

Resource depletion, technological change and market structure

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Abstract

Can technology neutralize the threat that depletion poses to resource availability? We offer new insights into this long-standing topic by analysing the US mining sector of iron ore, an important primary commodity used in a wide range of industrial productions. We develop a new econometric approach that allows to distinguish the sign of unobserved shocks, and we use it to study potential asymmetries between technology and scarcity. We find that technological progress produces stronger and more persistent effects on productivity and price than the natural action of resource depletion, with global market structure influencing the size of such effect.

KEYWORDS: Resource depletion, technological change, nonrenewable resources, structural vector autoregression, asymmetry, nonlinearity.

JEL CLASSIFICATION: C32; Q31; L72.

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1 Introduction

The long-run dynamics of primary commodity prices have important implications for economic growth, its long-run sustainability, as well as the definition of the macroeconomic policies of resource-exporting countries. We study the US mining sector that produces iron ore to understand the relative importance of technological progress and natural resource depletion in determining productivity in the extraction activity and the commodity real price in the long-run. To perform such analysis we develop a new structural vector autoregressive (SVAR) approach that allows to distinguish different shocks on the basis of their sign, and using our approach we also provide evidence of market structure as a further important, though often ignored, long-run determinant.

While volatility and short-run dynamics of commodity prices are determined by a multitude of temporary demand and supply factors, including political upheaval and speculative activities, the long-run real price, along with productivity, is considered as the main economic measure of resource scarcity and it is typically thought to be determined by two key forces, natural resource depletion and technological progress. The ability of technological change to counteract the consequences of resource depletion is a central topic in resource economics once we recognize its role in improving resource use efficiency, expanding existing reserves, and most importantly increasing the profitability of extraction from lower quality and less accessible deposits. An unremitting tug of war results from the opposing forces of depletion on one side, and technological innovation and exploration on the other (Cuddington and Nulle 2014), with policy makers and markets analysing any significant twist and turn in the price or other scarcity indicators to ascertain which of the two sides is having the upper hand. The fact that this is occurring against the backdrop of increasing demand for materials in the world economy (OECD 2019) makes any analysis of technological innovation and scarcity more politically and environmentally compelling.

A large empirical literature has explored explicitly or implicitly the role of technology in counteracting the consequences of increasing resource scarcity. A lot of effort, in particular, has been devoted in the statistical characterization of the long-run trend

of a large set of commodity prices, with the aim of testing some version of the very same question about the importance of resource scarcity, typically taking the form of the Hotelling theorem or the Prebisch-Singer hypothesis. But the outcome of such vast endeavor is far from clear, and if anything the evidence of distinct trends in real prices is very weak.¹ The reasons for such disappointing results are at least two: in the dynamics of commodity prices the variance tends to dominate the trend; other factors, beyond technology and depletion, may have substantial long-run influence.

We explore this same research question taking a different standpoint compared to the typical reduced-form univariate approach. We model technological change and natural resource depletion as unobserved shocks, the cumulative effect of which is expected to permanently influence the long-run dynamics of productivity and price. We extract these two shocks from a set of observables using a simple but plausible identification scheme within a SVAR model, and we examine in depth whether their effects are significantly different in terms of contemporaneous impact and time pattern.

To implement such analysis we have to overcome the limitations of a standard (linear) SVAR framework, in particular in terms of impulse responses that are symmetric with respect to the sign of the shock. The first contribution of our paper is then methodological, and consists in developing a new SVAR approach that captures asymmetric effects with respect to a structural shock by making use of a threshold function, in which this specific structural shock acts as threshold variable. This new approach is simple and general enough to be implementable in many different circumstances in applied research, whenever the sign of a shock is relevant for its economic interpretation. As a consequence, we also extend to our SVAR specification the definition of generalized impulse response function and we construct a new measure to calculate a historical decomposition that is suitable to this nonlinear SVAR framework.

In terms of results, we deliver one of the first applications of the SVAR methodology in the study of natural resources, outside of the oil market.² Once our model is applied on

¹Cuddington and Nulle (2014) talk about an “astonishing variety of long-run trends”.

²Jacks and Stuermer (2018), and Stuermer (2018) used a SVAR model to study the price of a set of commodities, including minerals.

US data for the mining sector of iron ore, an important material used in a wide range of industrial productions, we obtain substantive evidence that technological innovation affects productivity and price more strongly and more persistently than resource depletion. Secondly, we show that technological innovation dominated resource depletion as a driver of the cumulative price movements throughout the US history. Thirdly, we examine one specific dimension in which the discovered asymmetry may have its origin, namely the role of market structure in influencing the size of the effects of technology. By introducing a smooth transition function in our model we find that the response of price to technology is influenced by the degree of global market concentration. As the global market for iron ore becomes more concentrated, the effects of technological progress in mining produce stronger declines in the domestic real price of iron ore. We argue that such result derives from the fact that US mining firms tends to use technological advancements to cut more aggressively the domestic price of iron ore whenever they face a stronger competitive threat from a more concentrated global market. Such interpretation complements very well the evidence provided from previous studies on the US (Galdon-Sanchez and Schmitz 2002).

Finally, the whole set of our findings bears interesting implications for the Hotelling rule and the Prebisch-Singer hypothesis. Indeed, on the one side we confirm the considerable weight of technological change in the determination of the real price of an exhaustible primary commodity, but on the other side we show that strong market competition, as advocated by Prebisch (1950) and Singer (1950) as a feature more typical of commodities than manufacturers, is key in determining the magnitude of the price reaction to technological change.

The structure of the paper is the following. In section 2 we offer an overview of the existing theoretical and empirical literature on the topic. In section 3 we set up our core identification scheme within a linear SVAR model and we briefly present the results from its estimation. In section 4 we build our innovative SVAR approach with the purpose of distinguishing technological change from resource depletion; we examine the evidence about asymmetric effects on price; and we quantify the contribution of each shock to

the observed dynamics of productivity and price through a historical decomposition. In section 5 we explore the hypothesis of an interaction of technology with global market concentration. Section 6 offers some concluding remarks.

2 Theoretical and empirical context

There is no shortage of theoretical models predicting which direction the future price of non-renewable resources should be heading. By describing how the price exceeds marginal extraction cost by an amount equal to the user cost of consumption, the classical Hotelling model predicts that price is to rise over time at a rate equal to the interest rate. Despite the intuitive results, the basic Hotelling rule has not been validated by empirical analysis (Krautkraemer 1998, Kronenberg 2008, and Livernois 2008). In fact, any persistent increase in non-renewable commodity prices has failed for the most part to materialize, therefore questioning the empirical relevance of the basic Hotelling model, which excludes constant or falling prices for non-renewable resources. Theoretical extensions of the basic Hotelling model (e.g. Stiglitz 1976, Pindyck 1978, and Slade 1982) relax simplifying assumptions on factors such as explorations and discoveries, constant marginal costs, capital investments, capacity constraints, ore quality and market imperfections. Most of these factors can generate a decreasing resource price by lowering extraction cost but, eventually, the impact of increasing user cost outweighs decreases in extraction cost so that the price should increase after an initial decline, therefore evolving in a U-shape fashion (Slade and Thille 2009). Hotelling-type models including the additional factors mentioned above benefit from an improved empirical support (Slade and Thille 2009), although market data remain not completely reconciled with the theory (Krautkraemer 1998, Kronenberg 2008).

The Prebisch-Singer hypothesis (Prebisch 1950 and Singer 1950) offers a completely different perspective on long-run trends, as it predicts a decline in the price of primary commodities relative to that of manufactured goods. Theoretical arguments that have been advanced in its support include: the relative stronger competitive nature of com-

modity markets; the relative weakness of labour unions in commodity exporting countries compared to countries exporting manufactures; the incidence of innovations in transportation costs, which represents a higher proportion of the final price of commodities than manufactures; the lower income elasticity of demand for commodity; the dematerialization of advanced economies; the overestimation of inflation in manufactures due to ignored changes in product quality and composition.

The variety of theoretical predictions about the long-term direction of commodity prices is mirrored by the variety of trends in the actual data. Although there are examples illustrative of the Hotelling, the Prebisch Singer and U-shape models, none of them emerges as predominant, and as such there is no general tendency in the direction of the long-run trend in mineral commodity prices (Cuddington and Nulle 2014). If a conclusion can be drawn, it is the fact that depletion is not the only long-run factor that affects the price of non-renewable resources (Krautkraemer 1998). Other aspects, notably technological change, revisions in the expectations regarding the resource base, and modifications in the market structure must be playing a significant role in the long-run evolution of commodity prices. The four centuries worth of data in Harvey et al. (2010), the increasingly sophisticated univariate approaches including endogenous structural breaks (Arezki et al. 2014, Ghoshray 2011, Kellard and Wohar 2006, Kim et al. 2003), band-pass filters to extract gradually evolving long-run trends (Cuddington and Nulle 2014) and testing procedures that are robust to the statistical nature of the process generating the shocks (Harvey et al. 2010) have not helped to form a majority view in this debate.³ As an illustration of the differences in findings, Arezki et al. (2014) point out that about half the commodities show a decreasing trend in price, providing then some support for the Prebisch-Singer hypothesis, whereas Ghoshray (2011) and Kim et al. (2003) conclude that most commodities contain no significant negative trend, and Harvey et al. (2010, 2012) finding only 5 out of their 25 commodity series featuring a decreasing trend in price and 19 commodities showing no significant trend.

