Technology shocks and the Prebisch-Singer hypothesis*

(Preliminary draft. Please do not circulate.)

Vincenzo De Lipsis and Paolo Agnolucci†

University College London

Abstract

We explore the relationship between innovation, productivity and price in the mining sector of an important primary commodity, iron ore, using an innovative nonlinear SVAR approach. Our results shed lights on two distinct but related lines of research: the current evidence on the Prebisch-Singer hypothesis, by showing the importance of its main channel, the dominance of technological innovation over resource depletion as a determinant of the price of iron ore, and the role played by market integration; the current empirical understanding of the effects of competition on productivity and price, by showing the existence of an interaction between productivity changes and market structure.

Keywords: Prebisch-Singer, mining sector, productivity, market structure, competition, innovation.

JEL classification: L1; L7; N5; Q31.

*I would like to thank

†Institute for Sustainable Resources, Central House, 14 Upper Woburn Place, London WC1H 0NN; email: v.delipsis@ucl.ac.uk

1 Introduction

The determination of the real value of primary commodities have always been an important topic in economics. While the short run dynamics of price of commodities like minerals, agricultural raw materials and fuels is determined by a multitude of demand and supply related factors, the relative price in the long-run of such items is clearly associated with relative scarcity of resources, technological innovation, and long-term developments in the market structure. Contrary to classical economists who claimed the inevitable long-run increase in the real price of primary materials as a consequence of scarce land and declining productivity, Prebisch (1950) and Singer (1950) proposed an opposite story, which came to be known as the Prebisch-Singer hypothesis, and which predicts a long-run decline in the price of primary commodities relative to that of manufactured goods. While the list of theoretical arguments to explain such decline has been enriched over time with more detailed complementary theories, the main mechanism hinges on the idea that technological innovation has very different price implications in the commodity sector compared to the manufacturing sector, as a consequence of a different market structure. Because producers of manufactured goods benefit from substantive market power, both in the corresponding goods and labour market, technological progress in this sector does not translate into a substantial fall in prices, contrary to the commodity producing sector, which is instead exposed to stronger competitive pressure. The result of this structural difference is potentially one of the main reason to expect a gradual fall in the relative price of commodities in the long term.[1]

The Prebisch-Singer hypothesis has entered both the policy and academic debate for a long period, attracting in particular the interest of many applied researchers, interested in testing for the existence of a long-run trend in primary commodity prices. A renewed attention to the topic has been spurred by recent advancements in time series econometrics, some example of which are: Kim et al. (2003), Kellar and Wohar (2006),

[1]Other arguments for such a fall are: the considerable technological innovation that has abated 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 (see Radetzki, 2008).

Harvey et al. (2010), Ghoshray (2011), Arezki et al. (2014).[2] Overall, the large amount of empirical work accumulated so far highlights a mixed and weak evidence, such that it is safe to conclude that a long-run decline is not a systematic robust feature of the price of primary commodities.

The role of market structure in the main theoretical argument in support of the Prebisch-Singer hypothesis connects this same topic with another strand of literature that studies the relationship between competition and productivity. Theoretical reasons for expecting a positive effects of market competition on the level of productivity can be found in Scherer and Ross (1990), and Nickell (1996). While there is no lack of theory to justify this positive relationship, the empirical evidence in this respect is, instead, rather fragmentary. One exception is Galdon-Sanchez and Schmitz (2002), who exploit a particular historical event to analyse the consequences of an increase in competition in the global market of iron ore. They use the collapse of the world steel industry following the global recession in the 1980s as an exogenous shock to demand to study the effects of the ensuing increased competitive pressure on the labour productivity of certain iron ore producers. They find that higher market competition fostered huge rises in productivity in the countries of the Atlantic basin, including the US, something that Schmitz (2005) attributes to a change in work rules, rather than mines being closed, new products or new technology.

We propose a new empirical strategy to assess the importance of the Prebisch-Singer hypothesis, and in implementing such strategy we also provide an important characterization of the relation between competition, innovation and productivity. Rather then using the usual univariate approach to test for the existence of a negative trend in the real commodity price, we adopt a multivariate approach to explore the empirical relevance of the main underlying mechanism that is supposed to be responsible for such negative trend. More specifically, we address the two ingredients of its theoretical argument, that is the contribution of technological innovation in the dynamics of the iron ore price, and the role of the market structure. In investigating this channel, we obtain also important

[2]The special edition n.46 of the Journal of International Money and Finance was devoted to the topic. For a review, see for instance Baffes and Etienne (2016).

insights into the extent to which technological innovation has offset the detrimental effects of resource depletion in the mining sector. From a methodological perspective, we produce two contributions. We deliver one of the first applications of the structural VAR (SVAR) methodology in natural resource economics.[3] Secondly, we develop an innovative nonlinear SVAR approach that uses a threshold model to distinguish structural shocks of different sign.

Our results confirms the importance of the Prebisch-Singer hypothesis in its main mechanism, and can be summarized in three main points. First, we find an asymmetric response of price to positive and negative shock to productivity. Technological innovation produces increases in productivity that pushes the price level more strongly and more persistently than the falls in productivity caused by resource depletion. Second, we uncover that technological innovation dominated resource depletion as a driver of price movements in the US history. Finally, we obtain an important result on the link between market structure, competition, and productivity. We find strong evidence that the response of price to technology shocks is dependent on competition as represented by the degree of market international integration. The more integrated is the global market for iron ore the stronger is the effects of innovation on price.

The structure of the paper is the following. After describing the data we use in section 2, we illustrate the main features of the US mining sector in section 3. In section 4 we set up our core identification scheme within a linear SVAR model and we present the results from its estimation. In section 5 we build a innovative threshold SVAR model with the purpose of distinguishing technological progress from resource depletion and we examine the evidence about the presence of an asymmetric effect on price. In section 6 the same estimated model is used to provide a historical decomposition of the contribution of each shock to the dynamics of productivity and price. In section 7 we test for the potential role of competition as a result of international market integration. Section 8 provides concluding remarks.

[3] Jack and Stuermer (2018) and Stuermer (2018) have used a SVAR model to study the price of a set of commodities, including minerals.

