The Natural Resource Boom and The Uneven Fall of The Labor Share[α]

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December 15, 2022

Abstract

We study the effect of the upsurge of natural resources income from the commodity price boom of the 2000s on the functional distribution of income. To do so, we build a general equilibrium model of Dutch disease that characterizes how natural resource windfalls affect equilibrium factor shares. The theory shows that the response of factor shares to exogenous changes in commodity prices depends on the relative intensity of factors within the tradable and natural resource sectors. We construct estimates of income shares accruing to human capital, raw labor, physical capital, and natural resources, and quantify the effect of the resource boom on their distribution. For identification, we use a differential exposure design to instrument commodity prices. We find that a price-induced natural resource boom negatively impacts the total labor, human capital, and physical capital shares, while the raw labor share remains unchanged. Our estimates suggest that the natural resource boom explains nearly 22 percent of the global decline of the total labor share during the 2000s. We also find a redistribution effect within labor income that indicates an unevenly distributed fall of the labor share against human capital. Besides, we document an attenuation effect on the increasing trend of the physical capital share. These results imply that the commodity price boom of the 2000s slowed the pace of growth of inequality.

Keywords: Labor Share, Factor Income Shares, Natural Resource Boom, Commodity Price Boom, Dutch Disease, Human Capital, Inequality.
JEL Codes: D33, F14, J31, O13.

[α]We gratefully acknowledge financial support from the Inter-American Development Bank (IADB), through their funding of the "*Labor Share and Inequality in Latin America and the Caribbean*" project, and from Universidad de los Andes Research Vice-Chancellery and Economics Department. We are thankful to Christopher Pissarides, Matthias Kehrig, Brad Sturgill, Ralph Ossa, David Hemous, Orazio Attanasio, Hernan Ruffo, Simon Gilchrist, Marcela Eslava, Seth Benzell, David Kaplan, Camilo Acosta, Umberto Muratori, and seminar participants at the IADB, RIDGE, LACEA, Lindau Nobel Laureate Meetings, SEA, University of Zürich, UZH-HSG International Economics Workshop, World Inequality Conference, Paris School of Economics, Universidad de Los Andes and Universidad del Rosario for valuable suggestions. We are especially grateful to Brad Sturgill for kindly sharing his data on factor income shares.

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1 Introduction

What is the effect of a natural resource boom on the functional distribution of income? We address this question both theoretically and empirically. We analyze how the increase in natural resources income that resulted from the commodity price boom of the 2000s affected aggregate factor shares and their distribution. Moreover, we quantify the contribution of the commodity price boom to the global decline of the labor share. To do so, we construct estimates of income shares accruing to human capital, raw labor, physical capital, and natural resources, for a sample of 47 countries between 1995 and 2010.[1] We then derive a set of equations that characterize equilibrium factor shares in a model of Dutch disease, and study how aggregate and relative factor shares respond to exogenous changes in commodity prices.

From a theoretical perspective, standard models of Dutch disease predict that an increase in income derived from natural resources, driven either by an exogenous world price increase or a discovery, creates excess demand for non-traded products and generates a reallocation of factors and value added towards non-tradable sectors (Corden and Neary, 1982; Corden, 1984; Sachs and Warner, 1995, 2001). Thus, the effect of a natural resource boom on the functional distribution of income depends on the relative factor intensity across sectors: the income share of factors in which non-tradable production is more intensive grows, while that of factors in which -non-natural-resources- tradable production is more intensive falls.

We formalize this idea building a general equilibrium Dutch disease model with three sectors: tradable, non-tradable, and natural resources; and four factors of production: human capital, raw labor, physical capital, and a natural resource endowment. The model's solution provides a set of equations that describe how natural resources windfalls affect equilibrium factor shares. In particular, the theory predicts that an increase in the income share of the natural resources sector deferentially affects factor shares depending on the relative intensity of factors in the tradable and natural resources sectors.