The difficulties faced by reduced-form univariate approaches to provide a conclusive

³The special edition n.46 of the Journal of International Money and Finance was devoted to the topic. For a review see Baffes and Etienne (2016).

answer can be imputed to the number of factors at play, the fact that their relative importance can change across time, and the difficulty in capturing revisions to expectations regarding the quantity and quality of the resource base (Livernois 2008). Only by explicitly quantifying the relative importance of these underlying factors one can confidently assess their individual impact on the long-run commodity price, but empirical evidence on the relative contribution of depletion and technological change on price and other scarcity indicators is at best fragmented, perhaps due to the difficulty in disentangling the impact of these two factors when only the final net effect can be observed.

Typical empirical strategies to capture the effects of technological innovation include using measures like RD expenditure, patenting activities, or a variable counting the instances of adoption of a new technology. Lasserre and Ouellette (1988) assess the impact of technological change on total factor productivity (TFP) for the asbestos industry in Canada while controlling for the quality of the resource as measured by ore grade. Technological change delivered a 76% increase in TFP, although the observed effect was only 13% due to the influence of resource depletion. Aydin and Tilton (2000) assess the determinants of labour productivity in the US copper industry between 1975 and 1995, when it almost trebled. Based on a decomposition approach, they conclude that over three-quarters of this increase came from labour productivity growth at individual mines, a finding supporting the hypothesis that new technology and innovation are equally important or even more important than mineral endowment in shaping labour productivity trends. Schmitz (2005) discusses evidence of substantial improvements in labour productivity during the 1980s in the US iron ore industry within the Great Lakes region. These improvements were mainly the result of changes in work practices introduced to deal with the rising competition from Brazilian exporters. With regard to the impact of technological change and resource depletion on financial indicators, Cuddington and Moss (2001) estimate that finding costs for natural gas rose only by about 2% per year thanks to technological innovation, while it would have risen by 22% in its absence. Managi et al. (2004) propose a refinement of the same approach by measuring the relative importance of specific innovations as expressed by an industry survey. Using a detailed

micro-level data set they found that technological change more than offset resource depletion in offshore oil and gas production within the Gulf of Mexico. Finally, Boyce and Nostbakken (2011) assess exploration and development of U.S. oil and gas fields to empirically distinguish the Hotelling scarcity effect from the consequences attributable to technological progress. By looking at the number of exploratory and development wells, they conclude that the scarcity effect mattered the most.

Our contribution falls within this last strand of literature and consists in proposing a structural multivariate approach to analyse the relative importance of technology and resource depletion. In addition, by analysing the interaction between technology and market concentration, we also offer some important insights into the debate about the empirical relevance of the Prebisch-Singer hypothesis. The next two sections are devoted to describing our modelling approach, by illustrating the core part of our identification scheme in section 3 and then its extension to a nonlinear framework in section 4.

3 A SVAR model for the mining sector

A quantitative assessment of the ability of technological change to offset the consequences of natural resource depletion requires a structural model that allows to identify the exogenous sources of variation driving productivity and price. For this purpose we develop a simple SVAR model that can be employed to analyse a generic mining sector, and we use it to study the US iron ore industry in particular. This model makes use of a minimal but sufficient set of restrictions to identify the relevant causal relationship and to capture the potentially complex dynamic effects generated in the primary commodity market for iron ore. In addition, the advantage of this approach in treating technological progress as a sequence of random shocks fits well with the idea of innovation as an incremental and uncertain process. It is likely, indeed, that the technical and managerial advances in the mining industry have been numerous and spread over time in a way that it is difficult to pinpoint the timing of their introduction with sufficient confidence.

Apart from a large literature on the crude oil market (e.g. Kilian 2009, Kilian and

Murphy 2014), the only estimation of a SVAR in the field of natural resources can be found in Stuermer (2018), who uses it in combination with long-run restrictions to study the price dynamics of four minerals.⁴ In the following, we set up and motivate the core identification strategy incorporated in our SVAR model, and then we briefly discuss its plausibility in light of the estimation results.

3.1 Identification scheme

Our analysis of the impact of technology and resource depletion on productivity and price is grounded in a general definition of production function for the mining sector. Mining is characterized by high capital intensity, with large sunk costs due to investments being specific to the geological characteristics of the mines location, and lengthy lead time for investments aimed at altering the scale of production. As a consequence, mines tend to have some limited unutilized capacity to be able to expand production during an economic boom (e.g. Topp et al. 2008). Moreover, there is considerable evidence of capacity utilization being procyclical across industrial sectors (e.g. Basu and Fernald 2001), so that service flows generated from a unit of capital and labour vary over the cycle. In the case of mining, firms can change the work schedule, the organization in shifts, they can modify the rate at which machinery is employed, or other similar conditions.

It follows that the production function of iron ore can be written as

$$Y_t = A_t F(\tilde{K}_t, \tilde{L}_t), \quad (1)$$

where Y_t is the iron ore produced in period t , measured by “usable ore” which satisfies a certain standard grade, A_t is the efficiency level at time t , and \tilde{K}_t and \tilde{L}_t indicate the flow of capital and labour services (their effective units), which are defined as

$$\tilde{K}_t = Z_t K_t \quad (2)$$

$$\tilde{L}_t = E_t L_t \quad (3)$$

⁴Jacks and Stuermer (2018) use the same identification to analyse a larger set of commodities.

where K_t is the capital stock, multiplied by its degree of utilization Z_t , and L_t is labour in terms of hours worked, multiplied by the effort level E_t . As a consequence, observed labour productivity Y_t/L_t is a function of two components: the current efficiency level A_t , and the combination of K_t and L_t along with their utilization intensity.⁵

The efficiency level A_t is determined by two sets of factors, the natural characteristics of the mineral deposits and the technology employed in the mining activity. The first includes, in particular, quality and location of the mineral deposit (measured by metal grade and ease of access). The second reflects the current level of technology, here interpreted in a broad sense, which includes the adoption of new technical advancements in mining, as well as innovations in management.⁶ The efficiency level A_t is assumed exogenous with respect to the commodity market, at least over the short horizon. While sustained increases in demand can stimulate R&D investments that ultimately lead to improvements in mining technology, such process unfolds only over a long period of time and therefore cannot influence labour productivity within the year. Hence, A_t is driven by an exogenous process reflecting the current technology and the quality of existing mineral deposits, with both sources expected to determine labour productivity in the long-run, given that the actual grade of “usable ore” remains stable.⁷

⁵We do not make assumptions about the returns to scale, but if the production function was homogenous of degree one, as sometimes it is assumed in empirical work, like for instance in Schmitz (2005) and Topp et al. (2008), we could express labour productivity as

$$\frac{Y_t}{L_t} = A_t F_t \left(\frac{\tilde{K}_t}{\tilde{L}_t} \right) E_t \quad (4)$$

where the E_t term on the right hand side follows from the fact that it is not observed when calculating productivity, that is $\frac{Y_t}{L_t} = \frac{Y_t}{L_t} \frac{\tilde{L}_t}{L_t} = A_t F_t \left(\frac{\tilde{K}_t}{L_t} \right) E_t$. Boyd (1987) finds that for the US coal mining the elasticity of the returns to scale varies across mines depending on the capital-labour ratio, with an average of 1.24. Zheng and Bloch (2014) estimate a value of 0.94 for the Australian mining sector.

⁶Examples of technical innovations are: blasting methods, motorised drilling, geographical information systems, logging, automated trucks and trains, big data, waste management, grinding process, and heat recycling. Innovations in management practices correspond in particular to that part of the firms organization that relates to performance monitoring, definition of targets and system of incentives (Bloom and Van Reenen 2007). These are persistent features of a firm and an industry, and can be seen as a form of technology with permanent effects on productivity (Bloom et al. 2017).

⁷In general, both technology and deposit quality can affect the grade of the mineral as well as productivity. In our investigation we employ data on “usable ore”, that is the mineral after a first stage of processing to increase the metal content is performed. As the grade of usable ore is standard and effectively stable over time (including the period under analysis), any change in grade of the crude ore must have translated into a corresponding variation in productivity. For this reason there is no need to include grade as an additional variable in our SVAR model, as would instead be the case if the crude ore were used.

The second component influencing observed labour productivity is related to the presence of substantial fixed investments and a variable intensity in the use of inputs. The existence of unutilized capacity implies that there is no clear prediction for the change in labour productivity in response to an increase in demand for iron ore, as K_t is slow to adjust but the flow of capital services \tilde{K}_t is more flexible. Moreover, as labour represents a relatively small share of total inputs in mining, small variations in the intensity of labour utilization generate large changes in labour productivity.⁸ Variations in the amount and utilization intensity of capital and labour are typical temporary responses of the mining industry to the dynamics of market demand for iron ore, and so they affect labour productivity mostly in the short-run.

In sum, there are two ultimate sources of variation in labour productivity in the mining sector: a supply-side shock affecting the level of efficiency A_t , which is related to technological innovation (if positive) or resource depletion (if negative), and a demand-side shock originating in the industrial sectors using iron ore as an input.⁹

This set of mild theoretical assumptions are incorporated in an SVAR model of order p that describes the joint behavior of three annual variables over the period 1955-2015: output from the manufacturing sector (x_t), labour productivity in the production of iron ore (y_t), and the real price of iron ore (p_t). We choose the manufacturing industry since this is the sector that uses the largest share of iron ore produced in the US (Fellow et al. 2014) either directly or in the form of steel.¹⁰ Data on this variable are collected from the Bureau of Economic Analysis. We choose labour productivity in the US iron ore sector as this is the most reliable direct measure of the consequences of technology and depletion. This variable measures the amount of usable iron ore per hour worked and is obtained from the Bureau of Labour Statistics (BLS) for observations up to 2000 and from the United States Geological Survey for observations since 2001. Finally, we take the ratio

⁸Examples of such adjustments are: changes in the number and length of work shifts, modifications in the time machines are in operative mode.