2 Data description

The data used in our empirical analysis have annual frequency covering the period 1955-2015, and consist of: labour productivity in the iron one sector, the price of iron ore in the US market, the GDP deflator, output of the manufacturing sector, and our index of international market integration. Notice that both the productivity measure the price refers to usable iron ore, that is after the crude mineral has been subject to a first stage of processing (beneficiation) to increment its iron content. Labour productivity is measured as the real amount of usable iron ore per hour worked, and is the result of merging two series: the first one was obtained upon request from the Bureau of Labour Statistic (BLS), covering the period from 1955 to 2000, based on the SIC classification; the second part is calculated as output divided by hours worked, extracted from each of the United States Geological Survey (USGS) annual reports as of 2001 to 2014, and based on the NAICS classification. While the change in classification implies a change in some of the data compilation methods, such modifications are unlikely to be important for our time series analysis. The price of iron ore corresponds to the Producer Price Index, obtained from the BLS, which is a measure close to the perspective of the seller, so capturing price movements prior to the retail level. Both the output of the US manufacturing sector and the GDP implicit deflator is collected from the Bureau of Economic Analysis. Our measure of real price of iron ore is obtained as the ratio between the Producer Price Index and the GDP deflator. Finally, the index of iron ore international market integration is calculated using data about countries' exports of iron ore, expressed in US dollars, downloaded from the UN Comtrade database.[4]

3 A linear SVAR model for the mining sector

Assessing the importance of the main theoretical mechanism behind the Prebisch-Singer hypothesis requires a careful analysis of the determinants of the price of the commodity. We employ the SVAR methodology since it offers a suitable empirical strategy to assess

[4]See below for more details about how the index is calculated.

the effects of technological innovation on price by allowing to disentangle the different sources of exogenous variation. Two features in particular makes it appropriate to the analysis of the market of primary commodities: the possibility of identifying the relevant causal relationships without the need of stringent and often debatable theoretical restrictions, and the possibility of relying on a simple structure to capture complex dynamic relationships, both of which become handy when the time span of the available data is not particularly long. Nevertheless, apart from a large literature on the crude oil market, examples of such application are rather rare. One exception is Stuermer (2018), who uses a SVAR estimated with long-run restrictions to study the price dynamics of four minerals over long horizons.[5] In the following, we set up and motivate the core identification strategy used in our SVAR model, and then we discuss the results from its estimation.

3.1 Identification scheme

Since our main goal is to study the effects of technological innovation on the real price of iron ore, it becomes fundamental to disentangle technology from other sources of productivity and price variation. We start by providing a simple expression for labour productivity, given a definition of the production function that follows standard assumptions.[6] The output of the mining sector is

$$Y_t = A_t F(K_t, L_t), \tag{1}$$

where Y_t is output, A_t is the total factor productivity, K_t is capital and L_t is labour. Once we assume the industry production function is homogeneous of degree one, we have that labour productivity

$$\frac{Y_t}{L_t} = A_t F(\frac{K_t}{L_t}), \tag{2}$$

is a function of two components, the current efficiency level A_t, and the capital-labour ratio K_t/L_t. At this stage, it is important to clarify what determines these two com-

[5]Jacks and Stuermer (2018) use the same identification to analysis a larger set of commodities.

[6]We choose to use labour productivity as this is by far the most reliable and available measure.

ponents. The efficiency level A_t is likely to be exogenous with respect to the specific commodity market, at least over the short horizon. While we may think that sustained increases in demand for the commodity can stimulate R&D investments that ultimately lead to improved mining technology, such process is long and very uncertain. Hence, it is reasonable to assume that A_t is driven by an exogenous process that reflects current technology, organization and the quality of the existing mineral deposit.[7] As for the second component, K_t/L_t, we notice that the mining sector is in general highly capital-intensive.[8] There are large sunk costs considering that capital investments are specific to the location of the mines, and long lead times characterize the lag between decision to increase production capacity and the effective increase in output. As a consequence, since K_t is very slow to adjust over time, changes in output in response to the dynamics of demand imply changes in the labour force, and so in K_t/L_t. Moreover, given the high capital intensity, small changes in output tend to generate large changes in the level of labour productivity. Hence, we conclude that there are two ultimate sources of variation in labour productivity in the mining sector: a supply-side shock that affects the level of efficiency A_t, which is related to technological innovation and improved work practice (if positive), and resource depletion (if negative); and a demand shock, which originates in the industrial sectors that use the mineral as an input, and which triggers a variation in output that is obtained by varying the variable factor, labour, and thus the current capital-labour ratio.

This set of general theoretical assumptions are imposed on a SVAR model of order p that describes the joint behaviour of three variables: output from the manufacturing sector (x_t), labour productivity in the production of iron ore (y_t), and the real price of

[7]Notice that in general such factors may affect the grade of the mineral as well as the productivity. However, we consider usable ore, which refer to the mineral after a first stage of processing to increase the metal content is performed. Since the grade of the usable ore is very stable over time during the sample period, any change in grade of the crude ore must have translated into a variation in productivity. Hence, 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.

[8]XXX some figures on US.

iron ore (p_t). This SVAR can be written as

$$B_0 z_t = \nu + \sum_{i=1}^{p} B_i z_{t-i} + \varepsilon_t \tag{3}$$

where $z_t = [\Delta x_t, \Delta y_t, \Delta p_t]$ and ε_t is the vector of mutually and serially uncorrelated structural shocks.[9]

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

$$\begin{bmatrix} u_t^x \\ u_t^y \\ u_t^p \end{bmatrix} = \begin{bmatrix} c_{11} & 0 & 0 \\ c_{21} & c_{22} & 0 \\ c_{31} & c_{32} & c_{33} \end{bmatrix} \begin{bmatrix} \varepsilon_t^d \\ \varepsilon_t^a \\ \varepsilon_t^r \end{bmatrix}, \tag{4}$$

where u_t^x, u_t^y and u_t^p are respectively manufacturing output, labour productivity and real iron ore price, after subtracting their autoregressive part. As we can see, such structure defines three structural shocks. The first shock, ε_t^d, is our demand shock originating in the manufacturing sector, which represents a prime consumer of iron ore.[10] This shock affects labour productivity and the iron ore price within the same year. Accordingly, all three impact multipliers of the demand shock are left unrestricted. The second shock, ε_t^a, is our efficiency shock originated in the supply side, as a result of technological innovation, improved organization, or resource depletion. Since iron ore is only one of many inputs used in the production of manufactured goods, this shock is uncorrelated with the current level of manufacturing output. We impose a zero restriction on its impact multiplier on the manufacturing output, but leave unrestricted the effects on productivity and price. Finally, the third shock, ε_t^r, represents a set of other factors affecting market conditions and thus the iron ore price, but that are unrelated to either output or productivity. This shock includes, among other things, changes in the markup, the market structure and the labour supply.

[9] All variables are expressed in logs, while a lag length of 2 is selected for the estimation based on results from the information criteria and the tests for residual autocorrelation.

[10] Almost the entire iron ore production is used in the steel industry, which provides its output to a broad range of industries. The share of iron ore in some important US manufacturing sectors as of 2013 is: Automotive (26%), Machinery and equipment (10%), Appliances (4%). See Fellows et al. (2014).

