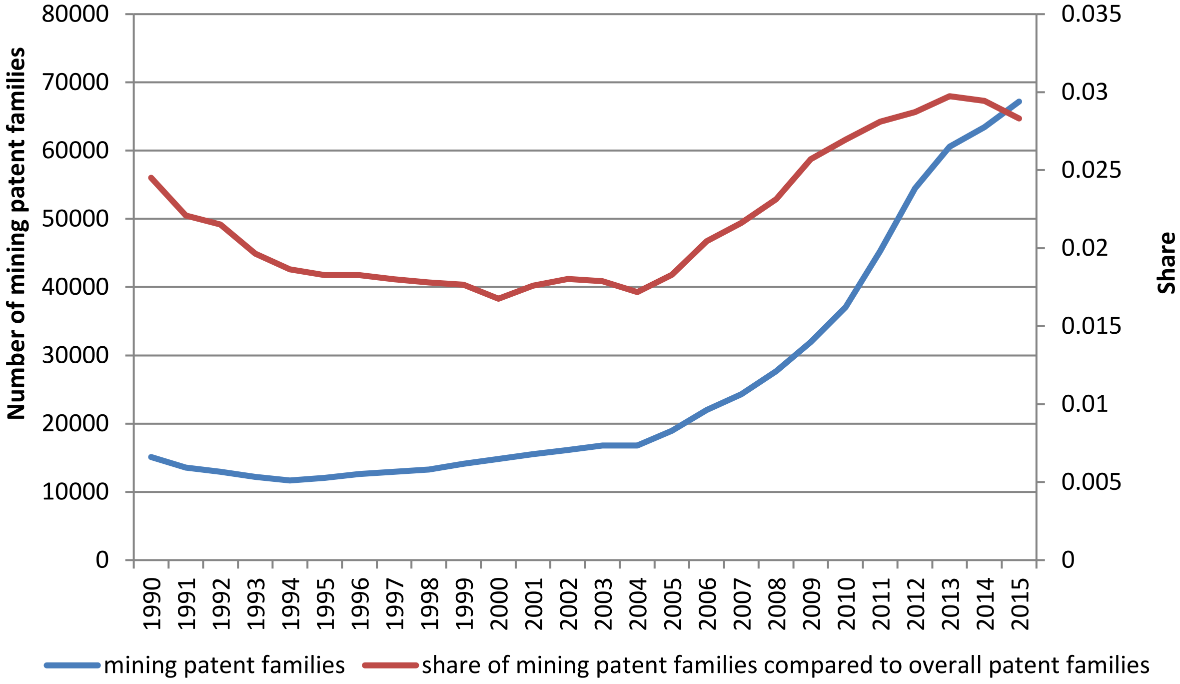
Source: WIPO Mining Database (2018) and OECD Business enterprise R&D expenditure by industry Database

In the rest of the paper the basic unit of analysis will be the patent family, the year will refer to the first filing year of the patent family and for the country we will use the country of origin. A patent family refers to all those patents applied in different jurisdictions for the same invention[5].

Figure 5 shows the evolution over time of the number of mining patent families. There is a clear increase over time with an exponential peak after the beginning of the 21st century. This peak relates to a global overall increase in patenting (WIPO, 2011, 2017). This is partially due to the appearance of China as a leader economy around that time. The overall number of Chinese patents – including mining patents – has steadily increased since then. Nowadays, China is a top patent filing country, second only to U.S. However, the mining patents represent an increasing share of total patent families, which suggests a faster mining technological change than average in the last decade. This contrasts with the slower pace of mining innovation in the early nineties.

[5] For all details about how we built the patent data, including patent family unique identifier and origin, refer to Daly (2019).

Figure 5. Number of mining patent families and share of mining patent families over total patent families



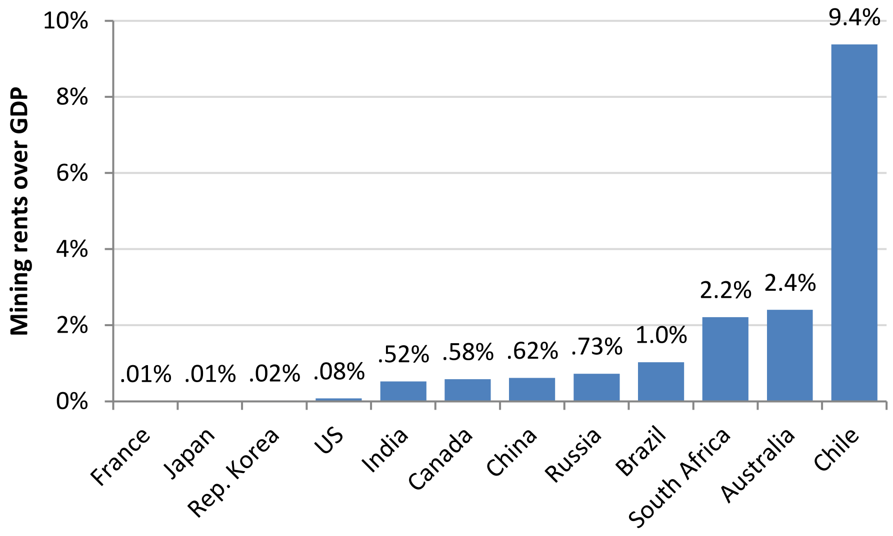
Source: WIPO Mining Database (2018)

In addition, we also make use of the mineral rents as a percentage of GDP as measure of the mining specialization a given economy. Figure 6 shows the mining specialization of selected countries displaying their percentage of mining rents over GDP. Countries like Chile, Australia and South Africa have mining rents representing a large share of the GDP, which is more than nine percent for the case of Chile. These countries are considered to be more specialized in the mining sector as their income relies considerably on mining activity. On the other hand, countries like France, Japan or South Korea derive only a very minimal, close to zero, portion of their GDP from pure mining activities. By definition, countries more specialized in the mining sector have a large portion of their economy relying on these mining rents, making them more exposed to the price fluctuations of minerals and metals. Therefore, we interpret this indicator as a proxy of the country exposure to the mining industry.

This doesn't mean that those countries do not play any role for the mining sector. As Figure 7 shows, the countries with less exposure to the mining industry are oriented more towards METS firms' activities rather than mining firms' activities[6]. On the other hand, countries that are more exposed to mining are also more specialized in mining firms' innovation. From the same figure we can discern that innovation in the "traditional" mining fields such as exploration and blasting is more concentrated in mining firms, while most of the services for the sector (environment, transport and to some extent also metallurgy) are developed by METS firms.

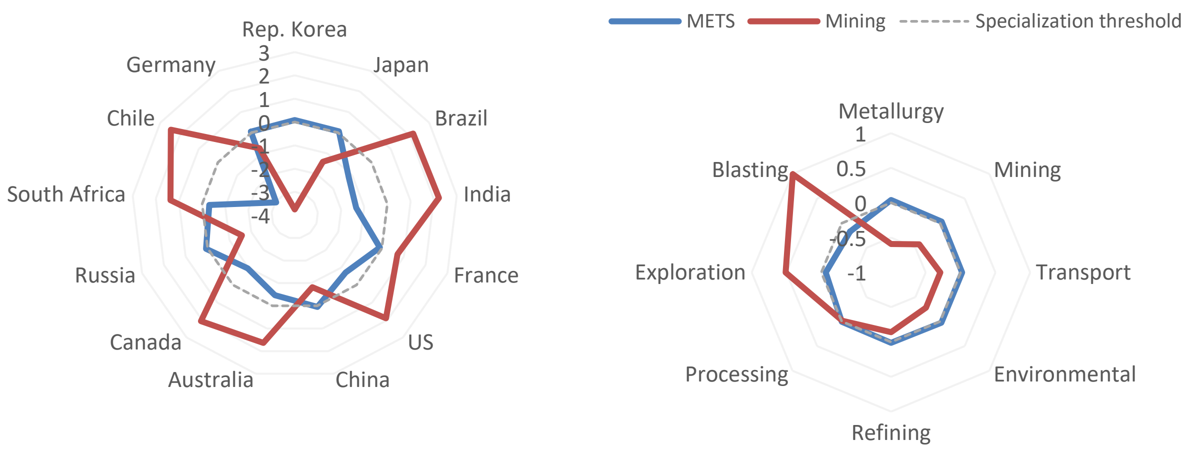
[6] To build this graph we calculated the relative specialization index (RSI), by country and technology for METS and mining firms' innovation. Positive RSIs mean that the country, within the pool of mining innovation, has relatively more innovation carried out by mining firms rather than METS compared to the world average. For the technology the interpretation is similar: it means that innovation in that technological field is, on average, carried out more by mining firms rather than METS.