⁹Random discoveries of new mineral deposits are unlikely to produce an increase in productivity, as discussed in Section 4.

¹⁰We also perform an estimation adding the output from the construction sector, which is the second most important user of iron ore in the US economy. In this case, results do not change qualitatively but the magnitude of the estimated asymmetry is lower when we introduce the nonlinear framework below, something which is likely due to the smaller variance of the construction output.

of the iron ore Producer Price Index and the GDP deflator to get an effective market indicator of scarcity. The Producer Price Index is collected from BLS and represents a measure close to the perspective of the seller, so mainly capturing price movements not influenced by dynamics in the retail market. Although there is a global market for iron ore, transportation costs remain high relative to its unit value (around 50 percent of delivered price), so the US producer price mostly reflects domestic scarcity conditions.

Standard application of the Dickey-Fuller test unequivocally indicates that all three variables follow I(1) processes, while the two Johansen tests exclude the presence of cointegration. As a result, our SVAR model can be written as

$$B_0 z_t = \nu + \sum_{l=1}^p B_l z_{t-l} + \varepsilon_t \quad (5)$$

where $z_t = [\Delta x_t, \Delta y_t, \Delta p_t]'$ is the vector containing our three variables expressed in first differences, B_0 is the matrix of structural contemporaneous parameters, B_l is the matrix of the structural parameters associated with the l -th lag of the same variables, where $l = 1..p$, ν is a vector of intercepts, and ε_t is the vector of mutually and serially uncorrelated structural shocks.¹¹ Our theoretical assumptions translate into the following identification structure that characterizes the contemporaneous relationship between reduced-form errors u_t and structural shocks ε_t

$$\begin{bmatrix} u_t^x \\ u_t^y \\ u_t^p \end{bmatrix} = \begin{bmatrix} c_{11} & 0 & 0 \\ c_{21} & c_{22} & 0 \\ c_{31} & c_{32} & c_{33} \end{bmatrix} \begin{bmatrix} \varepsilon_t^d \\ \varepsilon_t^a \\ \varepsilon_t^r \end{bmatrix}, \quad (6)$$

where u_t^x , u_t^y and u_t^p are respectively manufacturing output, labour productivity in the iron ore sector, and real iron ore price, after subtracting the effect of their past values, and c_{ij} is the impact multiplier of the j -th shock on the i -th variable.

The first shock, ε_t^d , is our *demand shock* originating in the manufacturing sector, which uses iron ore as an input. A change in the production level of manufactured goods implies

¹¹All variables are expressed in logs, while a lag length $p = 2$ is selected based on information criteria and standard tests for residual autocorrelation.

a change in the demand for iron ore, which mining companies accommodate adjusting \tilde{K}_t and \tilde{L}_t and so modifying labour productivity, as well as iron ore price. As this shock is potentially affecting all three variables within the same year, all three corresponding impact multipliers of the demand shock are left unrestricted. The second shock, ε_t^a , is our *efficiency shock* originated in the supply side of the iron ore industry, as a result of technological innovation or resource depletion. Since iron ore is only one of many inputs used in the production of manufactured goods, this shock is uncorrelated with manufacturing output and we therefore impose a zero restriction on the related impact multiplier but leave unrestricted the effects on productivity and price. Finally, the third shock, ε_t^r , is a *residual shock* representing other factors that affect market conditions and thus the iron ore price but that are unrelated to either manufacturing output or iron ore productivity, so the corresponding two impact multipliers are set to zero. This shock might include, among other things, changes in the markup and more in general the structure of the iron ore market.

3.2 Results

The cumulative impulse response functions (IRFs), displayed in Figure 1, describe the level of manufacturing output, labour productivity, and iron ore real price, as a proportional deviation from the initial level, in response to a typical increase (of one standard deviation) in the demand and the efficiency shocks.¹²

In response to a positive demand shock, there is an increase in the output in the manufacturing sector, which is met in the first year by an increase of 5% in productivity, a likely consequence of increased utilization intensity of both capital and labour, and no significant increase in price. As the output in the manufacturing sector grows further in the second year, this additional demand pressure is now accompanied by an increase in price as labour productivity returns to its initial level. The new equilibrium resulting from a positive demand shock is therefore characterized by a higher level of both manufacturing production and iron ore price, the latter by approximately 2%.

¹²Since the variables are in first differences, in all figures we will show the cumulative IRFs. Also, we plot IRFs for a period of only 5 years as no marked changes in their shape can be observed thereafter.

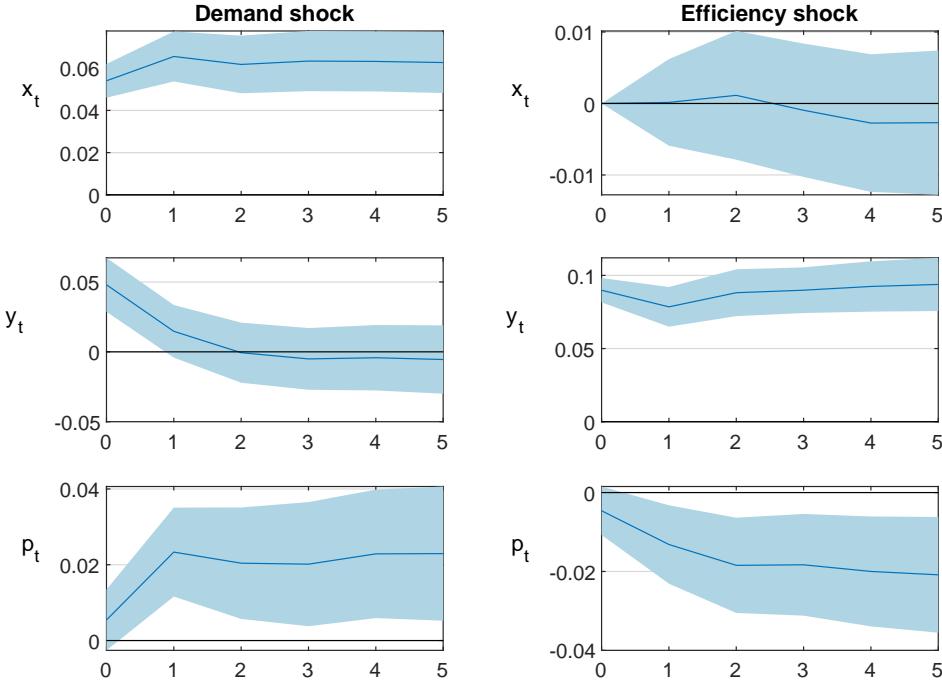


Figure 1: Impulse response to one standard deviation shock

A positive efficiency shock generates an immediate and persistent 10% increase in the productivity of labour in the iron ore industry and a gradual but permanent 2% decrease in iron ore price. As expected, no statistically significant change in manufacturing output takes place in response to an efficiency shock, a reflection of the fact that consumption of iron ore is a relatively minor component of the production process in the manufacturing sector.

Overall, the picture that emerges from the IRFs analysis confirms the plausibility of our identification scheme, as only technological change is able to generate a permanent increase in productivity, whereas a demand shock can only temporarily do that via a modification in the utilization intensity of the inputs.

4 Technological change vs resource depletion

We now focus our attention on the efficiency shock, which generates permanent changes in labour productivity by affecting the level of A_t . These variations in A_t can be distinguished in decreases resulting from the action of natural resource depletion and increases

due to technological change. As miners concentrate initially on high-quality and easily accessible deposits, depletion denotes the exhaustion of existing reserves and the shift to more remote deposits containing lower metal grade, therefore requiring increasing commitment of capital and labour, ultimately leading to decreases in productivity. On the other hand, productivity is increased in a persistent way by technological innovation, which consists in the introduction of technical advancements in exploration, extraction and processing of the mineral, as well as in management practices.¹³

Considering the very different nature of the sources of positive and negative changes in A_t , there is no reason to expect that the effect on productivity and price of a negative efficiency shock is symmetric to the effect of an equally-sized positive shock. In particular, there are a number of reasons why firms' expectations about future dynamics of productivity and price following a technology shock may be substantially different from those formed after a resource depletion shock. Technological progress often consists in the accumulation of innovations that build incrementally on previous advances. If mining firms expect further technological refinements in the near future after an innovation is introduced, price adjustments in anticipation of future productivity gains delivered by these refinements are plausible. In addition, technological innovation takes time to diffuse across the sector, with the speed of technological diffusion determined by institutional factors related to the market and the legal system, and in particular by market concentration. These aspects suggest that an aggregate measure of productivity should display a sustained increase for some time after an innovation is introduced, reflecting the gradually increasing number of firms that are adopting the new technology. Finally, mining firms may perceive a different degree of uncertainty in the shocks originating from technological innovation and those resulting from resource depletion. Uncertainty about the quality and size of existing mineral deposits may be considerably higher than that

¹³Discoveries that are not related to new technologies in exploration can still occur, but they are unlikely to have been important in the US for the period assessed in our study, and in any case more likely to bring up remote deposits characterized by lower rather than higher productivity. This is confirmed by the fact that the average grade of crude ore in existing reserves has gradually decreased over time, being 0.34 in 1971 and 0.26 in 2015 (USGS Mineral Yearbooks). In addition, individual discoveries would have only a limited influence on the aggregate labour productivity of the sector, which is a weighted average of the productivity in the individual mines. Other potential determinants of A_t that appear of negligible or secondary role in a country like the US are: political events, conflicts, extreme weather episodes.

associated with technology (Pindyck 1980), also because of the incremental nature of technological progress discussed above.