3.2 Results

After taking log-difference and selecting a lag length of 2, the estimates of model (4) produces the impulse response functions (IRFs) displayed in Figure 1.[11]

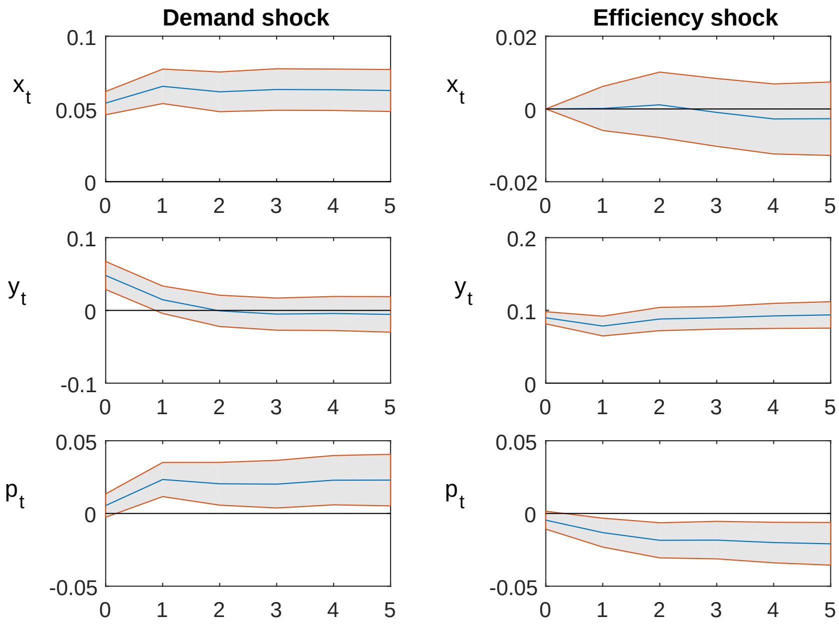

Figure 1: Impulse response to one unit shock

A positive demand shock, associated with a booming manufacturing sector, gives rise to an increase in the price of iron ore and its production, which in turn pushes up productivity, as a likely consequence of an initial underutilization of production capacity. As demand from the manufacturing sector keeps increasing, price rises further pulling this time productivity level down, as we approach full capacity utilization, until the productivity is back to its original long-run level. In the new equilibrium both price and quantity produced are higher. A positive productivity shock, as typically represented by the introduction of a technical innovation, generates a permanent jump in productivity, which is accompanied by a somewhat gradual but permanent decrease in price. As expected, there is no systematic association with a change in manufacturing output. Within the same year of the shock, as Table 1 shows, both shocks have a statistically significant influence on productivity but not on price.

[11] A lag order of 2 was chosen based on the suggestions from the standard information criteria and the tests for residual autocorrelation.

Table 1: Impact multipliers

	ε_t^d	ε_t^a	ε_t^r
x_t	1	0	0
	(0.00)	(0.00)	(0.00)
y_t	0.888	1	0
	(0.013)	(0.00)	(0.00)
p_t	0.100	-0.051	1
	(0.500)	(0.455)	(0.00)

Note: pvalues in brackets.

4 Technological innovation versus resource depletion

Productivity changes in the mining sector that are unrelated with demand factors may have different origins, but we can in general distinguish on one side the positive changes, due to technological advancements in extraction and processing, or improved management and work practice, and on the other, the negative changes, resulting from deposit exhaustion and declining iron content (grade).[12] In principle, nothing suggests that unexpected increases and decreases in productivity affect the price dynamics in a symmetric fashion. In fact, it is of particular interest to explore to which extent technological innovation has offset the detrimental effects that resource depletion exerts on the price of primary commodities. The linear SVAR model we used in the previous section imposes the restrictive assumption that impulse responses are symmetric with respect to the sign of the shock, as well as proportional to its magnitude. We decide to overcome such restriction and investigate whether unexpected positive shocks to productivity, mostly associated with technological innovation, and unexpected negative shocks to productivity, mostly reflecting resource depletion, are indeed characterized by a different effect on price and also a different persistence over time.

4.1 A threshold SVAR model

We develop an innovative nonlinear SVAR approach that is able to distinguish positive from negative productivity shocks. The model we propose is a threshold SVAR with two

[12] Other potential factors that appear of negligible or secondary role in a developed country like the US are: political events, conflicts, extreme weather episodes.

regimes, which can be written in its general form as

$$\begin{cases} B_0^{(1)} z_t = \nu^{(1)} + \sum_{i=1}^{p} B_i^{(1)} z_{t-i} + \varepsilon_t & \text{if } \varepsilon_{kt} \geq 0 \\ B_0^{(2)} z_t = \nu^{(2)} + \sum_{i=1}^{p} B_i^{(2)} z_{t-i} + \varepsilon_t & \text{if } \varepsilon_{kt} < 0 \end{cases} \tag{5}$$

where the superscript (l) is used to distinguish regime-specific parameters, with $l = 1, 2$, and ε_{kt} indicates the k-th structural shock that acts as a threshold variable determining at each date which regime is in force. Assuming that the regime-switching involves only the impact multipliers, but not the intercept or the slope of the VAR matrices, we can write the same model in its general reduced-form as

$$\begin{cases} z_t = \mu + \sum_{i=1}^{p} A_i z_{t-i} + C_0^{(1)} \varepsilon_t & \text{if } \varepsilon_{kt} \geq 0 \\ z_t = \mu + \sum_{i=1}^{p} A_i z_{t-i} + C_0^{(2)} \varepsilon_t & \text{if } \varepsilon_{kt} < 0 \end{cases} \tag{6}$$

where $C_0^{(l)}$ is the inverse of $B_0^{(l)}$.

The fact that the threshold variable is not observable, but requires instead the knowledge of the very system of equations where it is included generates an estimation problem. This problem is avoided if the structural shock representing the threshold variable is identified before the very equation in which it generates the corresponding nonlinearity. This is possible, for instance, in the presence of a triangular identification structure, which is exactly our case. We assume that the effect of productivity shocks on price is characterized by two regimes, which are triggered depending on the sign of the productivity shock, identified in the previous equation. So, once the second equation defining productivity is estimated, and the corresponding structural shock ε_t^a is identified, a threshold model can be estimated on the price equation.

The ensuing identification scheme we impose on the relationship between reduced-form errors and structural shocks is then

$$\begin{bmatrix} u_t^x \\ u_t^y \\ u_t^p \end{bmatrix} = \begin{bmatrix} c_{11} & 0 & 0 \\ c_{21} & c_{22} & 0 \\ c_{31} & c_{32}^{(1)} & c_{33} \end{bmatrix} \begin{bmatrix} \tilde{\varepsilon}_t^x \\ \varepsilon_t^T \\ \tilde{\varepsilon}_t^p \end{bmatrix} + \begin{bmatrix} c_{11} & 0 & 0 \\ c_{21} & c_{22} & 0 \\ c_{31} & c_{32}^{(2)} & c_{33} \end{bmatrix} \begin{bmatrix} \bar{\varepsilon}_t^x \\ \varepsilon_t^{RD} \\ \bar{\varepsilon}_t^p \end{bmatrix} \tag{7}$$

where $\varepsilon_t^T = I(\varepsilon_t^a \geq 0)\varepsilon_t^a$ 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, $\tilde{\varepsilon}_t^m = I(\varepsilon_t^a \geq 0)\varepsilon_t^m$ and $\bar{\varepsilon}_t^m = I(\varepsilon_t^a < 0)\varepsilon_t^m$, with $m = x, p$.