Figure 6. Country exposure to mining sector rents



Source: World Bank Development Indicators. Note: This graph has been constructed using the average mining rents over GDP for each country in the period 1970-2015.

Figure 7. Mining and METS firms innovation relative specialization, by country and mining technology



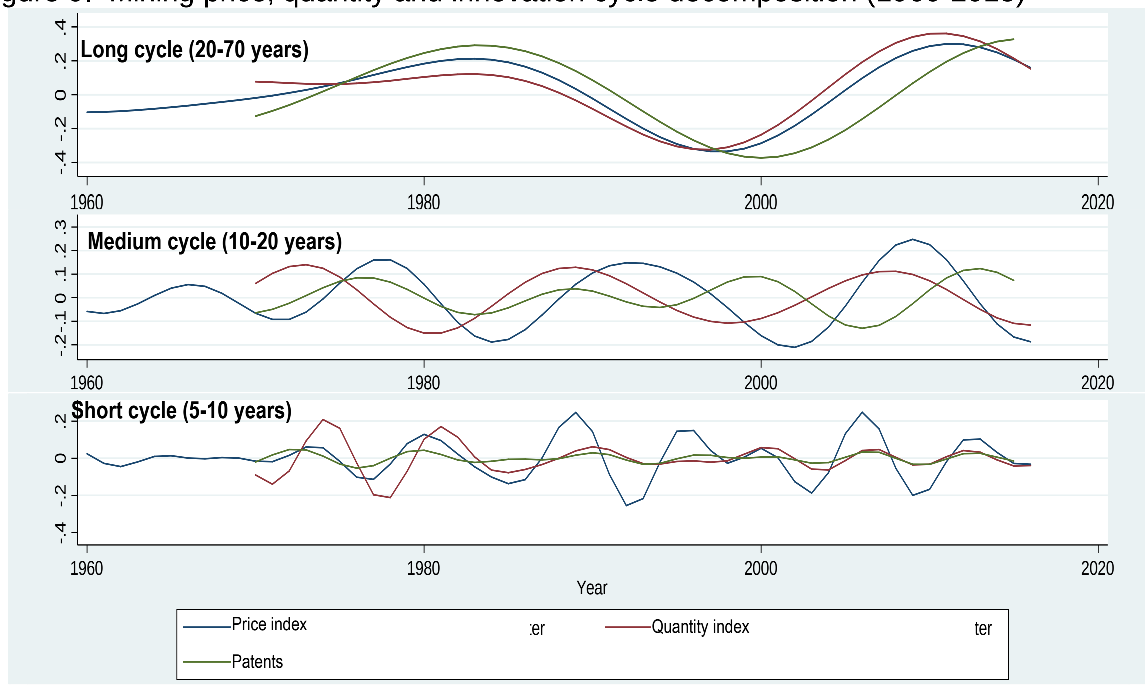
Source: WIPO Mining Database. Note: indicator reflects the relative specialization index (RSI) based patent portfolios of METS and mining firms broken down by country and technological field.

Figure 8 shows the evolution over time of the de-trended mining commodity price, quantity index and patents. Overall, there seems to be a strong positive correlation among these three indices. To better understand how expectations might be formed in the short and long run and what drives the observed correlation, we decompose each of these variables in the above-mentioned three cycles (Figure 9). A strong positive correlation is present for the long cycle for all the three variables, although innovation seems to lag slightly. In the medium cycle, innovation seems to be correlated with price but much less than before. For the short cycle components, changes in prices seem to affect innovation in the early years of our panel but not so much in more recent ones where innovation remains relatively flat. Moreover, both innovation and quantity short cycles are in sync.

Figure 8. Mining price, quantity and innovation co-evolution (1960-2015)

Source: World Bank Development Indicators and WIPO Mining Database. Notes: all indicators are in logs and de-trended.

Figure 9. Mining price, quantity and innovation cycle decomposition (1960-2015)



Source: World Bank Development Indicators and WIPO Mining Database. Notes: all indicators are in logs and de-trended.

Model specification

We test the hypotheses discussed in the previous section in two main frameworks. First, we make use of a time series estimation for the global mining activity. Our baseline specification is the following:

$$I_t = \boldsymbol{\beta P_{t-1}} + \vartheta D_{t-2} + \varepsilon_t \quad (1)$$

where *I* represents global innovation at time *t*, as measured by the number of mining patents filed in a given year; *P* is the commodity price and *D* the demand for mineral products. They are respectively lagged by one and two periods[7]. The coefficient of interest is $\boldsymbol{\beta}$. A positive $\boldsymbol{\beta}$ would suggest evidence of cyclicality validating hypothesis H1a, while if $\boldsymbol{\beta}$ is negative we fall into counter-cyclicality in accordance with hypothesis H1b.

Then, we substitute P_t by the different cycle components:

$$I_t = \boldsymbol{\beta_1 lc_{t-1}} + \boldsymbol{\beta_2 mc_{t-1}} + \boldsymbol{\beta_3 sc_{t-1}} + \boldsymbol{\beta_4 rc_{t-1}} + \vartheta D_{t-2} + \varepsilon_t \quad (2)$$

where $\boldsymbol{lc_t}, \boldsymbol{mc_t}, \boldsymbol{sc_t}$ and $\boldsymbol{rc_t}$ are respectively the long, medium, short and residual components of the price index. Equation (2) helps us disentangle the real channel of transmission of the effect of the price on innovation identifying which components play the biggest role in this. Positive $\boldsymbol{\beta_c}$ validates H1a, while negative ones play in favor of H1b. We expect $\boldsymbol{\beta_1}$ to be larger than $\boldsymbol{\beta_2}$ and $\boldsymbol{\beta_3}$ to confirm H2. In addition to revisiting hypotheses H1a, H1b and H2, this second framework allows to investigate H3, using as a dependent variable (I_t) the number of mining patents for each technology category and subsector within mining[8].

We then move to a panel estimation for the third framework by adding the country dimension *i*:

$$I_{i,t} = \alpha \Delta M_{i,t} + \beta P_{i,t-1} + \boldsymbol{\gamma}(\boldsymbol{P_{i,t-1}} \Delta \boldsymbol{M_{i,t}}) + \vartheta D_{t-2} + \mu_i + \varepsilon_{i,t} \quad (3)$$

When we substitute the different cycle components, (3) turns into:

$$I_{i,t} = \alpha \Delta M_{i,t} + \beta_1 lc_{i,t-1} + \boldsymbol{\gamma_1}\left(\boldsymbol{lc_{i,t-1}} \Delta \boldsymbol{M_{i,t}}\right) + \beta_2 mc_{i,t-1} + \boldsymbol{\gamma_2}\left(\boldsymbol{mc_{i,t-1}} \Delta \boldsymbol{M_{i,t}}\right) + \beta_3 sc_{i,t-1} + \boldsymbol{\gamma_3}\left(\boldsymbol{sc_{i,t-1}} \Delta \boldsymbol{M_{i,t}}\right) + \beta_4 rc_{i,t-1} + \boldsymbol{\gamma_4}\left(\boldsymbol{rc_{i,t-1}} \Delta \boldsymbol{M_{i,t}}\right) + \vartheta D_{t-2} + \mu_i + \varepsilon_{i,t} \quad (4)$$

In both (3) and (4), $\Delta M_{i,t}$ captures the exposure of a country to the mining sector. We also add country specific fixed effects μ_i in these specifications, in order to capture country specific idiosyncrasies, which are invariant over time.

In addition to revisiting hypotheses H1a, H1b and H2, this third framework allows to investigate H4. The coefficient $\boldsymbol{\gamma}$ captures whether the innovation of a country which is more exposed to the mining sector reacts more (if positive) or less (if negative) to changes in commodity prices.

Table 3 presents a summary of descriptive statistics of the variables used for the time series specification, either in their simple form or with the different mining categories, and the panel specification[9]. For the time series specification, we observe a big variation of both number of patents and the price index across the years under consideration. In a great extent, this

[7] To test the optimal lag period for the regressors we ran some correlation tests. Please see Appendix X for more details.
[8] Innovation in the mining sector focuses on the following fields (for a detailed description on how these categories are obtained refer to Daly (2019)): exploration, blasting, environment, processing, mining, transport, refining and metallurgy. These categories do not come in a sequential order as some of them may take place at different stages of the mine's life, for example transport or environmental innovation.
[9] Data refers to the time period 1970-2015.

variation accounts for the positive time trend observed in all three main indicators, which supports removing the trend in our econometric analysis. For the different mining categories specification, we observe that distribution of patents across categories is quite unbalanced: they are mostly concentrated in the mining, exploration, refining and environmental categories. Finally, METS firms file a much larger amount of mining patents compared to mining firms.