Apart from these arguments that are specific to the mining sector, there are also more general reasons to conjecture a potential asymmetric relationship between price and productivity. That the price responds asymmetrically to changes in input prices is a stylized fact that characterizes all sectors of the economy (see e.g. Peltzman 2000), and it is typically attributed to market power and adjustment costs.¹⁴ The direction of this price asymmetry is, however, unclear as the empirical evidence is not conclusive (Meyer and von Cramon-Taubadel 2004).

As a consequence of the discussion above we drop the restrictive assumption incorporated in the linear SVAR framework that the IRF of price is symmetric with respect to the sign of the efficiency shock. We therefore build a nonlinear threshold SVAR model that serves the specific purpose of investigating whether unexpected positive and negative efficiency shocks are effectively different with respect to their influence on productivity and price. In particular, we are interested in uncovering the possibility that technological innovation and natural resource depletion are systematically different in terms of duration of their effect on the level of labour productivity, magnitude of their contemporaneous impact on the real price of iron ore, and subsequent pattern of its response over time.

4.1 Identification scheme for a threshold SVAR model

We build an innovative SVAR model that allows positive and negative efficiency shocks to have different dynamic effects on the level of productivity and price by introducing two nonlinearities via a threshold function. The first one specifies that the contemporaneous effect on price of an efficiency shock depends on its sign; the second one postulates that the effect of lagged productivity on contemporaneous productivity and price depends on the sign of its past changes. We begin by defining a general model that features only the first

¹⁴Examples of evidence on the asymmetry due to market power are Borenstein et al. (1997), and Balke et al. (1998), while cases of asymmetry due to adjustment costs are analysed by Levy et al. (1997) and Dutta et al. (1999). In their review of the literature on agricultural economics, Meyer and Von Cramon-Taubadel (2004) underline how, contrary to adjustment costs, only market power can generate persistent asymmetries.

type of nonlinearity, the one associated with the sign of the shock. We consider a general case, where two regimes exist and all parameters are potentially regime-specific, and then discuss a restricted version that is suitable to our particular economic application. We eventually introduce the second nonlinearity in this restricted model.

In its general form, the threshold SVAR including the first nonlinearity is defined as

$$\begin{cases} B_0^{(1)} z_t = \nu^{(1)} + \sum_{l=1}^p B_l^{(1)} z_{t-l} + \varepsilon_t & \text{if } \varepsilon_{kt} \geq 0 \\ B_0^{(2)} z_t = \nu^{(2)} + \sum_{l=1}^p B_l^{(2)} z_{t-l} + \varepsilon_t & \text{if } \varepsilon_{kt} < 0 \end{cases} \quad (7)$$

where the superscript indicates the regime, and ε_{kt} represents the structural shock that acts as a threshold variable determining with its sign which of the two regimes is in force at each date. The reduced-form solution is a VAR where all parameters, intercepts and slopes, are potentially regime-specific. Allowing for the coefficients on past variables to depend on the sign of a specific structural shock is of difficult economic interpretation, so we assume that intercepts and slope coefficients are equal across the two regimes, while the impact multiplier matrix C_0 is allowed to differ, that is

$$\begin{cases} z_t = \mu + \sum_{l=1}^p A_l z_{t-l} + C_0^{(1)} \varepsilon_t & \text{if } \varepsilon_{kt} \geq 0 \\ z_t = \mu + \sum_{l=1}^p A_l z_{t-l} + C_0^{(2)} \varepsilon_t & \text{if } \varepsilon_{kt} < 0 \end{cases} \quad (8)$$

where $C_0^{(g)}$ is the inverse of $B_0^{(g)}$, with $g = 1, 2$, and μ is the reduced-form intercept.

The fact that the threshold variable is a structural shock rather than an observable makes estimation not feasible as we need to know the model in advance to identify ε_{kt} . However, such infeasibility problem does not exist when ε_{kt} is identified from a subset of equations not including the one in which it acts as a threshold. This is exactly our case, as we assume that the efficiency shock, identified in the 2nd equation defining labour productivity, acts as a threshold variable in the 3rd equation, where it allows us to distinguish the impact of positive and negative efficiency shocks on the real price of iron ore. Recalling the triangular structure of our linear SVAR in Section 3, the identification

scheme for our nonlinear SVAR can now be written in the following form

$$\begin{bmatrix} u_t^x \\ u_t^y \\ u_t^p \end{bmatrix} = \begin{bmatrix} c_{11} & 0 & 0 \\ c_{21} & c_{22} & 0 \\ c_{31} & c_{32}^{(1)} & c_{33} \end{bmatrix} \begin{bmatrix} \varepsilon_t^{d+} \\ \varepsilon_t^T \\ \varepsilon_t^{r+} \end{bmatrix} + \begin{bmatrix} c_{11} & 0 & 0 \\ c_{21} & c_{22} & 0 \\ c_{31} & c_{32}^{(2)} & c_{33} \end{bmatrix} \begin{bmatrix} \varepsilon_t^{d-} \\ \varepsilon_t^{RD} \\ \varepsilon_t^{r-} \end{bmatrix} \quad (9)$$

where $\varepsilon_t^T = I(\varepsilon_t^a > 0)\varepsilon_t^a$ is the *technology shock* and $\varepsilon_t^{RD} = I(\varepsilon_t^a < 0)\varepsilon_t^a$ is the *resource depletion shock*, $I(\cdot)$ is an indicator function that takes on the value of 1 if the event in the curly brackets occurs and 0 otherwise, $\varepsilon_t^{m+} = I(\varepsilon_t^a > 0)\varepsilon_t^m$ and $\varepsilon_t^{m-} = I(\varepsilon_t^a < 0)\varepsilon_t^m$, with $m = d, r$, and c_{ij} are the impact multipliers, which are constant except for $c_{32}^{(g)}$, which depends on the regime $g = 1, 2$.

We now introduce the nonlinearity associated with the persistence of productivity changes. The idea here is to capture a possible difference between technology and depletion in terms of persistence of their effects. Notice that in this case using the sign of the efficiency shock as a threshold variable would not make much sense as we are concerned here with the persistence of observable productivity. Hence, we include in both the productivity and price equations a threshold effect in the coefficient of lagged productivity using the sign of productivity growth in the previous period as threshold variable.

The final result is a nonlinear SVAR with two threshold effects, one with respect to the impact of efficiency shocks on contemporaneous price, as explained earlier, and one with respect to past productivity growth, allowing to capture the possibility of asymmetric persistence in the effects of efficiency shocks. This model can be formally written as

$$\left\{ \begin{array}{lcl} \Delta x_t & = & \mu_x + A_{11}(L)\Delta x_{t-1} + A_{12}(L)\Delta y_{t-1} + A_{13}(L)\Delta p_{t-1} + c_{0,11}\varepsilon_t^d \\ \Delta y_t & = & \mu_y + A_{21}(L)\Delta x_{t-1} + \tilde{A}_{22}(L)\Delta y_{t-2} + A_{23}(L)\Delta p_{t-1} + \\ & & + A_{22,1}^{(1)}I(\Delta y_{t-1} \geq 0)\Delta y_{t-1} + A_{22,1}^{(2)}I(\Delta y_{t-1} < 0)\Delta y_{t-1} + c_{21}\varepsilon_t^d + c_{22}\varepsilon_t^a \\ \Delta p_t & = & \mu_p + A_{31}(L)\Delta x_{t-1} + \tilde{A}_{32}(L)\Delta y_{t-2} + A_{33}(L)\Delta p_{t-1} + A_{32,1}^{(1)}I(\Delta y_{t-1} \geq 0)\Delta y_{t-1} + \\ & & + A_{32,1}^{(2)}I(\Delta y_{t-1} < 0)\Delta y_{t-1} + c_{31}\varepsilon_t^d + c_{32}^{(1)}\varepsilon_t^T + c_{32}^{(2)}\varepsilon_t^{RD} + c_{33}\varepsilon_t^r \end{array} \right. \quad (10)$$

where $A_{ij}(L)$ in general is a polynomial in the lag operator, which in the case of lagged productivity in the second and third equation includes two regime-dependent components

at the first lag, that is

$$\begin{aligned} A_{ij}(L) &= A_{ij,1}^{(1)} I(\Delta y_{t-1} \geq 0) + A_{ij,1}^{(2)} I(\Delta y_{t-1} < 0) + A_{ij,2} L + A_{ij,3} L^2 + \dots + A_{ij,p+1} L^p \\ \tilde{A}_{ij}(L) &= L^{-1} [A_{ij}(L) - A_{ij,1}^{(1)} I(\Delta y_{t-1} \geq 0) + A_{ij,1}^{(2)} I(\Delta y_{t-1} < 0)], \end{aligned}$$

where $A_{ij,1}^{(g)}$ is the coefficient on the first lag of productivity that is associated with regime g .

Model (10) can be estimated by single-equation Least Squares including as additional regressors in each equation the structural shock identified from the previous equations. It is important to stress that model (10) allows for potential nonlinearities without imposing them, so that one can assess the evidence for such asymmetries through statistical tests.