To explore the possibility that these two shocks exhibit also a different persistence, we introduce a second nonlinearity, this time on the coefficient of lagged productivity in both the productivity and price equations, using the sign of the change in productivity from the previous period as threshold variable. As a result, our model is a nonlinear SVAR with two thresholds, one with respect to the impact of productivity shocks on price, distinguishing the sign of these shocks, and one with respect to the effect of past productivity, distinguishing the sign of its change from the previous period.[13]

Once we impose our identification structure (7), our model can be written out as

$$\begin{cases} x_t &= \mu_x + A_{11}(L)x_{t-1} + A_{12}(L)y_{t-1} + A_{13}(L)p_{t-1} + c_{0,11}\varepsilon_t^d \\ y_t &= \mu_y + A_{21}(L)x_{t-1} + \tilde{A}_{22}(L)y_{t-1} + A_{23}(L)p_{t-1} + \\ &+ A_{22,1}^{(1)} I(\Delta y_{t-1} \geq 0)y_{t-1} + A_{22,1}^{(2)} I(\Delta y_{t-1} < 0)y_{t-1} + c_{0,21}\varepsilon_t^d + c_{0,22}\varepsilon_t^a \\ p_t &= \mu_p + A_{31}(L)x_{t-1} + \tilde{A}_{32}(L)y_{t-1} + A_{33}(L)p_{t-1} + A_{32,1}^{(1)} I(\Delta y_{t-1} \geq 0)y_{t-1} + \\ &+ A_{32,1}^{(2)} I(\Delta y_{t-1} < 0)y_{t-1} + c_{0,31}\varepsilon_t^d + c_{0,32}^{(1)}\varepsilon_t^T + c_{0,32}^{(2)}\varepsilon_t^{RD} + c_{0,33}\varepsilon_t^r, \end{cases} \tag{8}$$

where $A_{ij}(L)$ and $\tilde{A}_{ij}(L)$ are polynomial in the lag operator defined as

$$\begin{aligned} A_{ij}(L) &= A_{ij,1} + A_{ij,2}L + A_{ij,3}L^2 + ... + A_{ij,p+1}L^p \\ \tilde{A}_{ij}(L) &= L^{-1}(A_{ij}(L) - A_{ij,1}), \end{aligned}$$

[13]Recall that all our variables are in 1st differences.

$A_{ij}^{(l)}$ is the coefficient on lagged productivity that is associated with regime l, and $c_{0,ij}^{(l)}$ is the impact multiplier of shock j on variable i associated with regime l.

4.2 Evidence on asymmetric effects

Model (8) can be estimated by single-equation LS including each time the structural shock identified from the previous equation as an additional regressor. It is important to underline that model (8) allows for potential nonlinearities, without imposing them, so the evidence of such asymmetries needs to be carefully evaluated. We assess in particular the evidence about asymmetric response of price to technology shock and resource depletion shock 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 IRFs using 1 and 2 standard deviation shocks; 3) the outcome from the Wald test on symmetry.

In Figure 2 we display the instantaneously linear IRFs to the two shocks, where we change the sign of the impulse response to the resource depletion shock to allow a closer comparison. It is evident that technology shock produces a far larger decline in price, starting from the first period, while the different dynamics of productivity after the first period is the consequence of a clearly asymmetric persistence in such variable.

While the instantaneously linear IRFs remain useful to grasp an indication about how much in theory the two shocks may differ in their effects on productivity and price, a more rigorous assessment of the actual dynamics effects of the two shocks requires a Monte Carlo simulation that averages out all possible future shock scenarios as well as past histories. For this reason we calculate the unconditional generalized impulse response functions (GIRFs) to 1 and 2 standard deviation shocks, as in Kilian and Vigfusson (2011), displayed in Figure 3 and Figure 4.[14] Even considering only 1 standard deviation shocks, it is already apparent how the dynamic effect of technology is significant at all horizons using 1 standard deviation confidence band, while that of depletion is barely so after one period. This difference 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

[14] See also Kilian and Lutkepohl (2017).

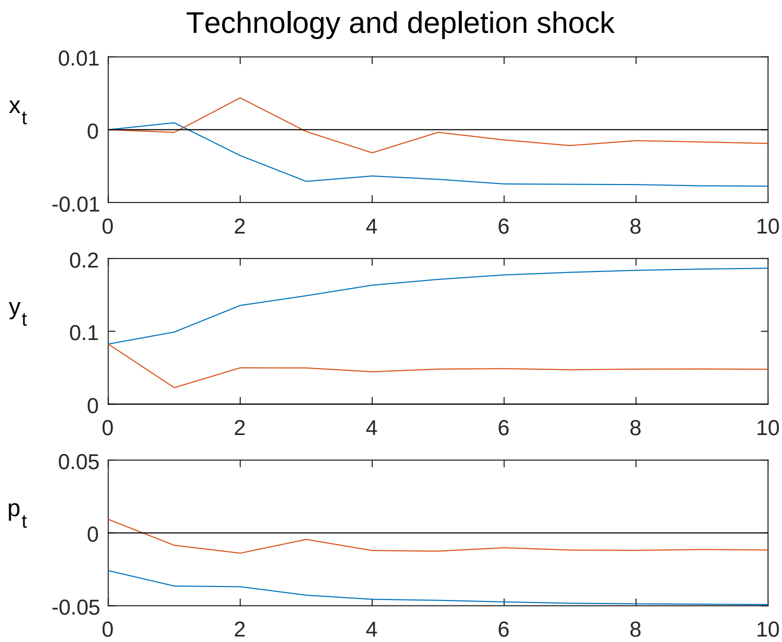

Figure 2: *Instantaneously linear impulse response to 1 std dev technology shock (blue) and depletion shock (red).*

over time, and thus permament, whereas that of depletion is never significant. Noticeable is also the role played by the nonlinearity in the persistence of productivity that kicks in when the shock is large enough. When the magnitude of the shock is 2 standard deviations, indeed, the ensuing increase in productivity grows over time in the case of technology, but falls a bit instead in the case of depletion. Nevertheless, both shocks produce permanent effects on the productivity level, compared to a demand shock that exerts only temporary deviations.

Table 2: Impact multipliers

	1 std dev shock				2 std dev shock			
	demand	*techno*	*depletion*	*residual*	*demand*	*techno*	*depletion*	*residual*
x_t	0.055	0.000	0.000	0.000	0.109	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
y_t	0.043	0.084	-0.081	0.000	0.086	0.166	-0.164	0.000
	(0.017)	(0.000)	(0.000)	(0.000)	(0.028)	(0.000)	(0.000)	(0.000)
p_t	0.002	-0.012	0.004	0.067	0.005	-0.038	-0.005	0.131
	(0.813)	(0.116)	(0.544)	(0.000)	(0.792)	(0.110)	(0.811)	(0.000)

Note: pvalues in brackets.

When we analyse the contemporaneous effect within the same year of the shock, shown in Table 2, we highlight that the impact multiplier of technology shock is in absolute value far bigger than that of the resource depletion shock, namely three and eight times the size of this latter in the case of respectively 1 and 2 standard deviations shock. Moreover, while the response to resource depletion is largely not significant, with a pvalue of 0.81 when the shock is 2 standard deviations, the within-year effect of technology shock is largely significant using the 1 standard deviation confidence band, with a pvalue of 0.11.