We use the empirical counterparts of the equilibrium factor shares theoretical equations, and the country-level panel of factor shares estimates, to study the empirical relevance of the model's predictions. We analyze both the response of aggregate labor and physical capital income shares to changes in commodity prices, and the redistribution of the labor share between raw labor compensation and human capital accumulation, as in Krueger (1999). For identification, we use a two-way fixed effects strategy and a differential exposure design. In particular, we leverage cross-country variation in the exposure to China's massive increase in demand for commodities in the late 1990s and 2000s, a key development behind the upswing in commodity prices (Kaplinsky, 2006; Erten and Ocampo, 2013; Costa et al., 2016), to instrument the price of natural resources.

[1]The countries in the sample represent approximately 73.72% of global GDP between 1995 and 2010.

We provide evidence for the validity of the instrument based on recent literature on identification in shift-share research designs (Goldsmith-Pinkham et al., 2020; Borusyak et al., 2022).

There are two stylized facts that motivate our work. First, the GDP-weighted average labor income share declined 5 percent between 1995 and 2010 (see Figure 1), our period of analysis, a fact that has been widely documented (Karabarbounis and Neiman, 2013; ILO, 2019; Autor et al., 2020). However, the rate at which the labor share fell was not constant: most of the decline (80.6 percent) happened between the years 2000 and 2005. Moreover, the aggregate patterns conceal important heterogeneities: the raw labor share fell continuously since 1995, with an estimated contraction of 20.5 percent, while the human capital share was comparatively more stable, but with a sharp decline of 4.1 percent between 2000 and 2005.

Second, we show that between 2000 and 2010, the period when the fall of the labor share accentuated, the natural resources share increased by 8.8 percent (see Figure 1), fueled by the sharp rise in commodity prices that began in the early 2000s. Although the physical capital share also grew during this period (by 5.2 percent), almost 41.9 percent of the income share gained by non-labor factors went to natural resources (see Figure 2). Actually, our estimates show that the factor income share that had the strongest proportional growth was that of natural resources, a fact that has not received much attention in the literature. We assess if the upsurge in natural resources income of the 2000s shaped these patterns of factor shares and their distribution.

We test if the commodity price boom can explain how income was redistributed across factors between 1995 and 2010. Our estimates show that a resource boom negatively impacts the total labor, human capital and physical capital shares, while the raw labor share remains unchanged. We find a negative impact on the total labor share of around 5 percentage points for an increase of one standard deviation of the natural resources share. This estimate suggests that the natural resource boom explains nearly 22 percent of the decline of the global labor share during the 2000s.

Furthermore, we find that the natural resource boom has a negative effect on the human capital to raw labor relative share: a one standard deviation increase in the natural resources share is associated with a 6 percentage points decline of the difference between the human capital and raw labor shares, equivalent to one fourth of the GDP-weighted average gap of 26.2 percentage points. Notably, this redistribution within labor income indicates that the global decline of the labor share was unevenly distributed against human capital. Nonetheless, we do not observe a redistribution effect between labor and physical capital. These are non-trivial effects that could help explain cyclical variations in inequality in countries heavily reliant on commodity exports, like those observed in Latin American countries over the last three decades (Gasparini and Lustig, 2011; Messina and Silva, 2017; Fernández and Messina, 2018).

The general implication is that a natural resource boom has a direct impact on the functional distribution of income: it takes income participation from reproducible factors -human capital and physical capital- but leaves unaffected the raw labor factor share. Reproducible factor shares tend to grow as economies grow (Zuleta, 2008a; Sturgill, 2012; Zuleta and Sturgill, 2015), so natural resource booms have an attenuation effect on this process. From a theoretical perspective, our estimates are consistent with a relatively large sectoral income share of human capital and physical capital in the tradable sector, which, through a Dutch disease mechanism, experiences a slow-down. They are also consistent with an equal or slightly larger sectoral income share of raw labor in the natural resources sector vis-à-vis the tradable sector.

Our contribution to the literature is threefold. First, we expand the Dutch disease literature centering on a dimension that is not entirely understood: the distributional consequences of resource booms. Second, we highlight important heterogeneities concealed behind the evolution of the income shares of capital and labor, once we separate reproducible and non-reproducible factors. Third, this is the first paper that presents the latest upsurge in commodity prices as a new mechanism behind the decline of the labor share in recent decades, and quantifies its contribution to the aggregate fall. Moreover, besides the direct effect of the natural resource boom on the total labor share, we also find a redistribution effect between human capital and raw labor, and an attenuation effect in the increasing trend of the share of reproducible factors.