4.2 Evidence on asymmetric effects

We assess the evidence about asymmetric response of iron ore price and productivity to technology and resource depletion shocks by looking at three pieces of information: 1) the difference in magnitude and shape of the two instantaneously linear IRFs; 2) the difference in the unconditional generalized IRFs using 1 and 2 standard deviation shocks; 3) the outcome from a Wald test on symmetry.

In Figure 2 we display the cumulative instantaneously linear IRFs to one standard deviation increase in technology and resource depletion shocks, with the IRFs of resource depletion flipped with respect to the x-axis to permit an easier comparison with the IRFs associated with technology. It is evident that neither shock has a marked impact on the output of the manufacturing sector, therefore confirming the results from the model assuming symmetry. The effect of resource depletion on labour productivity is highest in the first period, when there is a fall of almost 10% but the impact halves from the second period onwards. On the contrary, the pattern of labour productivity is very different when we consider a technology shock, as its effect builds up steadily over time to reach double the initial size, that is 20%, after approximately 8 years. This time pattern in productivity is consistent with the idea that technological progress proceeds as a sequence of incremental steps, as well as reflecting the gradual diffusion of cost-reducing

innovations. The effect of a technology shock on price has a similar time pattern, with an immediate impact of about -3%, and gradually increasing across time to reach -5% after 8 years, while that of a resource depletion shock is very close to zero throughout the same horizon, except the small initial decrease. It becomes clear from Figure 2 that technology shocks produce a far larger impact on price than resource depletion shocks, with differences in the IRFs starting in the first period, as a consequence of the threshold in the impact multiplier introduced in the price equation, and evolving differently across time, as a consequence of the threshold related to past productivity growth.

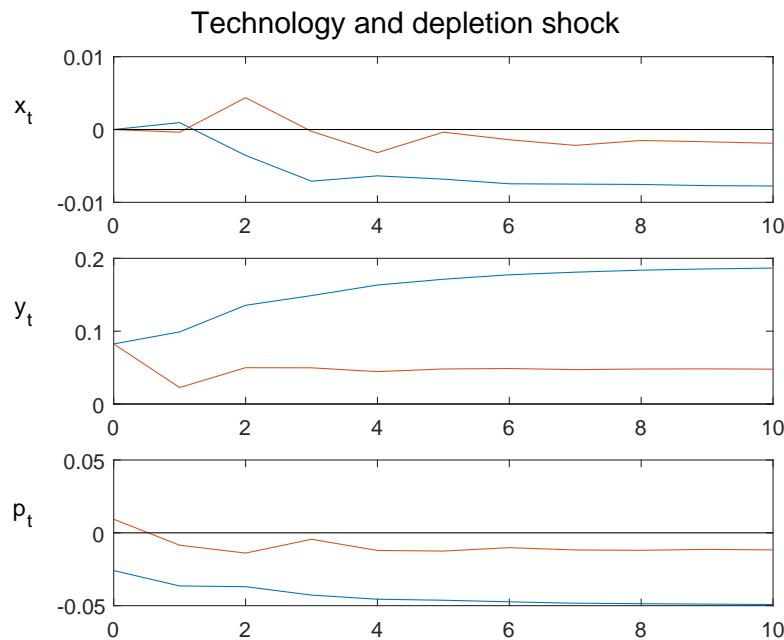


Figure 2: Instantaneously linear impulse response to 1 std dev technology shock (blue) and depletion shock (red).

While the instantaneously linear IRFs remain a useful tool to get an indication of how much different can the effects potentially be assuming no other shock taking place in the meantime, a more complete assessment of the dynamic effects of the two shocks is obtained through a Monte Carlo simulation that averages out all possible future shock scenarios as well as past histories. We follow Kilian and Vigfusson (2011) in calculating unconditional generalized impulse response functions (GIRFs) to 1 and 2 standard deviation shocks, displayed in Figure 3 and Figure 4 respectively.¹⁵

Considering 1 standard deviation shocks, both technology and depletion have significant effects on price after the first period, but only the former generates a significant change within the same year. The magnitude of the multiplier is substantially greater for technology, -1.2% at period 0 and -3.5% at period 5, against 0.4% and 2.6% respectively for depletion. Only a very modest asymmetry emerges with respect to productivity, as after 5 periods it is 9.8% higher in response to a technology shock and 8.8% lower in response to a depletion shock.

The difference in the consequences of the two shocks becomes striking when we consider a shock of 2 standard deviations. In this case, the effect of technology on price is large, significant and increasing over time (and thus permanent), whereas that of depletion is never significant except for period 2, and with a size that is less than half that of technology (e.g. 4% against -8.5% in period 5). This asymmetry is prominent also in relation to the dynamics of productivity. Indeed, after a technology shock the ensuing increase in productivity builds up over time with an acceleration between period 1 and 2, but on the contrary decreases (in absolute value) after the first period in the case of depletion. Both shocks produce significant permanent effects on the productivity level, compared to the demand shock that gives rise only to temporary deviations.

We conclude this subsection with a more formal verification of the asymmetric effects by adapting to our nonlinear threshold SVAR the same procedure that Kilian and Vigfusson (2011) use to calculate the Wald test of unconditionally symmetric response functions in the case of a censored variable model. If we let $\theta_{ij}(h, \delta)$ be the $h \times 1$ vector of

¹⁵We set the number of replications to 100 for the histories and 10,000 for the future shock scenarios.

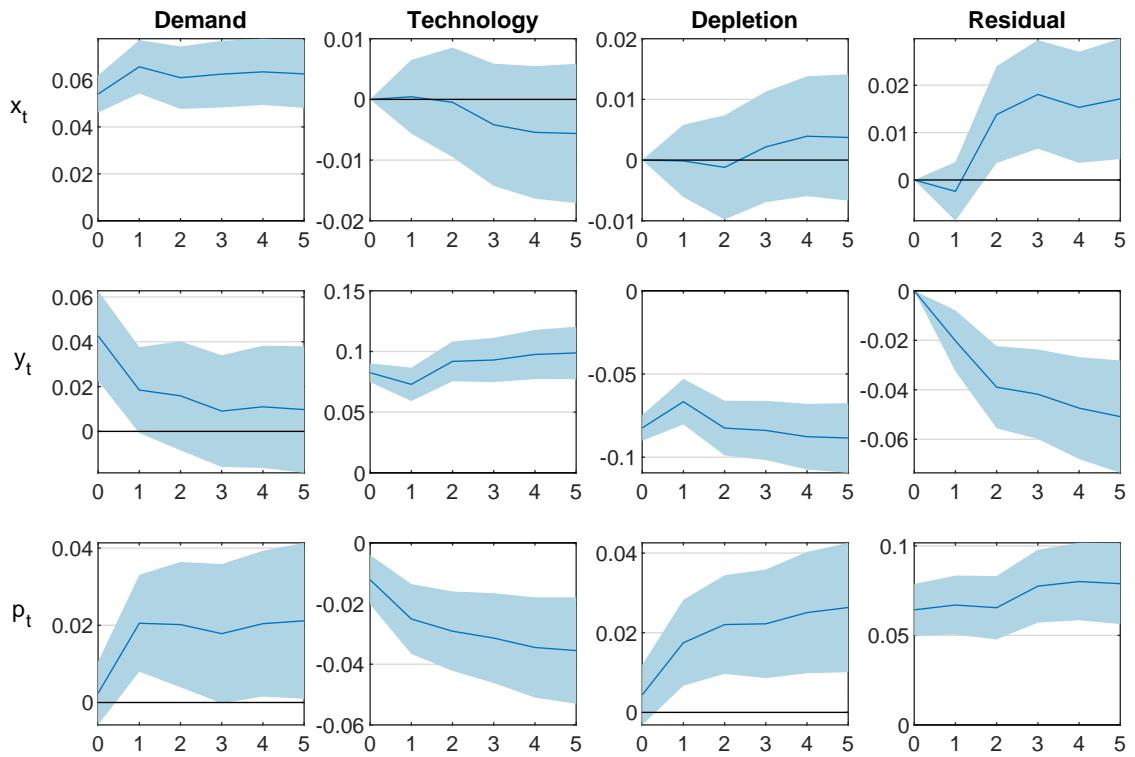


Figure 3: *Unconditional GIRFs to 1 std dev shock, with 1 std dev confidence band.*