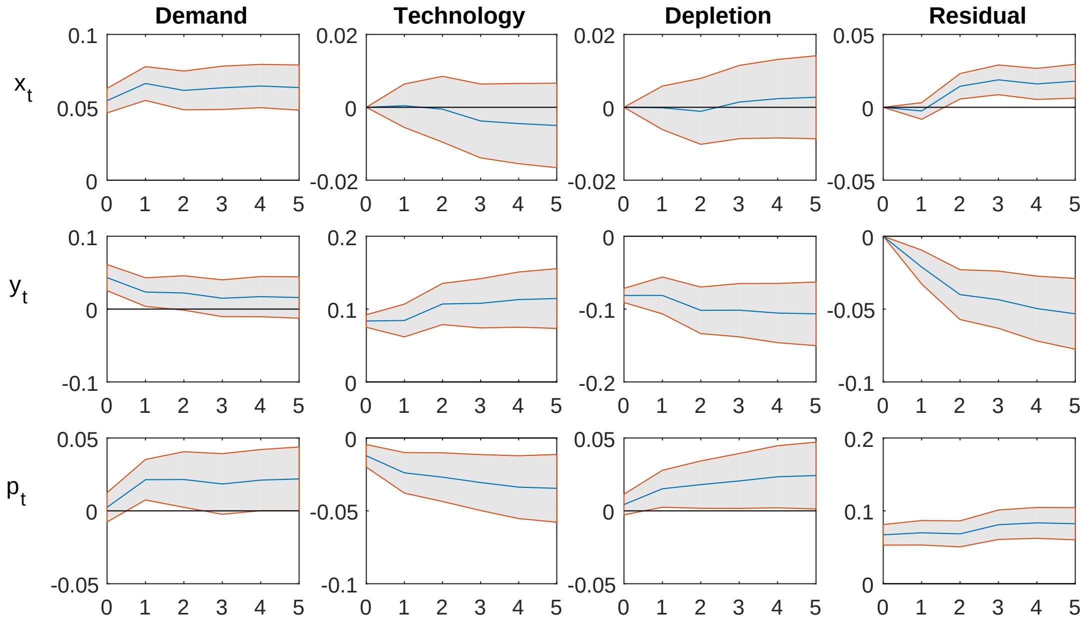

Figure 3: *Unconditional GIRFs to 1 std dev shock, with 1 std dev confidence band.*

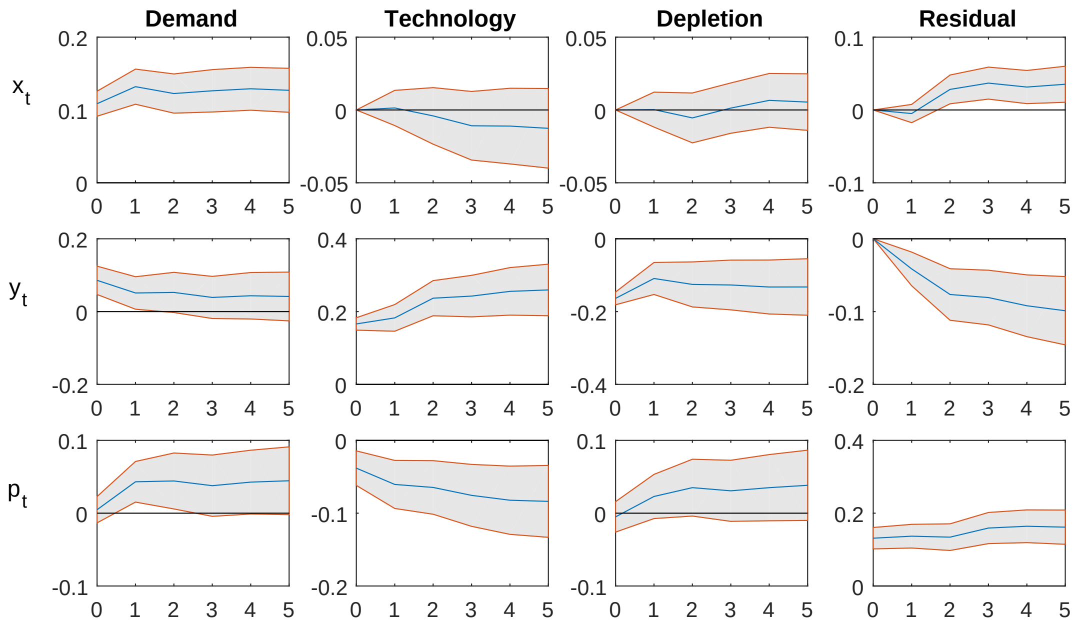

Figure 4: *Unconditional GIRFs to 2 std dev shock, with 1 std dev confidence band.*

A more formal verification of the asymmetric effects of technology and resource depletion shocks can be performed using the same procedure that Kilian and Vigfusson (2011) propose 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 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

$$\left[\hat{\theta}_{ij}(h, \delta) + \hat{\theta}_{ij}(h, -\delta)\right]' \hat{\Sigma}^{-1} \left[\hat{\theta}_{ij}(h, \delta) + \hat{\theta}_{ij}(h, -\delta)\right], \tag{9}$$

where $\hat{\Sigma}^{-1}$ is the bootstrap estimate of the covariance matrix of $\theta_{ij}(h, \delta) + \theta_{ij}(h, -\delta)$. We calculate both this statistic and a version that considers only one individual horizon. Table 3 displays the outcome of such test in the case of a shock of 2 standard deviations, using 1000 bootstrap replications and 500 random histories. What emerges from this table is that there is sharp evidence of a nonlinearity in the persistence of productivity as testified by the fact that the test rejects symmetry of the individual IRF at all horizons using a significance level of 10%.[15] As for the effects on price, the evidence is weaker, with some sign of asymmetry only at the impact, when the statistic has a pvalue of 0.22.[16]

Table 3: Wald test on symmetry

	productivity				price			
h	*IRF*	*pv*	*IRFs*	*pv*	*IRF*	*pv*	*IRFs*	*pv*
0	0.025	0.875	0.025	0.875	1.492	0.222	1.492	0.222
1	3.847	0.050	3.996	0.136	0.749	0.387	1.628	0.443
2	4.410	0.036	4.800	0.187	0.374	0.541	1.715	0.634
3	3.833	0.050	4.842	0.304	0.663	0.416	2.219	0.696
4	3.539	0.060	4.846	0.435	0.648	0.421	2.223	0.818
5	3.430	0.064	4.849	0.563	0.570	0.450	2.332	0.887

Note: Wald test on unconditionally symmetric response functions in the case of 2 standard deviation shocks. Entries are test statistics and pvalues for the individual (*IRF*) and the set of impulse response functions up to a certain horizon (*IRFs*).