The divergence of patenting behavior is also apparent across countries. When we move to the panel specification, we find country-year observations ranging from only one mining patent to more than 30,000. Following a similar trend, there are countries for which mining activity represents a negligible part of their GDP, while in other countries this percentage goes up to more than 20 percent, like in Chile.

Table 3. Descriptive statistics of main variables

Variable	Obs	Unit of measure	Mean	Std. Dev.	Min	Max
Time series specification						
Mining patents	46	Number of patents	14868.8	10829.5	5658	48774
Price Index	46	2010 = 100	47.73	26.29	16.46	113.49
Mining quantity index	46	2010 = 100	45.39	27.30	20.26	108.24
Mining Categories Specification						
Patents of mining cat.	46	Number of patents	5296.67	3672.59	1749	16976
Patents of blasting cat.	46	Number of patents	78.00	54.49	26	235
Patents of environmental cat.	46	Number of patents	1611.17	1386.21	491	5714
Patents of exploration cat.	46	Number of patents	3301.04	3121.29	1013	13213
Patents of metallurgy cat.	46	Number of patents	159.46	83.47	84	489
Patents of processing cat.	46	Number of patents	594.04	595.26	131	2858
Patents of refining cat.	46	Number of patents	3173.67	1240.71	2021	6789
Patents of transport cat.	46	Number of patents	789.80	830.07	218	3387
Mining vs. METS Specification*						
Mining firm patents	46	Number of patents	387.13	467.85	64	1839
METS firm patents	46	Number of patents	4249.46	6443.97	123	25008
Panel Specification						
Mining patents (by origin country)	1505	Number of patents	380.70	1974.21	1	37163
Price Index	1505	2010 = 100	53.96	28.30	16.46	113.49
Mining quantity index	1505	2010 = 100	166.63	549.99	.1175	10933.4
Mining rent as % of GDP	1505	Percentage	0.82	2.06	0	20.95

Source: World Bank Development Indicators and WIPO Mining Database. Notes: (*) figures are based on a subsample of mining patents for which the applicant's sector can be identified.

4 Results

Table 4 reports the test for equations (1) (first column) and (2) (second column). It finds a positive and significant effect of both commodity prices and quantity on mining innovation validating hypothesis H1a. This implies that high commodity prices, as well as high demand for mining products, boost innovation in the sector.

If we look more specifically at different price cycles (second column), we realize that the price effect is mainly driven by variations in the long cycle components which confirms hypothesis H2. Shorter term components are found not to have any effect on mining innovation[10].

Table 4: Time series estimation

	Dependent Variable: Log. of mining patents applications worldwide	
	(1)	(2)
Log. of Price Index (1st Lag)	0.357*** (0.109)	--
Long cycle component of Log. of Price Index (1st Lag)	--	1.107*** (0.105)
Medium cycle component of Log. of Price Index (1st Lag)	--	0.557 (0.150)
Short cycle component of Log. of Price Index (1st Lag)	--	0.167 (0.188)
Residual cycle component of Log. of Price Index (1st Lag)	--	-0.218 (0.237)
Log. of mining quantity (2nd Lag)	0.523*** (0.073)	0.202*** (0.053)
Observations	44	44
Years	1970-2016	1970-2016
R-squared	0.72	0.85

*Notes: The model is estimated with the OLS estimator. The dependent variable is included in logarithmic terms. All variables included in the model are detrended. A constant is included in each specification. Robust standard errors in parentheses. *, ** and *** respectively denote significance at 10%, 5% and 1% levels.*

Tables 5a and 5b replicate the analysis in Table 4 using as a dependent variable a mining sub-category, instead of the full sample of mining patents. We still find an overall pro-cyclical effect of price changes on mining innovation (see Table 5a) as predicted by H1a. H2 is confirmed, also in this sub-category scenario, in Table 5b. The effect of long cycle price shocks on mining innovation is positive and significant for almost all sub-categories. Only environmental mining patents seem less responsive suggesting that other factors may play a bigger role in explaining them, for example environmental regulation as is discussed in Andersen and Noailly (forthcoming). We find mixed evidence for H3 as the core mining technologies, namely blasting and exploration (see Figure 5) are among the slower and faster subcategories to react to price shocks, respectively.

[10] We tried to add to the regressors the squared value of the residual component of the price but it did not change the results so we decided to omit it. Appendix B presents all tables with the squared residual component of the price cycle.

Table 5a: Time series estimation, different mining categories

	Blasting (1)	Environment (2)	Exploration (3)	Metallurgy (4)	Mining (5)	Processing (6)	Refining (7)	Transport (8)
Log. of Price Index	0.095	0.149*	0.345***	0.053	0.508**	0.448***	0.219**	0.491***
(1st Lag)	(0.100)	(0.079)	(0.127)	(0.120)	(0.137)	(0.143)	(0.086)	(0.139)
Log. of mining quantity	0.139**	0.490***	0.582***	0.358***	0.439***	0.472***	0.485***	0.757***
(2nd Lag)	(0.062)	(0.049)	(0.079)	(0.075)	(0.085)	(0.089)	(0.054)	(0.087)
Observations	44	44	44	44	44	44	44	44
Years	1970-2016	1970-2016	1970-2016	1970-2016	1970-2016	1970-2016	1970-2016	1970-2016
R-squared	0.18	0.77	0.69	0.41	0.62	0.60	0.76	0.77

*Notes: The model is estimated with the seemingly unrelated estimator (SUR). The dependent variable is included in logarithmic terms. All variables included in the model are detrended. A constant is included in each specification. Robust standard errors in parentheses. *, ** and *** respectively denote significance at 10%, 5% and 1% levels.*

Table 5b: Time series estimation, different mining categories

	Blasting (1)	Environment (2)	Exploration (3)	Metallurgy (4)	Mining (5)	Processing (6)	Refining (7)	Transport (8)
Long cycle of Log. of Price	0.397**	0.232*	1.320***	0.591***	1.513***	1.302***	0.591***	1.421***
Index (1st Lag)	(0.170)	(0.141)	(0.143)	(0.187)	(0.176)	(0.211)	(0.140)	(0.191)
Medium cycle of Log. of	0.059	0.174	-0.224	-0.363*	0.127	0.256	0.178	0.147
Price Index (1st Lag)	(0.173)	(0.143)	(0.146)	(0.190)	(0.179)	(0.215)	(0.143)	(0.195)
Short cycle of Log. of	0.086	0.215	0.248	0.202	0.146	0.094	0.079	0.236
Price Index (1st Lag)	(0.182)	(0.151)	(0.154)	(0.200)	(0.188)	(0.226)	(0.150)	(0.205)
Residual cycle of Log. of	-0.406*	-0.171	-0.321	-0.463*	-0.124	-0.259	-0.196	-0.246
Price Index (1st Lag)	(0.237)	(0.196)	(0.200)	(0.260)	(0.244)	(0.293)	(0.195)	(0.266)
Log. of mining quantity	-0.035	0.414***	0.188***	0.127	0.026	0.087	0.299***	0.352***
(2nd Lag)	(0.087)	(0.072)	(0.073)	(0.095)	(0.090)	(0.108)	(0.071)	(0.078)
Observations	44	44	44	44	44	44	44	44
Years	1970-2016	1970-2016	1970-2016	1970-2016	1970-2016	1970-2016	1970-2016	1970-2016
R-squared	0.30	0.79	0.89	0.58	0.82	0.74	0.81	0.87

*Notes: The model is estimated with the seemingly unrelated estimator (SUR). The dependent variable is included in logarithmic terms. All variables included in the model are detrended. A constant is included in each specification. Robust standard errors in parentheses. *, ** and *** respectively denote significance at 10%, 5% and 1% levels.*

We also explore how mining and METS firms react to commodity price changes. In this exercise our sample shrinks because we are only able to categorize firms appearing in Bureau Van Dijk's Orbis database under specific NACE Rev.2 codes[11]. We consider their mining patents as dependent variables and we run a similar analysis to the one carried out before. In Table 6 we report the same set of estimation run on two different samples: only mining firms' innovation (first and third columns) and only METS firms' innovation (second and forth columns). Only the innovation from METS firms seem to react to price changes; while we don't find any significant effect of prices on innovation from mining firms. This points toward the validation of H3.