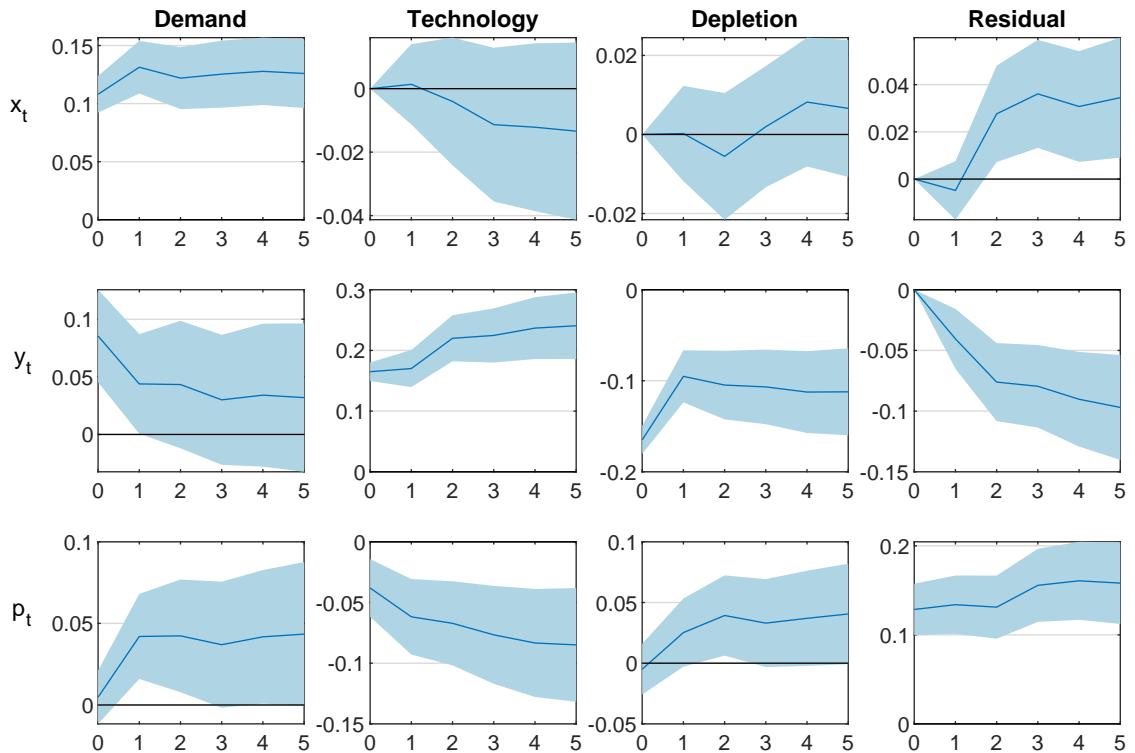


Figure 4: *Unconditional GIRFs to 2 std dev shock, with 1 std dev confidence band.*

IRFs of the i -th variable to a j -th shock of size δ at horizon 1 through h , this procedure tests the hypothesis $\theta_{ij}(h, \delta) = -\theta_{ij}(h, -\delta)$. The Wald test statistic is defined as

$$\left[\hat{\theta}_{ij}(h, \delta) + \hat{\theta}_{ij}(h, -\delta) \right]' \hat{\Sigma}^{-1} \left[\hat{\theta}_{ij}(h, \delta) + \hat{\theta}_{ij}(h, -\delta) \right], \quad (11)$$

where $\hat{\Sigma}^{-1}$ is the bootstrap estimate of the covariance matrix of $\theta_{ij}(h, \delta) + \theta_{ij}(h, -\delta)$. We calculate this statistic, which considers jointly all horizons up to h , and also a version that considers only one individual horizon at a time. Table 1 displays the result of such test in the case of a shock of 1 standard deviation, using 1,000 bootstrap replications. The outcome of this test suggests the presence of asymmetric effects in both productivity and price, but in a statistically conclusive way only for the former variable. Indeed, the individual impulse responses of productivity are significantly different with pvalues below 6% in all but the first period, which is expected since the threshold effect is in force with one period lag (see equation 10). With respect to price, we can reject the null of symmetry only at 20% in the first period, though the fact that pvalues of individual impulse responses remain close to this low level throughout all horizons suggests a likely problem of power, which is not surprising given the relatively small sample on which the model is estimated.

Table 1: Wald test on symmetry

h	productivity				price			
	IRF	$p v$	$IRFs$	$p v$	IRF	$p v$	$IRFs$	$p v$
0	0.165	0.685	0.165	0.685	1.692	0.193	1.692	0.193
1	3.752	0.053	3.886	0.143	1.430	0.232	1.742	0.419
2	4.508	0.034	4.853	0.183	1.180	0.277	1.821	0.610
3	4.340	0.037	4.879	0.300	1.459	0.227	2.096	0.718
4	3.989	0.046	4.887	0.430	1.446	0.229	2.097	0.836
5	3.856	0.050	4.954	0.550	1.382	0.240	2.154	0.905

Note: Wald test on unconditionally symmetric response functions in the case of 1 standard deviation shocks. Entries are test statistics and pvalues for the individual impulse responses (IRF) and the joint set of impulse responses up to horizon h ($IRFs$).

4.3 A historical decomposition

After presenting substantial evidence that technology yields stronger and more persistent effects on productivity and price than resource depletion, we now want to evaluate the contribution of each shock to the historical dynamics of these two variables. The outcome of such investigation is far from obvious, given the nonlinearities included in the model, and has important economic implications since it allows an assessment of the overall historical importance of technological progress compared to natural resource depletion. We follow the main logic of Kilian and Vigfusson (2017) in calculating a historical decomposition via Monte Carlo simulations, but we modify their procedure in an important way.

Let us define by $v_{p,T}(h, \Omega_0)$ the contribution to the determination of the price level of the sequence of technology shocks from 0, the first available observation, to h , where we condition on Ω_0 , the information set available at time 0, and by $v_{p,RD}(h, \Omega_0)$ the corresponding quantity for the resource depletion shock. These quantities are calculated as the difference between two conditional expectations

$$v_{p,T}(h, \Omega_0) = E \left[p_h | \{ \varepsilon_l^T \}_{l=0}^h, \Omega_0 \right] - E [p_h |, \Omega_0] \quad (12)$$

$$v_{p,RD}(h, \Omega_0) = E \left[p_h | \{ \varepsilon_l^{RD} \}_{l=0}^h, \Omega_0 \right] - E [p_h |, \Omega_0] \quad (13)$$

where the first expectation in each difference conditions on the estimated series of ε_t^T or ε_t^{RD} up to horizon h .¹⁶ We propose a simple measure to evaluate the relative contribution of each shock to the observed level of a variable in each period. We label this quantity as the “absolute contribution”, and we compute it as the share of the contribution of a certain shock with respect to the sum of the contributions of all shocks, with all quantities expressed in absolute value. So, the contribution of the shock k in the variable i observed in period h is

$$s_{i,k}(h, \Omega_0) = \frac{|v_{i,k}(h, \Omega_0)|}{\sum_{j \in J} |v_{i,j}(h, \Omega_0)|}, \quad (14)$$

where $J = \{d, T, RD, r\}$ and $k \in J$.

¹⁶Same calculation can obviously be performed for the other structural shocks, ε_t^d and ε_t^r .

The result of this calculation, beginning at 1958, which is the first available starting point, is plotted in Figure 5 for each of the three variables. As expected, the demand shock explains most of the movements in the manufacturing output throughout the sample, with the exception of the last few years. In the case of labour productivity, the historical variation is almost completely explained by technology and resource depletion shocks, with the contribution of the former dominating the latter, a feature related to its stronger persistence. Also in the case of price the contribution of technology shocks surpasses that of resource depletion shocks for most of the sample period. Nevertheless, we observe that the relative importance of the four shocks in the price dynamics varies considerably across the years, and the fact that the residual shock has sometimes played an important role in the price movements signals the presence of other relevant factors, such as developments in the market structure. Overall, as highlighted by the average absolute contributions displayed in Table 2, it is evident that technology has historically been the dominant driver of both productivity and price, overcoming the influence of resource depletion. As to the price of iron ore, the average contribution of technology is 36% against 30% of resource depletion and 10% of demand.

Table 2: Average absolute contribution

	<i>demand</i>	<i>techno</i>	<i>depletion</i>	<i>residual</i>
x_t	0.605	0.152	0.127	0.115
y_t	0.034	0.492	0.417	0.056
p_t	0.100	0.363	0.304	0.233

Note: Contribution of each shock in terms of absolute values, averaged across all observations.

5 The role of global market concentration

So far we have shown that efficiency shocks have asymmetric effects and that this feature has made technology the dominant driver in the historical movements of iron ore real price. As discussed in section 4, there is a host of possible economic factors responsible for such asymmetry. In this section, we are going to examine one specific dimension in which the discovered asymmetry may have its origin, the role of market structure and competitive pressure.