[15] The failure to reject at h=0 explains why the test does not reject when considering the whole set of impulse response functions up to a certain horizon.

[16] We underline that such results are still informative given the annual frequency of our data and the rather limited sample size of 58 observations, which is likely to prevent the test from having enough power.

5 A historical decomposition

In the previous section we presented substantial evidence about the fact that technology shocks generates stronger and more persistent effects on productivity and price than resource depletion shocks. Nevertheless, it remains interesting to verify whether the asymmetric effects of a typical shock also translated into a larger contribution to the historical observed dynamics of productivity and price. The outcome of such investigation is far from obvious, given that the model includes important nonlinearities, and carries important economic implications since it allows to build a general assessment of the overall historical importance that technological innovations had compared to the phenomenon of natural resource depletion in determining the real value of iron ore.

We follow Kilian and Vigfusson (2017) in calculating a historical decomposition via Monte Carlo simulation, adapting their procedure to our specific case.[17] Let us define by $d_{p,T}(h, \Omega_0)$ the contribution of technology shocks to the determination of price, starting from *t=0*, that is the first available observation, and by $d_{p,RD}(h, \Omega_0)$ the corresponding quantity for the resource depletion shock. These quantities are calculated as the difference between two conditional expectations

$$
\begin{aligned}
d_{p,T}(h, \Omega_0) &= E\left[p_h | \left\{\varepsilon_i^T\right\}_{i=0}^h, \Omega_0\right] - E\left[p_h|, \Omega_0\right] \quad (10) \\
d_{p,RD}(h, \Omega_0) &= E\left[p_h | \left\{\varepsilon_i^{RD}\right\}_{i=0}^h, \Omega_0\right] - E\left[p_h|, \Omega_0\right] \quad (11)
\end{aligned}
$$

where the first expectation in each difference conditions on the estimated series of ε_t^T or $\varepsilon_t^R D$ up to horizon h. Same calculation can obviously be performed for the other structural shocks, ε_t^d and ε_t^r. Because it is informative to have a measure of the relative contribution of each shock to the observed value of a variable, but the usual quantity that serves this purpose, the Forecast Error Variance Decomposition, is not clear how it can be calculated in the case of a nonlinear SVAR model, we propose a simple measure to evaluate the relative importance of each shock in the determination of a variable at each period. We label this quantity as the "absolute contribution", and we compute it as

[17]Such historical decomposition is called 'Conditional Prediction Error Decomposition' in Kilian and Lutkepohl (2017).

the share of the contribution of a certain shock with respect the sum of the contributions of all shocks, with all quantities expressed in absolute value

$$s_{ij}(t,\Omega_0) = \frac{|d_{i,j}(t,\Omega_0)|}{\sum_{l=0}^{k} |d_{i,l}(t,\Omega_0)|}, \tag{12}$$

where $s_{ij}(t,\Omega_0)$ is the share of the j-th shock in the i-th variable in period t. The result of this calculation 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. As for labour productivity, technology shock dominated the resource depletion shock, as a result of a stronger persistence in its effects. Finally, the scenario is more complex as to the contributions of each shock to the real price of iron ore. We observe that, apart from very few years, the contribution of technology shocks surpassed that of resource depletion shocks, with different intensities over different periods, and with the other omitted factors captured by the residual shock still playing an important role. Overall, as highlighted by the average absolute contribution, displayed in Table 4, it is evident that technology has historically been the dominant driver of both productivity and price, overcoming the contribution of resource depletion. As to the price of iron ore, the average contribution of technology is 36% against 30% of resource depletion and a still relevant 23% from the residual shock.

Table 4: Average absolute contribution

	demand	*techno*	*depletion*	*residual*
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.

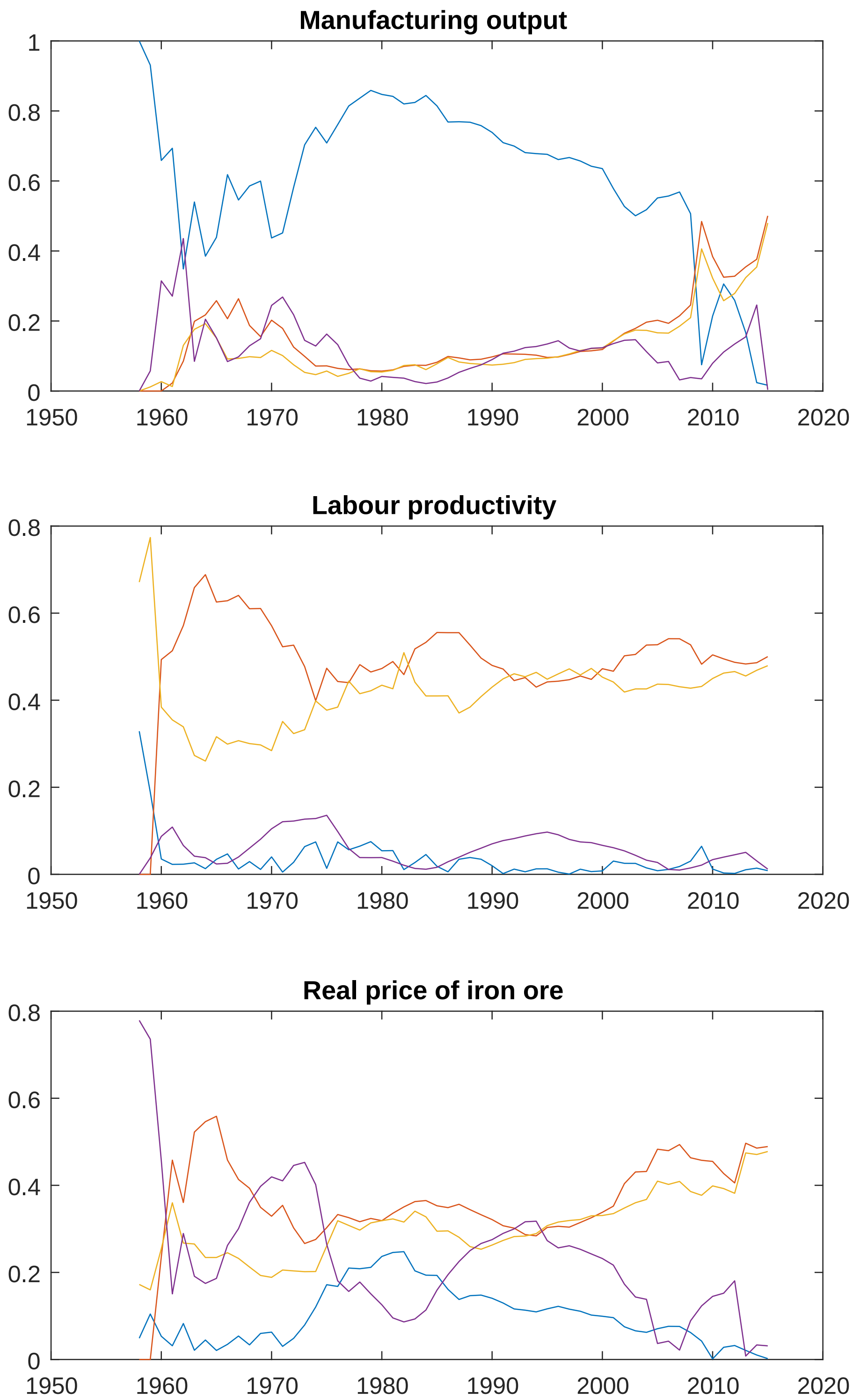

Figure 5: Absolute contribution of demand shock (blue), technology shock (red), resource depletion shock (yellow) and residual shock (magenta).