Nevertheless, this could also be explained by the high rate of technology outsourcing which we observe in the mining industry. Given that most of the time mining firms prefer to acquire technology from the specialized suppliers rather than producing it in house, METS firms will be the ones absorbing the price variations and adapting their innovation accordingly. This may also explain why we do not observe an effect of price on patents in the shorter periods. Mining firms are the ones directly exposed to the price variations. Therefore, it will take some time for this effect to be transferred to METS firms, which will then adapt their innovation decisions accordingly.

[11] We classify mining firms as those companies operating in NACE sectors: 0500, 0510, 0520, 0700, 0710, 0720, 0729, 0721, 0811, 0812, 0891, 0892 and 0899; and we categorize METS firms as those companies operating in sectors: 2892, 2822, 0990 and 0910.

Table 6: Time series estimation, mining vs METS firms

	Dependent Variable: Log. of mining patents applications worldwide			
	Mining firms (1)	METS (2)	Mining firms (3)	METS (4)
Log. of Price Index (1st Lag)	-0.032 (0.143)	0.708*** (0.229)	--	--
Long cycle component of Log. of Price Index (1st Lag)	--	--	-0.139 (0.259)	1.260*** (0.391)
Medium cycle component of Log. of Price Index (1st Lag)	--	--	0.124 (0.263)	1.047*** (0.398)
Short cycle component of Log. of Price Index (1st Lag)	--	--	0.120 (0.277)	-0.199 (0.419)
Residual cycle component of Log. of Price Index (1st Lag)	--	--	-0.368 (0.360)	0.518 (0.544)
Log. of mining quantity (2nd Lag)	0.766*** (0.089)	0.290** (0.143)	0.744*** (0.132)	0.046 (0.200)
Observations	44	44	44	44
Years	1970-2016	1970-2016	1970-2016	1970-2016
R-squared	0.67	0.36	0.69	0.45

*Notes: The model is estimated with the seemingly unrelated estimator (SUR). The dependent variable is included in logarithmic terms. All variables included in the model are detrended. A constant is included in each specification. Robust standard errors in parentheses. *, ** and *** respectively denote significance at 10%, 5% and 1% levels.*

Table 7: Panel estimation

	Dependent Variable: Log. of mining patents by applicant country			
	(1a)	(1b)	(2a)	(2b)
Log. of Price Index (1st Lag)	0.177*** (0.064)	0.191** (0.076)	--	--
Mining rent as % of GDP	--	0.045* (0.024)	--	0.014 (0.026)
Price Index x Mining rent as % of GDP	--	-0.065*** (0.017)	--	--
Long cycle of log. of Price Index (1st Lag)	--	--	0.396*** (0.126)	0.278** (0.139)
LC # Mining rent As % of GDP	--	--	--	0.196*** (0.065)
Medium cycle of log. of Price Index (1st Lag)	--	--	0.069 (0.139)	0.247* (0.126)
MC # Mining rent As % of GDP	--	--	--	-0.313*** (0.061)
Short cycle of log. of Price Index (1st Lag)	--	--	0.006 (0.096)	0.029 (0.108)
SC # Mining rent as % of GDP	--	--	--	-0.069*** (0.020)
Residual cycle of log. of Price Index (1st Lag)	--	--	-0.157 (0.143)	-0.141 (0.149)
RC # Mining rent As % of GDP	--	--	--	0.022 (0.028)
Log. of mining quantity (2nd Lag)	0.026 (0.018)	0.020 (0.017)	-0.002 (0.017)	0.001 (0.017)
Observations	1505	1505	1505	1505
No. Countries	54	54	54	54
Years	1970-2016	1970-2016	1970-2016	1970-2016

*Notes: The model is estimated with the Fixed-effects estimator. The dependent variable is included in logarithmic terms. All variables included in the model are detrended. Country fixed-effects and a constant are included in each specification. Robust standard errors in parentheses. *, ** and *** respectively denote significance at 10%, 5% and 1% levels.*

Table 7 and 8 show the results for the panel specifications reported in the third (columns 1a and 1b) and fourth (columns 2a and 2b) equations, respectively, with the aggregate price index and with country-specific prices. The two specifications evolve quite similarly showing that the use of a World Price Index does not distort findings compared to a country-specific one. We tried the simple regression (columns a) and we then add the country exposure to the mining sector and the interaction term between the price and the country exposure (columns b).

Table 8: Panel estimation, using country-specific price index

Dependent Variable: Log. of mining patents by applicant country				
	(1a)	(1b)	(2a)	(2b)
Log. of Price Index (1st Lag)	0.083** (0.034)	0.086** (0.034)	--	--
Mining rent as % of GDP	--	0.044 (0.039)	--	0.049 (0.047)
Price Index # Mining rent as % of GDP	--	-0.025 (0.022)	--	--
Long cycle component of log. of Price Index (1st Lag)	--	--	0.318*** (0.113)	0.302** (0.121)
LC # Mining rent As % of GDP	--	--	--	0.013 (0.033)
Medium cycle component of log. of Price Index (1st Lag)	--	--	0.016 (0.055)	0.102 (0.063)
MC # Mining rent As % of GDP	--	--	--	-0.142** (0.068)
Short cycle component of log. of Price Index (1st Lag)	--	--	0.018 (0.040)	0.038 (0.043)
SC # Mining rent As % of GDP	--	--	--	-0.041 (0.029)
Residual cycle component of log. of Price Index (1st Lag)	--	--	0.022 (0.080)	-0.016 (0.085)
RC # Mining rent As % of GDP	--	--	--	0.045 (0.041)
Log. of mining quantity (2nd Lag)	0.020 (0.019)	0.012 (0.019)	0.009 (0.020)	-0.001 (0.020)
Observations	1063	1063	1063	1063
No. Countries	39	39	39	39
Years	1970-2016	1970-2016	1970-2016	1970-2016

*Notes: The model is estimated with the Fixed-effects estimator. The dependent variable is included in logarithmic terms. All variables included in the model are detrended. Country fixed-effects and a constant are included in each specification. Robust standard errors in parentheses. *, ** and *** respectively denote significance at 10%, 5% and 1% levels.*

Mining prices maintain a positive effect on mining innovation (as predicted by H1a), which is mostly capturing the long cycle component. The only main difference with the time-series specification is that the mining demand loses its significance, which is probably due to the country-fixed effects. The country exposure to the mining sector (measured by mining rents as a percentage of GDP) is found to have a positive effect on innovation only for the case of country-invariant price index (Table 7), although only statistically significant at ten percent. It is found non-significant for the country-specific price index (Table 8). Therefore, more exposed countries will, on average, innovate more in mining technologies than non-mining ones. The interaction between the price effect and exposure to the mining sector is found to be negative and significant in Table 7, while it loses its significance in Table 8. This means that less-exposed countries will be the ones that react more to price changes.
An explanation for this could be found in the fact that METS companies, which are among the top innovators, are not necessarily located in mining countries (see Figure 5). They can develop their technology in their home country and then sell it to mining firms operating in other countries.

If we have a closer look at this phenomenon introducing the distinction across price cycles (second columns), we confirm what has been found before: the long cycle component of price is found to influence positively the innovation rate confirming again H2. In addition through the introduction of the interaction term, we find that mining countries react more to price changes in the long cycles (see Figure 10: the higher the exposure of a country to the mining sector the bigger will be the reaction of innovation to price changes), while non-mining ones react more on the medium and short-term (see Figures 11 and 12: the lower the exposure of a country to the mining sector the bigger will be the reaction of its innovation to price changes; for countries which are very exposed to the mining activity an increase in commodity price in the medium and short-term will have counter-cyclical effects on innovation). Mining countries are slower to absorb the price effect, compared to METS countries, which mostly affects them in the long run. This confirms our idea that mining firms are on average less flexible than METS firms in adapting to price changes. There is therefore a need for highly-dependent mining countries to implement counter-cyclical policies able to defeat the negative effects of commodities down cycles, as anticipated in hypothesis H4. The fact that these countries rely extensively on mining rents makes them particularly vulnerable to commodity price depression, jeopardizing their ability to remain competitive in the market. This condition affects METS countries less, which rely only marginally on mining activity. Their diversification becomes a strong attribute in periods of low prices.