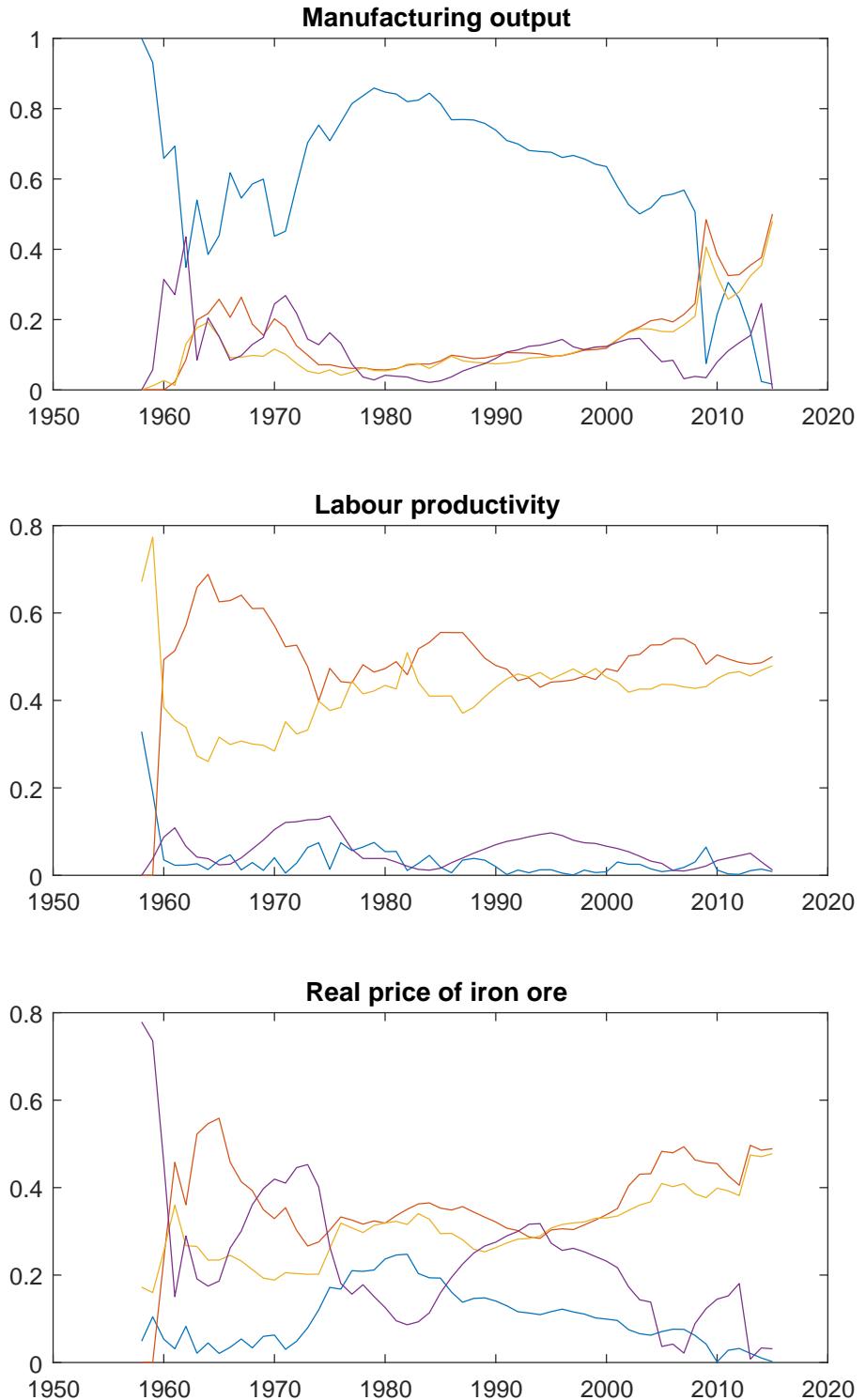


Figure 5: Absolute contribution of demand shock (blue), technology shock (red), resource depletion shock (yellow) and residual shock (magenta).

As a result of high entry cost barriers, the iron ore market, similarly to other natural resource industries, tends to be characterized by an oligopolistic structure. The US iron ore sector is no exception, and its degree of market concentration has remained almost unchanged at least since 1990, and most likely also in the previous period.¹⁷

At the same time, iron ore is a commodity that is traded in a global market, following an integration process that started in the 1950s, fostered by innovations in both transportation and mining operations.¹⁸ Despite increasing volumes of world exports and greater international price convergence over time, the considerable incidence of transportation costs and geographical distance imply that national markets still exist to a considerable extent (Lundmark 2018). The iron ore production in the US has been characterized by relatively high costs compared to most exporting countries.¹⁹ This aspect explains why US mines have traditionally tended to satisfy national demand, but at the same time it has made the US iron ore sector particularly exposed to competition from abroad.

Apart from the relative stability of US domestic market concentration, Schmitz (2005) argues that the existing local conditions in terms of tax and union regime has effectively prevented domestic competitive pressure from spurring productivity. So we focus our attention on the role played by international competition, and in particular on one of its main determinants, global market concentration. There are four reasons a more concentrated global market may exert a higher competitive threat on the domestic US mining sector: 1) larger firms enjoy considerable economies of scale; 2) they have easier access to financial resources to fund R&D investments generating future innovations; 3) higher concentration is typically associated with faster diffusion of new technology; 4) for a long time US mining activities have faced a cost disadvantage with respect to foreign firms.²⁰

¹⁷From the USGS reports we know that approximately 9 mines operated by five companies has accounted for 99% of the iron ore production each year from 1990 to 2015. See the Mineral Yearbooks from USGS website <https://www.usgs.gov/centers/nmic/iron-ore-statistics-and-information>. We did not find documentation on the shares of the operating companies for the years before 1990, but we deduce from the name of the mining companies mentioned in the reports that the concentration is unlikely to have been subject to substantial changes.

¹⁸In the last decade, approximately 50% of world production has been exported. For an overview of the globalization of commodity markets, see Radetzki (2008) and De Lipsis et al. (2017).

¹⁹This is the result of many factors, such as old age of the mines, the steady deepening of the pits, the deterioration of metal grade, and the ensuing high milling costs (e.g. Fellows et al. 2014).

²⁰A vast empirical literature in industrial organization has studied how diffusion of new technologies is influenced by the existent degree of market concentration, with the majority of evidence highlighting the

The first two points are nothing more than an extended version of the theoretical argument whereby greater domestic industrial concentration yields higher export performance (White 1974, and Krugman 1984).²¹ If we consider the non-US mining firms and their propensity to export to the US market, a higher concentration among them can be expected to increase the threat of their exports entering the US market, and especially so for a commodity such as the iron ore, which in all likelihood benefits from large economies of scale.

Contrary to concentration in the US domestic market, the degree of global concentration has been far from constant. As an example, the share of non-fuel metal production controlled by the 10 largest companies has grown from 20% in 1990 to 35% in 2008 (Ericsson, 2010). Since mid-1990s the global mining industry has experienced an increasing number of mergers and acquisitions, which has intensified considerably since 2005 (Ericsson, 2012). As for the iron ore, it is since early 2000s that the world production has become dominated by three companies accounting for 55% of world supply (Lawrence and Nehring 2015). So, while global concentration has increased over the whole period under study, it is in particular in the last decade that a limited number of large companies has acquired a growing share of the world mining industry.

As market structure is fundamental to understand the link between production costs and price level, it follows that the degree of global market concentration, by acting as a source of competitive pressure, is likely to influence the extent to which cost changes due to technological innovations and resource depletion translate into price changes. While in perfect competition the effects of technology and depletion are symmetric as price reflects marginal costs, by contrast, in the presence of market power and the competitive threat of foreign producers, we expect the price level to fall more strongly in response to technological innovation than it increases in response to resource depletion. Moreover,

fact that larger firms adopt new technologies sooner and that the number of firms in an industry has a negative effect on the time of adoption (see, e.g., Davies and Davies 1979, Reinganum 1981, Hannah and McDowell 1984, Hall 2004). At the same time, a positive role is played also by the competitive pressure that, for instance, the threat of new entrants represents for an incumbent firm that otherwise would be slow in adopting the new technologies (e.g. Geroski 2000).

²¹Even though the number of empirical studies disproving such hypothesis is greater than those confirming it, with one notable confirmation obtained by Pagoulatos and Sorensen (1976), we notice that it is verified in the case of the US steel industry (Parsons and Ray 1975).

we postulate that this asymmetry is greater the stronger is the competitive threat from abroad, that is the higher is the degree of global market concentration. In the following subsection we test this hypothesis by first investigating the empirical relevance of an interaction between technology and depletion with global concentration, and then by verifying whether an asymmetric effect follows.

5.1 Evidence of interaction

Following the arguments above, we expect market concentration to exert its influence in the form of an interaction with technology and depletion shocks, rather than being a direct determinant of the price level. This is confirmed by our data, as a preliminary analysis of the correlation structure of our concentration index with the existing variables of our SVAR model reveals no significant relations.

Hence, we investigate whether the effects on price of technology and resource depletion shocks are affected by the degree of global market concentration by constructing a concentration index and introducing a Logistic Smooth Transition model in the price equation of model (10), where this concentration index acts as threshold variable.²² The flexibility of the Smooth Transition model allows us to capture any nonlinear effect related to global concentration, whether it unfolds as a gradual adjustment or as a sudden switch between different regimes.

To avoid the risk of modelling a spurious nonlinearity, along with inconsistent estimates, it is important to test in advance for the presence of such nonlinearity (Hubrich and Terasvirta 2013). Therefore, we first test for any interaction that concentration may separately have with technology and depletion shocks, using the procedure proposed by Terasvirta (1994). In our application, the test is based on an auxiliary regression that adds to the existing right-hand side variables of the price equation an interaction terms

²²Global market concentration is constructed using the Herfindahl formula on the world shares of iron ore exports of each country, expressed in US dollars, and collected from the UN Comtrade database. The time series of this index is displayed in Figure 6. We use countries share in world exports as a proxy for global concentration, as time series data on firms share of world iron ore production is difficult to find. Since the US share of world exports has been very small, averaging 2.2% over the whole period and staying above 4% only until 1968, this index represents *de facto* the degree of concentration among foreign mining firms.

between ε_t^T (or ε_t^{RD}) and the first three powers of the concentration index. The outcome of this test for respectively technology shocks and depletion shocks, using different lags of the threshold variable, is displayed in Table 3. A striking difference emerges between the two shocks. There is no sign at all of an interaction between depletion and concentration, at any distance in time, whereas there is unambiguous evidence of concentration interacting with technology, as the corresponding F test strongly rejects the null of linearity, with very small pvalues, and with the largest statistic obtained when the delay parameter is 0.