6 The role of market integration

In this section we study the second component of the mechanism behind the Prebisch-Singer hypothesis, that is the role of market structure and competition in shaping the effects that technological innovation produces on the dynamics of price.

As a result of high entry cost barriers the iron ore sector, like many other natural resources, is naturally inclined to have an oligopolistic structure with high market concentration. US iron ore sector is no exception, and the degree of such market concentration has been rather stable over much of the period under study (XXX Is it true? Maybe some numbers of that?). At the same time, as for many other commodities, the iron ore market has experienced a gradual globalization process since the 1950s, fostered by technological innovations in both transportation and mining operations.[18]. The increased volume of world exports and the actual greater price convergence confirm the transition from a situation of many national and then regional markets to the emergence of one single global market. While the US has been rather self-sufficient for most of the period under study, with minor imports from Canada, its production has been characterized by high costs compared to most of the exporting countries. This is the result of many factors, among which the old age of the mines, the steady deepening of the pits, the deterioration of the metal grade, and the ensuing high milling costs (see Fellows et al., 2014). Such costs make the US iron ore sector particularly exposed to competition from abroad.[19]

In light of these considerations, we decide to use a measure of the degree of international market integration to capture the potential variations in the competitive pressure faced by the US mining firms. We take the world shares of the iron ore exports of each country and we use them to construct a Herfindahl index. Given that regional markets still exist as a consequence of unavoidable transportation costs, an increase in such index reflects two possible phenomena: a higher international market integration where fewer

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

[19]Galdon-Sanchez and Schmitz (2002) examine one important historical episode of increased competition.

countries export to the rest of the world, rather than many countries supplying many different regional markets; a higher market concentration where fewer firms benefit from larger economies of scale, but also exercise increased market power. Irrespective of which of the two effects prevails, the likely outcome with respect to the US mining sector is an increased competitive pressure.[20]

To investigate the possible interaction between competition and technological innovation in its effect on price we introduce a Logistic Smooth Transition model in the price equation of model (8) using our integration index as threshold variable. We do not hold *a priori* assumptions about the nature of such interaction, so the flexibility of a Smooth Transition model allows to capture general nonlinear effects triggered by an external variable, whether they are describable as a gradual adjustment over time, or as abrupt switches between different regimes. Before fitting such model for the price equation, though, we first test for the presence of nonlinear effects using the procedure proposed by Terasvirta (1994). In our application, the test is based on an auxiliary regression that includes only the interaction terms between ε_t^T and the first three powers of the integration index. As shown in Table 5, there is unambiguous evidence of a nonlinearity involving our integration index, with the F test rejecting the null of linearity with very small pvalues, and with the largest statistic obtained when the delay parameter is 0.

Table 5: Terasvirta test

lag	stat	pv
0	8.457	0.00022
1	4.007	0.01468
2	4.788	0.00658
3	3.730	0.01965
4	1.232	0.31218
5	0.525	0.66776

Hence, we pick the contemporaneous integration index as threshold variable, and we replace the price equation in model (8) with a specification that includes a Logistic

[20]The idea that the global iron ore market, especially after the increased frequency of mergers and takeovers during the 2000s, can be described as a highly competitive oligopoly is common in the news (see, for instance, Russel, 2015). Some empirical studies conclude that a negative impact on competition from mergers in the iron ore industry can be excluded (Warell, 2007).

Smooth Transition model for the impact of technology shocks ε_t^T

$$\begin{aligned} p_t &= \mu_p + A_{31}(L)x_{t-1} + \tilde{A}_{32}(L)y_{t-1} + A_{33}(L)p_{t-1} + A_{32,1}^{(1)} I(\Delta y_{t-1} \geq 0) y_{t-1} + \\ &+ A_{32,1}^{(2)} I(\Delta y_{t-1} < 0) y_{t-1} + c_{0,31}\varepsilon_t^d + [1 - G(w_t)]\, c_{0,32}^{(1a)}\varepsilon_t^T + G(w_t) c_{0,32}^{(1b)}\varepsilon_t^T + c_{0,32}^{(2)}\varepsilon_t^{RD} + c_{0,33}\varepsilon_t^r, \end{aligned} \tag{13}$$

where $G(w_t) = \left[1 + e^{-\gamma(w_t - \omega)}\right]^{-1}$ is the transition function, γ is the smoothness parameter, and w_t is the threshold variable, which in our case is the integration index described above. We estimate the model by Nonlinear Least Squares and we obtain $\hat{\gamma} = 119$, which describes a rather fast adjustment of the impact of technology on price depending on the market structure, and $\hat{\omega} = 0.25$, which would correspond to approximately 4 exporting countries.[21] Such estimates, combined with the historical path of market integration, give rise to the impact multiplier for technology shocks presented in Figure 6. The main outcome of this estimation is clear: a stronger international competition resulting from market integration makes productivity gains due to technological innovation generate larger declines in price. In particular, while this multiplier has been -0.02 for most of the time, there are two historical circumstances in which the rise in market integration has produced an increase in the magnitude of this impact: a temporary change during the second half of the 1980s, and the period that starts from 2008, when market integration exceeded the threshold level producing a substantial increase of the impact of technology shock to -0.32.

The temporary increased impact of technology shocks in the second half on 1980s matches the timing of the historical episode of increased competition studied in Galdon-Sanchez and Schmitz (2002). According to these authors, the collapse of the steel industry following the 1980s recession produced an increase in competitive pressure that led to a change of the work practice in the US mining firms, which ultimately translated into higher productivity. Our results offer a complementary picture that confirms such inter-

[21] Notice that given 4 countries, the lowest value of the index is 0.25, which is reached when each country has equal shares of the market. Thus, a value of 0.25 corresponds exactly to 4 or more countries. We observe that the value of our index matches the fact that 4 large firms have indeed operated in the global iron ore market during last decade. Also, since the mining sector has historically been dominated by national monopolies across the world, still today there tend to be a leading mining firm in each exporting country.