Figure 10. Average marginal effect of long cycle component of price index on innovation with 95% confidence intervals

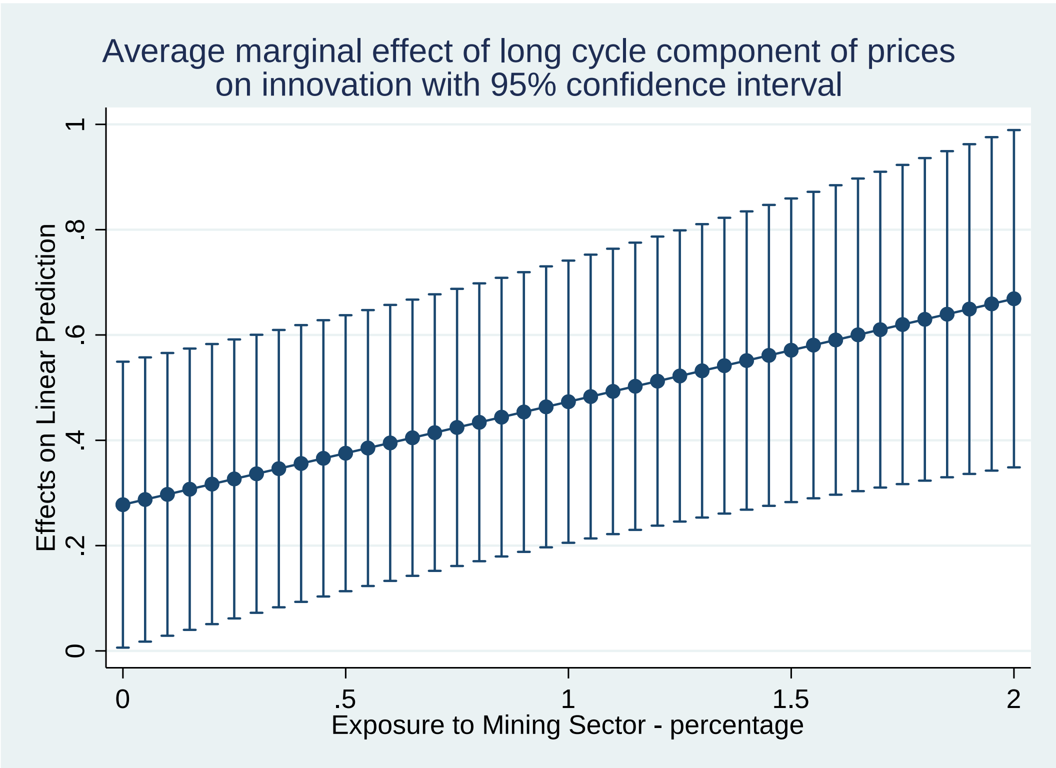


Figure 11. Average marginal effect of medium cycle component of price index on innovation with 95% confidence intervals

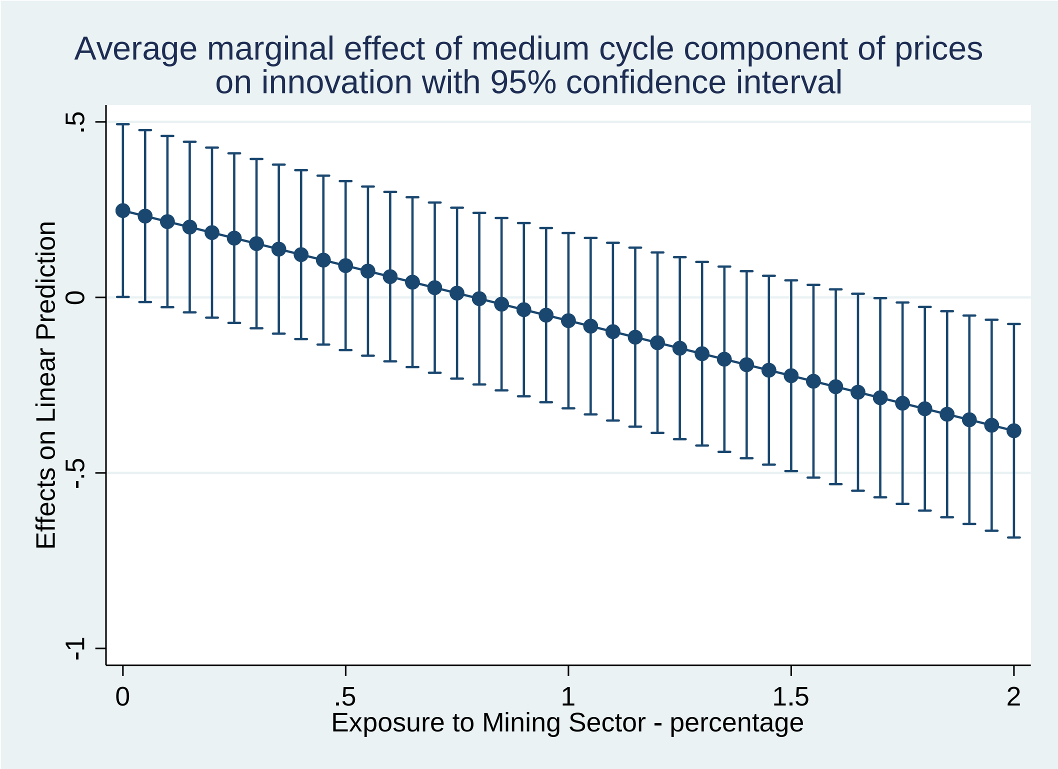
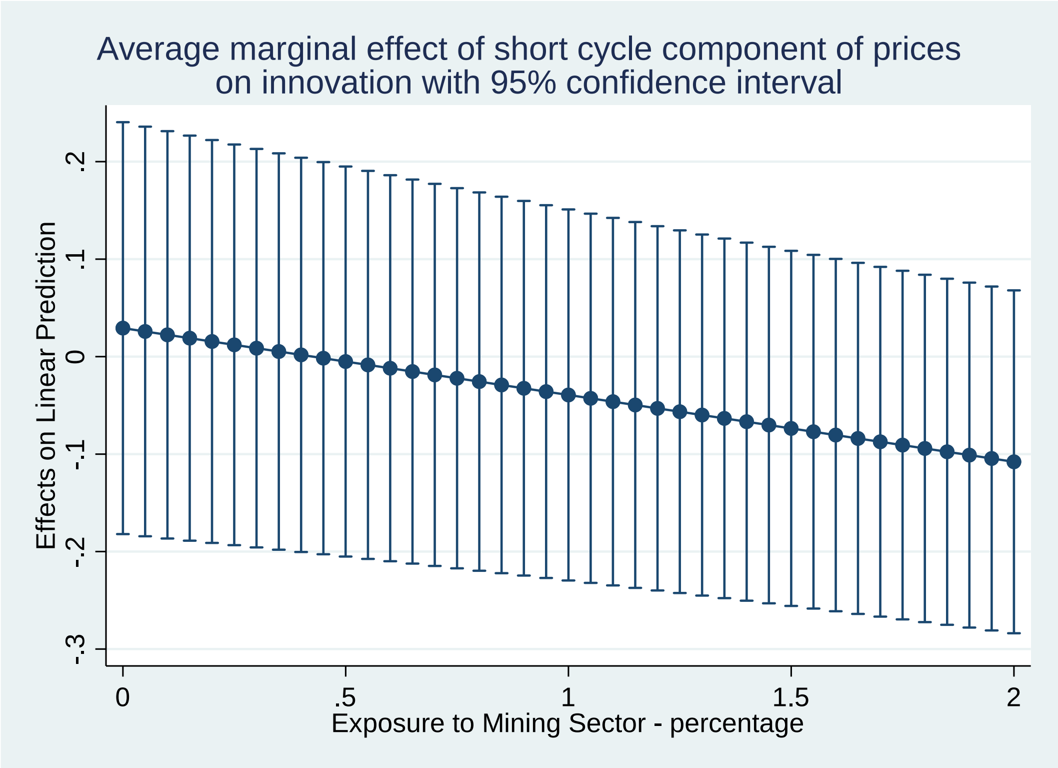


Figure 12. Average marginal effect of short cycle component of price index on innovation with 95% confidence intervals



5 Concluding remarks

In this paper we studied the relation between economic cycles and innovation in the mining sector. In particular, we exploited how the business cycle of this sector is tied in with mining commodity price fluctuation. In doing so, we focus on the impact of mineral and metal price changes on the sector's innovation.

We discussed the transmission mechanisms based on the adaptation of the existing literature on the cyclicality of innovation to the singularities of the mining sector. We hypothesized a pro-cyclical impact if the transmission is based on higher prices generating higher direct or indirect disposable income that is in turn invested in innovation; and, a counter-cyclical impact if lower prices increase the pressure to reduce cost and increase efficiency through new technologies. We also conjectured that price variation is more likely to affect innovation if perceived as long-lasting shocks, if innovators are more technologically diversified and if countries are more specialized in mining.

To test these hypotheses, we relied on novel mining innovation data for the period 1970-2015 based on patent information and a series of economic indicators related to the mining sector based on data from the World Bank. We conducted the econometric analyses using both time series and panel data. Our main contribution was to disentangle the effects of price cycles of different lengths, namely long-term, medium-term, short-term and residual. To identify them we used the Christian and Fitzgerald's band-pass filter and isolated four components of the price.