Table 3: Terasvirta test

lag	techno		depletion	
	stat	pv	stat	pv
0	8.457	0.0002	0.532	0.6630
1	4.007	0.0147	0.343	0.7944
2	4.788	0.0066	0.092	0.9640
3	3.730	0.0197	0.282	0.8379
4	1.232	0.3122	0.383	0.7659
5	0.525	0.6678	0.229	0.8756

Hence, we replace the price equation in model (10) with a specification that includes a Logistic Smooth Transition model for the impact of technology shocks ε_t^T

$$\begin{aligned} \Delta p_t = & \mu_p + A_{31}(L)\Delta x_{t-1} + \tilde{A}_{32}(L)\Delta y_{t-1} + A_{33}(L)\Delta p_{t-1} + \\ & + A_{32,1}^{(1)}I(\Delta y_{t-1} \geq 0)\Delta y_{t-1} + A_{32,1}^{(2)}I(\Delta y_{t-1} < 0)\Delta y_{t-1} + \\ & + c_{31}\varepsilon_t^d + [1 - G(w_t)]c_{32}^{(1a)}\varepsilon_t^T + G(w_t)c_{32}^{(1b)}\varepsilon_t^T + c_{32}^{(2)}\varepsilon_t^{RD} + c_{33}\varepsilon_t^r, \end{aligned} \quad (15)$$

where $G(w_t) = [1 + e^{-\gamma(w_t - \bar{w})}]^{-1}$ is the transition function, γ is the smoothness parameter, w_t is the threshold variable, in our case the concentration index, and \bar{w} is the value of the index at which the transition between the two regimes takes place. We estimate the model by Nonlinear Least Squares and we obtain $\hat{\gamma} = 119$, which describes a quite fast transition from one regime to the other following a change in global market concentration, and $\bar{w} = 0.25$, which corresponds to an effective number of 4 equally-sized exporting countries. Such estimates, combined with the historical path of global market concentration, give rise to the impact multiplier of price to 1 standard deviation technology shock

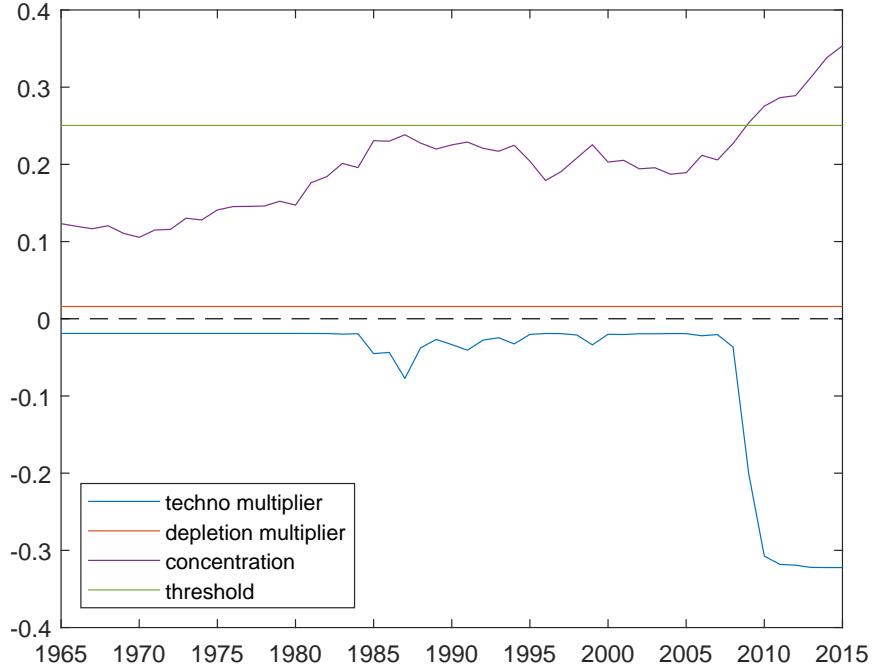


Figure 6: Model with concentration index

presented in Figure 6.

Overall, we found strong evidence of global market concentration interacting positively with technological innovation amplifying its effect on price, but no significant interaction between concentration and resource depletion. The impact multiplier of technology shocks has been almost -2% for most of the period under study, except in two main historical circumstances when the rise in global market concentration has triggered an increase in the size of this impact: a temporary change during the second half of the 1980s, when it grew to almost -8%, and the years after 2009, when global market concentration exceeded the threshold level making the impact of technology shocks increase up to -32%. We interpret these results as evidence that the competitive threat of large foreign mining companies entering the US market have induced US firms to cut their price more aggressively as soon as technological advancements allowed them to reduce production costs. Combined with a multiplier of resource depletion that remains constant at 1.6%, this interaction with concentration explains at least part of the asymmetry we previously found to exist between the effects of technology and those of resource depletion.

5.2 Comparison with Schmitz (2005)

The modest but prolonged rise in the impact of technology shocks that we found to occur during second half of the 1980s, and which continues to a smaller extent also in the first half of the 1990s, matches a historical episode that has been studied by Galdon-Sanchez and Schmitz (2002) and Schmitz (2005). During the 1980s labour productivity in the iron ore sector increased considerably, and these authors attribute such increase to a rise in the international competition that US mining firms faced as a result of the collapse of the steel industry of the Pacific basin occurred in 1979-1982, mainly triggered by the recession of the early 1980s. Threatened by the more competitive iron ore of the Brazilian producers, US mining firms, according to these authors, were forced to implement a drastic overhaul of their work practices.

Although our approach and focus is different, as we examine the systematic response of price to an exogenous technology shock, while their analysis is a qualitative case study centered on productivity, our results offer further insights into this historical episode that are distinct and complementary to theirs. It is useful to clarify a few points that help understand our findings compared to those of Schmitz (2005).

We can exclude that our concentration index simply mirrors the size of the global iron ore market, and thus the fact that a rise in this index during the 1980s reflects just a shrinking of the market. While the early 1980s collapse in the steel industry produced a substantial contraction in the demand for iron ore, it is also true that a contemporaneous increase in global market concentration was taking place at a rather steady pace already since 1971 and until 1987 (Figure 6). In addition, the normalized version of our Herfindahl index, which reflects merely the inequality in the market shares ignoring firms numerosity, exhibits the same time pattern.

Schmitz (2005) attributes most of the 1980s productivity rise to improved work practices, but he also acknowledges that in the same periods several minor technical advancements were introduced in the mining industry.²³ Even if those technical advancements contributed only marginally to the observed increase in productivity, our estimation sug-

²³Examples taken from the same author are: improvements in blasting techniques, IT systems for trucks arrangement, new grinding methods, procedures for heat recycling.

gests that the ensuing reductions in production costs were used by US mining firms to cut their prices more aggressively as a consequence of a more concentrated global market.

We find that there is another very different historical instance, in 2009, in which the response of price to technology becomes stronger but without a concurrent prolonged decline in steel production. We obtain that around that year a radical regime switch took place as global market concentration reached unprecedented levels, something which is confirmed by the intense wave of mergers and acquisitions activities that took place especially since 2005.²⁴ Also, our definition of technology includes management practices, which might be seen as a similar concept to what Schmitz (2005) defines as work practices, but since our shock is by construction orthogonal to the business cycle, we can easily discard the risk that it is representing in fact a demand shock.

Hence, we conclude that not only, as Schmitz (2005) highlighted, did the increased competition produced by a large negative demand shock foster better work practices in an attempt to raise productivity, but also, as we found, any gain due to technological innovation in general were exploited by the US mining firms to cut more sharply the price of iron ore, in response to higher competitive pressure arising from a more concentrated global market.

6 Concluding remarks

The assumption that primary resources are scarce is at the core of the economics discipline, and the idea that technological progress may offer the solution to the problem of future resource availability is at the center of the research in resource economics in particular. In this paper, we conducted an empirical investigation on the US mining sector that produces iron ore to gain insights into this important topic.

Rather than using a reduced-form univariate approach that examines the observed long-run trend in the real price, we showed that only adopting a structural multivariate

²⁴Another potential factor explaining the increased multiplier of technology in this period is the move towards more market-driven pricing mechanisms occurring in metal markets since mid-2000s. Though there is not much evidence of a significant impact of these transformations on the dynamics of iron ore prices (Warell 2014), we cannot exclude that this change contributed to intensify international competition in the iron ore market.

method of analysis we can evaluate the role played by each long-run determinant, which is often not evident from a mere consideration of the price trend. To this aim we developed a new econometric approach that permits to compare and test the potentially different consequences of technological change and natural resource depletion. Our analysis is limited to the iron ore industry, but the methodology we proposed is applicable to any mining industry, suggesting further research aimed at obtaining a more general picture of the mining sector as whole.

We found that the effects of technology on productivity and price is stronger and more persistent than that of natural resource depletion, which explains also its dominant role as a long-run driver of the real price throughout the US history. This conclusion is in line with those scholars that advocate an analysis of the resource scarcity issue using a more optimistic “opportunity cost paradigm” (Tilton et al. 2018). But the idea that technology may be capable to offset the problems of scarcity does not appear so unrealistic if one looks at the latest interest generated around the development of technologies that will in the not-so-distant future allow extraterrestrial mining.

Moreover, we found evidence that market structure is an important long-run determinant of the real price, something which empirical research on primary commodities has often ignored. In particular, we showed that global market concentration exerts a key influence on how technological change affects the domestic price level. As global market becomes more concentrated the ensuing greater competitive threat faced by US domestic firms induce them to use any technological innovation to cut their price more aggressively. This finding provides indirect empirical support to the main theoretical mechanism behind the Prebisch-Singer hypothesis. In its original form, this hypothesis was based on the idea that differences in market structure explain why technological innovation may have different effects on the price level in different sectors. As competition level tends to be higher in primary commodities than manufactured goods, a negative long-run trend in their relative price should result. We do not make an explicit comparison with the effects of technology in the manufacturing sector, but we are able to confirm the importance of market structure and competition level in determining the extent to which innovation

generates a decline in commodity prices.

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