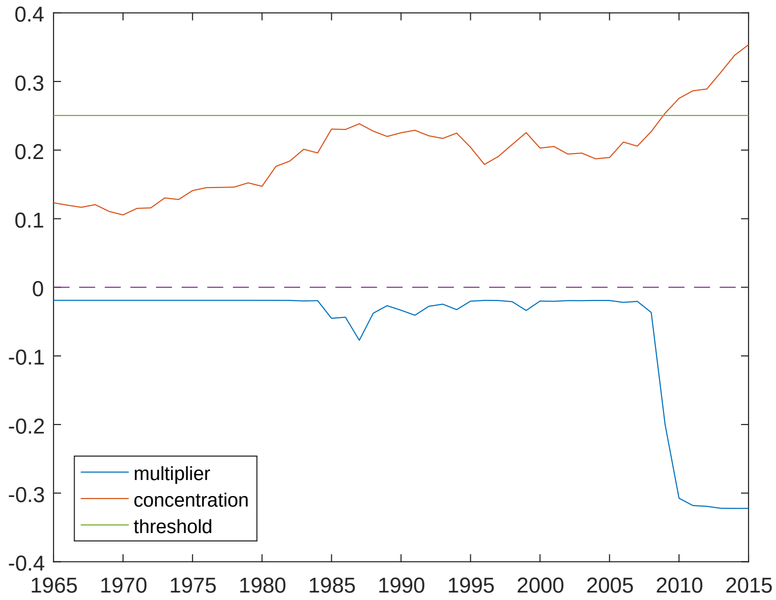

Figure 6: Model with integration index

pretation. Not only did the increased competition produced by changed world economic conditions stimulate improved work practice in an attempt to raise productivity, but more in general any type of efficiency gain, including those due to technological innovation, translated more strongly and quickly into a fall in the real price of iron ore, as a result of higher competitive pressure.

The period that begins in 2008 can be better understood if one considers the fact that the global iron ore market is commonly described as having the features of a highly competitive oligopolistic market.[22] Nevertheless, the rise in the degree of market integration was accompanied also by a more general increase of the competitive pressure in the market. Mostly fueled by the fast growth of the Chinese economy and its large demand for minerals, there were an expansion in traded volume of iron ore, which led to a change from long-term contracts to more market-driven pricing mechanisms, with prices reset at higher frequency (quarterly), and to a stronger and more global competition for exploration and mining investments, with multinationals facing competition from new small mining companies based in China, India and other developing countries.[23] All these accompanying aspects contributed to a drastic change in the competitive conditions of the

[22]See, for instance, Russel (2015). XXX Add some others.
[23]See, for instance, Ericsson (2012) and Tamvakis (2015).

US iron ore industry.

7 Conclusion

In the face of no concluding evidence about the empirical relevance of the Prebisch-Singer hypothesis, we explored instead the actual importance of its main underlying theoretical mechanism, that is the implications of technological innovation for the evolution of the real value of primary commodities. In investigating this channel we obtained important insights into the relationships between productivity, innovation and market structure. We focused on the US market for iron ore, a key commodity given its large use in transport, building, and the many engineering and industrial applications.

To tackle our research question we developed a new nonlinear SVAR methodology based on a threshold model that allows to distinguish the sign of the structural shocks. We obtained three main findings: the real value of iron ore is more responsive to technology shocks than resource depletion shocks; technological innovation has more than offset the detrimental effects of natural resource depletion in the determination of the historical price or iron ore in the US; the level of competition as represented by international market integration influences substantially the response of price to technological innovation by increasing the intensity of its effects.

References

Arezki, R., Hadri, K., Loungani, P. and Rao, Y., 2014. Testing the PrebischSinger hypothesis since 1650: Evidence from panel techniques that allow for multiple breaks. *Journal of International Money and Finance*, 42, pp.208-223.

De Lipsis, V., Agnolucci, P. and Bleischwitz, R., 2017. The international commodity trade: Stylized facts. In *Routledge Handbook of the Resource Nexus* (pp. 297-318). Routledge.

Ericsson, M., 2012. Mining industry corporate actors analysis. *Polinares Working Paper* 16, Center for Eastern Studies.

Fellows, M., Farooki, M., Hinde C. and Cooper C., 2014. *U.S. Mines to Market*. SNL Metals and Mining.

Galdon-Sanchez, J.E. and Schmitz Jr, J.A., 2002. Competitive pressure and labor productivity: World iron-ore markets in the 1980's. *American Economic Review*, 92(4), pp.1222-1235.

Ghoshray, A., 2011. A reexamination of trends in primary commodity prices. *Journal of Development Economics*, 95(2), pp.242-251.

Harvey, D.I., Kellard, N.M., Madsen, J.B. and Wohar, M.E., 2010. The Prebisch-Singer hypothesis: four centuries of evidence. *The Review of Economics and Statistics*, 92(2), pp.367-377.

Jacks, D.S. and Stuermer, M., 2018. What drives commodity price booms and busts?. *Energy Economics*, forthcoming.

John Baffes, B. and Etienne, X.L., 2016. Analysing food price trends in the context of Engels Law and the Prebisch-Singer hypothesis. *Oxford Economic Papers*, 68(3), pp.688-713.

Kellard, N. and Wohar, M.E., 2006. On the prevalence of trends in primary commodity prices. *Journal of Development Economics*, 79(1), pp.146-167.

Kilian, L. and Ltkepohl, H., 2017. *Structural vector autoregressive analysis*. Cambridge University Press.

Kilian, L. and Vigfusson, R.J., 2011. Are the responses of the US economy asymmetric in energy price increases and decreases?. *Quantitative Economics*, 2(3), pp.419-453.

Kilian, L. and Vigfusson, R.J., 2017. The role of oil price shocks in causing US recessions. *Journal of Money, Credit and Banking*, 49(8), pp.1747-1776.

Kim, T.H., Pfaffenzeller, S., Rayner, T. and Newbold, P., 2003. Testing for linear trend with application to relative primary commodity prices. *Journal of Time Series Analysis*, 24(5), pp.539-551.

Nickell, S.J., 1996. Competition and corporate performance. *Journal of Political Economy*, 104(4), pp.724-746.

Prebisch, R., 1950. The economic development of Latin America and its principal problems. *United Nations*, New York.

Radetzki, M., 2008. *A handbook of primary commodities in the global economy*. Cambridge University Press.

Russel, C., 2015. Should iron ore miners become an oligopoly to rescue prices?. *Reuters*.

Scherer, F. M. and Ross, D., 1990. *Industrial market structure and economic performance*. Boston, MA: Houghton Mifflin.

Schmitz Jr, J.A., 2005. What determines productivity? Lessons from the dramatic recovery of the US and Canadian iron ore industries following their early 1980s crisis. *Journal of Political Economy*, 113(3), pp.582-625.

Singer, H.W., 1950. The distribution of gains between investing and borrowing countries. *The American Economic Review*, 40(2), pp.473-485.

Sturmer, M., 2018. 150 years of boom and bust: what drives mineral commodity prices?. *Macroeconomic Dynamics*, pp.1-16.

Tamvakis, M., 2015. *Commodity trade and finance*. Informa Law from Routledge.

Terasvirta, T., 1994. Specification, estimation, and evaluation of smooth transition autoregressive models. *Journal of the American Statistical Association*, 89(425), pp.208-218.

Warell, L., 2007. A horizontal merger in the iron ore industry: An event study approach. *Resources Policy*, 32(4), pp.191-204.