Our setting attempted to circumvent several identification issues. We accounted for the time lag between changes in demand, commodity prices and innovation. To establish the optimal lag between these variables, we ran a series of correlation tests. We identified the price cycles using the Christian and Fitzgerald band-pass filter as in Cuddington and Jerret (2008). Complementary robustness checks included tests for country-specific mineral and metal price index; the removal of countries whose economies are highly relying on the mining sector; and, the addition of the squared residual price cycle component to control for price instability.

Overall, we found that mining innovation is pro-cyclical, increasing in periods of commodity price boom and slowing down during recessions. We found little evidence of counter-cyclical innovation. It is worth noting that these two mechanisms may co-exist. Hence, a stronger pro-cyclical effect may be hiding a weaker counter-cyclical one. Our model cannot resolve this question, but it does indicate that if a counter-cyclical effect exists it is weaker than the pro-cyclical one in most of our estimations.

We found consistent empirical evidence on long price cycles affecting mining innovation more than shorter ones. Indeed, most of the pro-cyclical effect is related to the long-cycle component of the price variation. This is coherent with the long decision-making timeline associated with the mining sector, where a bulk of the technological changes happen when mines are opened or closed.

We also found evidence that the transmission of the pro-cyclical effect happens indirectly through the METS firms. When comparing mining and METS firms, we found that only METS firms were responsive to adapt their innovation to price changes. Moreover, the estimations indicate that METS are more responsive and faster to adapt their innovation to price changes than the industry average.

According to our estimations, economies specializing in mining produce more mining innovation, but they are also less reactive to price changes. Nevertheless, this behavior varies substantially across the length of price cycles. More specialized economies react even more pro-cyclically to changes of the long cycle component of price than more diversified ones. Conversely, highly specialized economies may observe counter-cyclical responses to medium and short cycle components, while diversified economies may observe pro-cyclical responses also for the medium cycle component.

These results indicate that mining dependent economies put in place counter-cyclical measures based on innovation to cope with shorter term downturns of the business cycle. It also means that, in the upturn, they are less reactive than more diversified economies. The latter are likely to have innovation systems also more technologically diversified composed by innovative METS firms able to adapt new technologies to the mining sector.

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Appendices

A – Building country-specific prices

We extract the data on commodity trade by country of origin for export and import from Feenstra et al. (2005) data (https://atlas.media.mit.edu/en/resources/data/). All of the product data shown on the site is classified using SITC (Standard International Trade Classification). For historical SITC classification data (1962 - 2000), we use data from The Center for International Data. For more recent data (2001 - 2014), we use data provided by UN COMTRADE.

We calculated the top materials exported globally:

SITC	Exports (bn US)
3222	1,220
2815	919
2820	561
2871	510
2882	422
2873	259
2816	248
2879	186
2890	172
2872	150
3232	141
2875	123
2881	72.8
3221	70.3
2874	65.7
2877	57.1
3224	19.6
3223	14.4
2876	14.0
2860	11.9
3231	5.87
2814	5.15

The top SITC codes are Coal (3222), Iron Ore (2815 and 2816), Scrap or iron ore (2820), Copper (2871), Other non-ferrous metal waste and scrap (2882), Aluminum (2873), Ores and concentrates of other non-ferrous base metals (2879), Ores and concentrates of precious metals, waste, scrap (2890), Nickel (2872), Coke(3232).

We proxy all the Iron ore derivative prices (2814, 2815, 2816) with Iron ore spot prices from the World Bank. All coal derivatives (3221, 3222, 3223, 3224, 3231, 3232) are proxied with the cooking coal prices from Cohen et al. (2018) [12]. For the precious metals (2890) we take an average of the price of gold, platinum and silver from the World Bank. For Nickel (2872), Copper (2871), Aluminum (2873), Lead (2874), Zinc (2875) and Tin (2876) we use prices

[12] Note that in that paper there are country specific coal prices. But since we want to build a general country index, we decided to take US prices of coking coal and then build the index with them. The coking coal data is only available from 1978 to 2015 so we will restrict our time frame from that year on until 2015 included. The right cut is not a problem since trade data is only available up to 2014 and also patent data in 2016-2017 are not reliable due to incomplete data.

from World Bank. For the rest (2820, 2860, 2877, 2879, 2881, 2882) we use the World Bank aggregated metal index. The metals and minerals price at time *t* for country *c* is calculated as $p_t^c = \sum_k p_{k,t}$ where $k \in$ Aluminium, Copper, Lead, Nickel, Tin, Zinc, Coal, Iron Ore, Precious Metals, Others. All prices are expressed in real/constant 2010 USD.

In this sample, there are 124 territories with incomplete panels when we consider country price WB:

AD	BA	BY	DM	GM	KE	LR	MM	NP	SA	SY	UA	VU
AE	BB	BZ	EE	GN	KG	LS	MN	NR	SC	SZ	UG	WS
AF	BD	CD	ET	GP	KH	LT	MO	OM	SD	TC	UM	YE
AG	BF	CF	FK	GQ	KI	LU	MP	PF	SH	TD	UY	ZW
AI	BJ	CK	GA	GU	KN	LV	MQ	PG	SI	TJ	UZ	
AM	BM	CM	GD	HN	KP	LY	MR	PN	SK	TK	VA	
AO	BN	CR	GE	HR	KW	MD	MS	PY	SL	TN	VC	
AS	BS	CU	GF	HT	KY	MH	MU	QA	SM	TO	VE	
AW	BV	CV	GH	IQ	KZ	MK	MW	RE	SO	TT	VG	
AZ	BW	CZ	GI	IR	LA	ML	NA	RU	ST	TW	VN	

And 79 territories with complete panel:

AL	CA	DO	GT	JM	MY	PE	SR
AR	CG	DZ	GY	JO	MZ	PH	SV
AT	CH	EC	HK	JP	NC	PK	TG
AU	CI	EG	HU	KR	NE	PL	TH
BE	CL	ES	ID	LB	NG	PT	TR
BG	CN	FI	IE	LK	NI	RO	TZ
BH	CO	FJ	IL	MA	NL	RW	US
BI	CY	FR	IN	MG	NO	SE	ZA
BO	DE	GB	IS	MT	NZ	SG	ZM
BR	DK	GR	IT	MX	PA	SN	

We decided to only keep the territories with complete panels.

B - Adding squared residual components of price

Here we replicate the main tables introducing the squared residual component of price cycle. Results do not vary much and this variable is, most of the time, insignificant. It is only significant, but with a negative sign, for the blasting category in Table B3 and, with a positive sign, in the panel estimation using country-specific price index. In the latter case this indicates that mining innovation tends to react more to periods of high variation compared to relatively stable periods.

Table B1: Time series estimation

	Dependent Variable: Log. of mining patents applications worldwide	
	(1)	(2)
Long cycle component of Log. of Price Index (1st Lag)	1.107***	1.090***
	(0.105)	(0.114)
Medium cycle component of Log. of Price Index (1st Lag)	0.557	0.004
	(0.150)	(0.156)
Short cycle component of Log. of Price Index (1st Lag)	0.167	0.172
	(0.188)	(0.189)
Residual cycle component of Log. of Price Index (1st Lag)	-0.218	-0.166
	(0.237)	(0.194)
Squared of resid. cycle comp. of Log. of Price Index (1st Lag)	--	0.574
		(1.169)
Log. of Quantity Index (2nd Lag)	0.202***	0.208***
	(0.053)	(0.053)
Observations	44	44
Years	1970-2016	1970-2016
R-squared	0.85	0.85

*Notes: The model is estimated with the OLS estimator. The dependent variable is included in logarithmic terms. All variables included in the model are detrended. A constant is included in each specification. Robust standard errors in parentheses. *, ** and *** respectively denote significance at 10%, 5% and 1% levels.*