Therefore, our work relates to three strands of the literature. First, we expand the literature on the effects of resource booms on the composition of output and employment (Corden and Neary, 1982; Corden, 1984; Sachs and Warner, 1995, 2001; Ferraro and Peretto, 2018). In the theory of Dutch disease, resource revenues lead to an appreciation of the real exchange rate, which harms the competitiveness of the non-resources exports sector, leading to deindustrialization and worst growth prospects. The empirical evidence on Dutch disease is extensive but not conclusive (van der Ploeg, 2011): some countries have benefited from resource booms while others had poor performance, with recent evidence showing that factors like the type of input-output linkages across sectors (Allcott and Keniston, 2018) and the institutional environment (Mehlum et al., 2006; Robinson et al., 2006) play a central role in determining winners and losers.

We focus on a dimension that is much less understood: the distributional impact of resource booms. Leamer et al. (1999) argues that when natural resources are widely available, they absorb scarce capital that would otherwise flow into more skilled-labor intensive sectors, like manufacturing, lowering worker's incentive to accumulate human capital. Here, income inequality is linked to factor endowments via production: natural resources tend to favor production in sectors characterized by greater inequality, a point that is also emphasized by Sokoloff and Engerman (2000).

Goderis and Malone (2011) make a related argument. The authors show that if non-tradable sectors are more intensive in unskilled labor vis-à-vis (non-resource) tradable sectors, a natural resource windfall will reduce the labor earnings Gini coefficient. Sectoral factor intensity is then key to their story. We build on Goderis and Malone (2011) theoretical framework, but we extend the model to include physical capital as a factor of production -a feature that allows us to study the effect of natural resource booms on both aggregate labor and physical capital income shares- and natural resources as an additional production sector. Moreover, when estimating the model parameters, we use direct measures of each factor share, including the natural resource share.[2] This allows us to link more closely our econometric specifications to the theoretically derived equations, instead of relying on broad measures of inequality like the Gini coefficient.

Second, we relate to the literature showing that the capital-labor dichotomy that dominates the study of factor shares provides an incomplete picture (Zuleta, 2008a; Sturgill, 2012, 2014; Zuleta and Sturgill, 2015; Dawson and Sturgill, 2022). Caselli and Feyrer (2007), in a work analyzing whether the marginal product of capital is equalized across countries, argued that standard measures of capital income shares are incomplete because they fail to take into account differences between reproducible (physical) and non-reproducible (land and natural resources) capital.[3] In a similar spirit, Krueger (1999) pointed the fact that labor shares are directly affected by the level of human capital in the population, arguing that one should distinguish between the raw labor share and the human capital share. This is not only appealing from a theoretical perspective, but it also has empirical implications.

There is extensive evidence that the share of reproducible factors (human and physical capital) is positively correlated with income per capita, while the share of non-reproducible factors (raw labor and natural resources) is negatively correlated with income per capita (Blanchard et al., 1997; Krueger, 1999; Acemoglu, 2002; Caselli and Feyrer, 2007; Zuleta, 2008b; Zuleta et al., 2010; Sturgill, 2012, 2014; Zuleta and Sturgill, 2015). Moreover, even if the relative income share of capital to labor happened to be stable, it can conceal important heterogeneities. For example, we show that the decline of the labor share is largely accounted by the decline in the share of income going to raw labor. Also, most of the increase in the total capital share is accounted by a sharp rise in the share of income going to natural resources, although there are heterogeneities across countries.

Finally, we relate to the literature studying the decline of the labor share in recent decades (ILO, 2019; Grossman and Oberfield, 2021). Little consensus exists on the causes of this phenomena. Some explanations include high substitutability between capital and labor in the context of a fall of the relative price of capital (Karabarbounis and Neiman,

[2] We discuss in detail the estimation of factor shares in Section 3.