Table B2: Time series estimation, different mining categories

	Blasting	Environment	Exploration	Metallurgy	Mining	Processing	Refining	Transport
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Long cycle comp. of Log. of Price Index (1st Lag)	0.452**	0.202	1.310***	0.589***	1.491***	1.311***	0.583***	1.418***
	(0.168)	(0.142)	(0.146)	(0.190)	(0.178)	(0.215)	(0.143)	(0.195)
Medium cycle comp. of Log. of Price Index (1st Lag)	0.096	0.154	-0.231	-0.365*	0.112	0.262	0.172	0.145
	(0.169)	(0.142)	(0.147)	(0.192)	(0.179)	(0.216)	(0.144)	(0.196)
Short cycle comp. of Log. of Price Index (1st Lag)	0.073	0.223	0.251	0.203	0.152	0.092	0.081	0.237
	(0.177)	(0.149)	(0.154)	(0.200)	(0.187)	(0.226)	(0.150)	(0.205)
Residual cycle comp. of Log. of Price Index (1st Lag)	-0.572**	-0.082	-0.289	-0.456	-0.058	-0.286	-0.169	-0.236
	(0.249)	(0.210)	(0.216)	(0.282)	(0.264)	(0.319)	(0.211)	(0.289)
Squared of resid. cycle comp. of Log. of Price Index (1st Lag)	-1.864*	1.005	0.351	0.078	0.731	-0.298	0.301	0.108
	(1.087)	(0.916)	(0.945)	(1.232)	(1.152)	(1.391)	(0.923)	(1.262)
Log. of Quantity Index (2nd Lag)	-0.055	0.424***	0.191***	0.128	0.034	0.084	0.302***	0.353***
	(0.085)	(0.072)	(0.074)	(0.096)	(0.090)	(0.109)	(0.072)	(0.098)
Observations	44	44	44	44	44	44	44	44
Years	1970-2016	1970-2016	1970-2016	1970-2016	1970-2016	1970-2016	1970-2016	1970-2016
R-squared	0.35	0.79	0.89	0.58	0.82	0.75	0.81	0.87

*Notes: The model is estimated with the seemingly unrelated estimator (SUR). The dependent variable is included in logarithmic terms. All variables included in the model are detrended. A constant is included in each specification. Robust standard errors in parentheses. *, ** and *** respectively denote significance at 10%, 5% and 1% levels.*

Table B3: Time series estimation, mining firms vs METS

	Dependent Variable: Log. of mining patents applications worldwide			
	Mining firms	METS	Mining firms	METS
	(1)	(2)	(3)	(4)
Long cycle component of Log. of Price Index (1st Lag)	-0.139	1.260***	-0.172	1.203***
	(0.259)	(0.391)	(0.262)	(0.396)
Medium cycle component of Log. of Price Index (1st Lag)	0.124	1.047***	0.101	1.009***
	(0.263)	(0.398)	(0.264)	(0.399)
Short cycle component of Log. of Price Index (1st Lag)	0.120	-0.199	0.128	-0.185
	(0.277)	(0.419)	(0.276)	(0.417)
Residual cycle component of Log. of Price Index (1st Lag)	-0.368	0.518	-0.266	0.689
	(0.360)	(0.544)	(0.389)	(0.587)
Squared of resid. cycle comp. of Log. of Price Index (1st Lag)	--	--	1.135	1.911
			(1.699)	(2.565)
Log. of Quantity Index (2nd Lag)	0.744***	0.046	0.756***	0.066
	(0.132)	(0.200)	(0.133)	(0.200)
Observations	44	44	44	44
Years	1970-2016	1970-2016	1970-2016	1970-2016
R-squared	0.69	0.45	0.69	0.45

*Notes: The model is estimated with the seemingly unrelated estimator (SUR). The dependent variable is included in logarithmic terms. All variables included in the model are detrended. A constant is included in each specification. Robust standard errors in parentheses. *, ** and *** respectively denote significance at 10%, 5% and 1% levels.*

Table B4: Panel estimation

	Dependent Variable: Log. of mining patents by applicant country			
	(1)	(2)	(3)	(4)
Mining rent as % Of GDP	--	--	0.014	0.013
			(0.026)	(0.025)
Long cycle component of Log. of Price Index (1st Lag)	0.396***	0.399***	0.278**	0.283**
	(0.126)	(0.126)	(0.139)	(0.137)
LC # Mining rent As % of GDP	--	--	0.196***	0.196***
			(0.065)	(0.065)
Medium cycle component of Log. of Price Index (1st Lag)	0.069	0.074	0.247*	0.254**
	(0.139)	(0.136)	(0.126)	(0.125)
MC # Mining rent As % of GDP	--	--	-0.313***	-0.313***
			(0.061)	(0.061)
Short cycle component of Log. of Price Index (1st Lag)	0.006	0.002	0.029	0.025
	(0.096)	(0.096)	(0.108)	(0.108)
SC # Mining rent As % of GDP	--	--	-0.069***	-0.069***
			(0.020)	(0.020)
Residual cycle component of Log. of Price Index (1st Lag)	-0.157	-0.185	-0.141	-0.176
	(0.143)	(0.161)	(0.149)	(0.160)
RC # Mining rent As % of GDP	--	--	0.022	0.018
			(0.028)	(0.029)
Squared of resid. cycle comp. of Log. of Price Index (1st Lag)	--	-0.246	--	-0.342
		(0.496)		(0.537)
Log. of Quantity Index (2nd Lag)	-0.002	-0.002	0.001	0.001
	(0.017)	(0.017)	(0.017)	(0.017)
Observations	1505	1505	1505	1505
No. Countries	54	54	54	54
Years	1970-2016	1970-2016	1970-2016	1970-2016

*Notes: The model is estimated with the Fixed-effects estimator. The dependent variable is included in logarithmic terms. All variables included in the model are detrended. Country fixed-effects and a constant are included in each specification. Robust standard errors in parentheses. *, ** and *** respectively denote significance at 10%, 5% and 1% levels.*

Table B5: Panel estimation, using country-specific price index

Dependent Variable: Log. of mining patents by applicant country	(1)	(2)	(3)	(4)
Mining rent as % of GDP	--	--	0.049 (0.047)	0.046 (0.048)
Long cycle component of Log. of Price Index (1st Lag)	0.318*** (0.113)	0.310*** (0.113)	0.302** (0.121)	0.302** (0.121)
LC # Mining rent As % of GDP	--	--	0.013 (0.033)	0.002 (0.032)
Medium cycle component of Log. of Price Index (1st Lag)	0.016 (0.055)	0.019 (0.055)	0.102 (0.063)	0.105 (0.062)
MC # Mining rent As % of GDP	--	--	-0.142** (0.068)	-0.140** (0.068)
Short cycle component of Log. of Price Index (1st Lag)	0.018 (0.040)	0.028 (0.040)	0.038 (0.043)	0.044 (0.043)
SC # Mining rent As % of GDP	--	--	-0.041 (0.029)	-0.036 (0.027)
Residual cycle component of Log. of Price Index (1st Lag)	0.022 (0.080)	0.017 (0.079)	-0.016 (0.085)	-0.025 (0.084)
RC # Mining rent As % of GDP	--	--	0.045 (0.041)	0.054 (0.043)
Squared of resid. cycle comp. of Log. of Price Index (1st Lag)	--	1.435** (0.556)	--	1.329** (0.625)
Log. of Quantity Index (2nd Lag)	0.009 (0.020)	0.009 (0.020)	-0.001 (0.020)	-0.006 (0.019)
Observations	1063	1063	1063	1063
No. Countries	39	39	39	39
Years	1970-2016	1970-2016	1970-2016	1970-2016

*Notes: The model is estimated with the Fixed-effects estimator. The dependent variable is included in logarithmic terms. All variables included in the model are detrended. Country fixed-effects and a constant are included in each specification. Robust standard errors in parentheses. *, ** and *** respectively denote significance at 10%, 5% and 1% levels.*

C – Removing Chile from the estimation

In our sample Chile is the country which is the most exposed to the mining sector: in one year its level of exposure reached 20.95%. There may be the possibility that it distorts our estimation. We, therefore, replicate the main tables excluding Chile. The main results are confirmed, particularly the cyclical effect of long-term price shocks on innovation. With this specification the effect of prices on environmental mining innovation completely disappears (see Table C3), confirming our hypothesis that this type of innovation may be reacting to some other factors like for example environmental policy. In addition, in the panel estimations (see Table C5 and C6) the positive and significant effect of the long price cycle component is confirmed, demonstrating that the presence of Chile was not affecting our original findings.

Table C1: Time series estimation

	Dependent Variable: Log. of mining patents applications worldwide	
	(1)	(2)
Log. of Price Index (1st Lag)	0.327*** (0.109)	--
Long cycle component of Log. of Price Index (1st Lag)	--	1.107*** (0.110)
Medium cycle component of Log. of Price Index (1st Lag)	--	0.555 (0.151)
Short cycle component of Log. of Price Index (1st Lag)	--	0.167 (0.187)
Residual cycle component of Log. of Price Index (1st Lag)	--	-0.212 (0.234)
Log. of Quantity Index (2nd Lag)	0.508*** (0.068)	0.204*** (0.053)
Observations	44	44
Years	1970-2016	1970-2016
R-squared	0.74	0.85

*Notes: The model is estimated with the OLS estimator. The dependent variable is included in logarithmic terms. All variables included in the model are detrended. A constant is included in each specification. Robust standard errors in parentheses. *, ** and *** respectively denote significance at 10%, 5% and 1% levels.*

Table C2: Time series estimation, different mining categories

	Blasting	Environment	Exploration	Metallurgy	Mining	Processing	Refining	Transport
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log. of Price Index (1st Lag)	0.087 (0.101)	0.129 (0.080)	0.312*** (0.125)	0.031 (0.120)	0.476** (0.134)	0.420*** (0.142)	0.195** (0.085)	0.449*** (0.136)
Log. of Quantity Index (2nd Lag)	0.132** (0.059)	0.465*** (0.047)	0.563*** (0.073)	0.347*** (0.070)	0.435*** (0.079)	0.462*** (0.083)	0.465*** (0.050)	0.731*** (0.080)
Observations	44	44	44	44	44	44	44	44
Years	1970-2016	1970-2016	1970-2016	1970-2016	1970-2016	1970-2016	1970-2016	1970-2016
R-squared	0.18	0.77	0.71	0.43	0.64	0.62	0.77	0.78

*Notes: The model is estimated with the seemingly unrelated estimator (SUR). The dependent variable is included in logarithmic terms. All variables included in the model are detrended. A constant is included in each specification. Robust standard errors in parentheses. *, ** and *** respectively denote significance at 10%, 5% and 1% levels.*

Table C3: Time series estimation, different mining categories

	Blasting (1)	Environment (2)	Exploration (3)	Metallurgy (4)	Mining (5)	Processing (6)	Refining (7)	Transport (8)
Long cycle comp. of Log. of Price Index (1st Lag)	0.412**	0.177	1.300***	0.571***	1.488***	1.275***	0.546***	1.367***
	(0.179)	(0.147)	(0.151)	(0.196)	(0.184)	(0.221)	(0.147)	(0.200)
Medium cycle comp. of Log. of Price Index (1st Lag)	0.060	0.174	-0.224	-0.363*	0.123	0.258	0.179	0.146
	(0.173)	(0.143)	(0.146)	(0.190)	(0.178)	(0.215)	(0.142)	(0.194)
Short cycle comp. of Log. of Price Index (1st Lag)	0.084	0.215	0.247	0.198	0.147	0.100	0.078	0.233
	(0.183)	(0.151)	(0.154)	(0.200)	(0.188)	(0.226)	(0.150)	(0.204)
Residual cycle comp. of Log. of Price Index (1st Lag)	-0.419*	-0.175	-0.326	-0.462*	-0.108	-0.251	-0.195	-0.241
	(0.237)	(0.196)	(0.200)	(0.260)	(0.243)	(0.293)	(0.194)	(0.265)
Log. of Quantity Index (2nd Lag)	-0.043	0.406***	0.182***	0.127	0.040	0.095	0.296***	0.351***
	(0.085)	(0.070)	(0.072)	(0.094)	(0.088)	(0.106)	(0.070)	(0.095)
Observations	44	44	44	44	44	44	44	44
Years	1970-2016	1970-2016	1970-2016	1970-2016	1970-2016	1970-2016	1970-2016	1970-2016
R-squared	0.30	0.79	0.88	0.58	0.82	0.75	0.81	0.87

*Notes: The model is estimated with the seemingly unrelated estimator (SUR). The dependent variable is included in logarithmic terms. All variables included in the model are detrended. A constant is included in each specification. Robust standard errors in parentheses. *, ** and *** respectively denote significance at 10%, 5% and 1% levels.*

Table C4: Time series estimation, mining vs METS firms

	Dependent Variable: Log. of mining patents applications worldwide			
	Mining firms (1)	METS (2)	Mining firms (3)	METS (4)
Log. of Price Index (1st Lag)	-0.059	0.674***	--	--
	(0.145)	(0.229)		
Long cycle component of Log. of Price Index (1st Lag)	--	--	-0.240	1.173***
			(0.272)	(0.409)
Medium cycle component of Log. of Price Index (1st Lag)	--	--	0.136	1.030***
			(0.264)	(0.397)
Short cycle component of Log. of Price Index (1st Lag)	--	--	0.123	-0.197
			(0.278)	(0.418)
Residual cycle component of Log. of Price Index (1st Lag)	--	--	-0.388	0.576
			(0.360)	(0.542)
Log. of Quantity Index (2nd Lag)	0.724***	0.304**	0.729***	0.098
	(0.085)	(0.134)	(0.130)	(0.195)
Observations	44	44	44	44
Years	1970-2016	1970-2016	1970-2016	1970-2016
R-squared	0.67	0.37	0.68	0.45

*Notes: The model is estimated with the seemingly unrelated estimator (SUR). The dependent variable is included in logarithmic terms. All variables included in the model are detrended. A constant is included in each specification. Robust standard errors in parentheses. *, ** and *** respectively denote significance at 10%, 5% and 1% levels.*

Table C5: Panel estimation

	Dependent Variable: Log. of mining patents by applicant country			
	(1a)	(1b)	(2a)	(2b)
Log. of Price Index (1st Lag)	0.182*** (0.067)	0.137 (0.089)	--	--
Mining rent as % Of GDP	--	0.023* (0.013)	--	0.014 (0.042)
Price Index # Mining rent as % of GDP	--	-0.004 (0.017)	--	--
Long cycle comp. of Log. of Price Index (1st Lag)	--	--	0.349*** (0.121)	0.367** (0.140)
LC # Mining rent As % of GDP	--	--	--	-0.008 (0.183)
Medium cycle comp. of Log. of Price Index (1st Lag)	--	--	0.142 (0.120)	0.235* (0.132)
MC # Mining rent As % of GDP	--	--	--	-0.171 (0.103)
Short cycle comp. of Log. of Price Index (1st Lag)	--	--	0.011 (0.099)	0.082 (0.111)
SC # Mining rent As % of GDP	--	--	--	-0.140*** (0.050)
Residual cycle comp. of Log. of Price Index (1st Lag)	--	--	-0.129 (0.018)	-0.175 (0.151)
RC # Mining rent As % of GDP	--	--	--	0.069 (0.062)
Log. of Quantity Index (2nd Lag)	0.023 (0.017)	0.013 (0.015)	-0.002 (0.005)	-0.003 (0.016)
Observations	1469	1469	1469	1469
No Countries	53	53	53	53
Years	1970-2016	1970-2016	1970-2016	1970-2016

*Notes: The model is estimated with the Fixed-effects estimator. The dependent variable is included in logarithmic terms. All variables included in the model are detrended. Country fixed-effects and a constant are included in each specification. Robust standard errors in parentheses. *, ** and *** respectively denote significance at 10%, 5% and 1% levels.*

Table C6: Panel estimation, using country-specific price index

Dependent Variable: Log. of mining patents by applicant country				
	(1a)	(1b)	(2a)	(2b)
Log. of Price Index (1st Lag)	0.082** (0.034)	0.087** (0.035)	--	--
Mining rent as % Of GDP	--	-0.018 (0.023)	--	-0.026 (0.020)
Price Index # Mining rent as % of GDP	--	-0.002 (0.029)	--	--
Long cycle component of Log. of Price Index (1st Lag)	--	--	0.309*** (0.114)	0.315** (0.125)
LC # Mining rent As % of GDP	--	--	--	0.030 (0.108)
Medium cycle component of Log. of Price Index (1st Lag)	--	--	0.032 (0.054)	0.078 (0.060)
MC # Mining rent As % of GDP	--	--	--	-0.075* (0.042)
Short cycle component of Log. of Price Index (1st Lag)	--	--	0.018 (0.041)	0.045 (0.044)
SC # Mining rent As % of GDP	--	--	--	-0.059 (0.049)
Residual cycle component of Log. of Price Index (1st Lag)	--	--	0.017 (0.080)	-0.011 (0.088)
RC # Mining rent As % of GDP	--	--	--	0.074 (0.053)
Log. of Quantity Index (2nd Lag)	0.017 (0.019)	0.020 (0.019)	0.007 (0.020)	0.009 (0.020)
Observations	1034	1034	1034	1034
No Countries	38	38	38	38
Years	1970-2016	1970-2016	1970-2016	1970-2016

*Notes: The model is estimated with the Fixed-effects estimator. The dependent variable is included in logarithmic terms. All variables included in the model are detrended. Country fixed-effects and a constant are included in each specification. Robust standard errors in parentheses. *, ** and *** respectively denote significance at 10%, 5% and 1% levels.*