[3] More recently, Monge-Naranjo et al. (2019) presented evidence contrary to that of Caselli and Feyrer (2007). They show that alternative measures of the natural resources income share are consistent with significant factor missalocation across countries.

2013); increasing product market concentration by firms with high markups and a low labor share of value added (Autor et al., 2020); automation (Acemoglu and Restrepo, 2018); reallocation of value added towards the low end of the labor share distribution (Kehrig and Vincent, 2021); declining bargaining power of workers (Henley, 1987; Macpherson, 1990; Fichtenbaum, 2009, 2011; Young and Zuleta, 2013); biased technological innovations (Zeira, 1998; Boldrin and Levine, 2002; Zuleta, 2008b; Peretto and Seater, 2013); capitalization of intellectual property products in national accounts (Koh et al., 2020); international trade (Burstein and Vogel, 2011; González Rozada and Ruffo, 2021; Leblebicioğlu and Weinberger, 2021); changes in the institutional setting (Giammarioli et al., 2002; Berthold et al., 2002; Bentolila and Saint-Paul, 2003; Bental and Demougin, 2010; Dawson and Sturgill, 2022); FDI and offshoring (Dunning, 1988; Elsby et al., 2013); and even measurement issues (Elsby et al., 2013; Rognlie, 2016, 2018; Gutiérrez and Piton, 2020).[4]

We study a new complementary mechanism that can be particularly relevant for countries that are heavily reliant on the exploitation of natural resources: the latest upsurge in commodity prices. We show that the total labor share was negatively affected by the boom in commodity prices, and that there was a redistribution of the labor share between human capital and raw labor that favored the latter. However, the natural resource boom is not an accurate explanation to account for the evolution of the total labor share relative to the physical capital share, because it affects both in similar magnitudes.

In this paper we highlight a Dutch disease mechanism that spurs reallocation patterns of value added as an explanation for the global decline of the labor share and changes in factor shares. We argue that the main engine operating behind the commodity price boom impact on factor shares is a price-induced change in natural resources income fueled by shifts in the international demand for commodities. This evidence supports that demand side forces play a leading role in the global decline of the labor share (Kehrig and Vincent, 2021; Grossman and Oberfield, 2021).

2 Theory: Natural Resource Booms and Factor Shares

In this section we develop a model that characterizes how aggregate and relative factor income shares respond to exogenous changes in commodity prices. We use the model to clarify ideas about the empirical strategy in Section 4.

[4] Grossman and Oberfield (2021) provide an extensive review of some prevalent explanations for the global decline of the labor share in recent decades.

2.1 Production and Factor Income Shares

The economy has three sectors: a non-tradable sector (N), a tradable sector (T), and a natural resource sector (R). The tradable and non-tradable sectors produce consumption goods with production technologies that make use of three factors: physical capital (K), raw labor (L), and human capital (H):

$$Y_{S'} = Y_{S'}\left(K_{S'}, L_{S'}, H_{S'}\right), \tag{2.1}$$

where $F_{S'}$ is the amount of factor $F \in \{K, L, H\}$ used in sector $S' \in \{N, T\}$.

The output of the natural resource sector Y_R is a commodity (e.g. crude oil, coal, timber, etc.) either consumed internally or traded at international markets, that is produced using the same three factors plus an exogenous and fixed natural resources endowment E (e.g. petroleum reservoirs, coal mines, forest land, etc.):

$$Y_R = Y_R\left(K_R, L_R, H_R, E\right), \tag{2.2}$$

so any production in this sector requires extracting resources from the endowment E.

We define the sectoral factor income shares as

$$\alpha_{F,S} \equiv \frac{r_{F,S}F_S}{P_S Y_S}, \tag{2.3}$$

where $r_{F,S}$ is the unit price of factors $F \in \{K, L, H\}$ in sector $S \in \{N, T, R\}$, and P_S is either the unit price of the consumption good from the tradable or non-tradable sectors, or the unit price of the natural resource output (henceforth the commodity price). We assume that all factors are fully employed, $F_N + F_T + F_R = F$, and there is perfect factor mobility, so factor prices are equalized across sectors: $r_{F,S} = r_F \; \forall S$.

We do not assume a specific market structure, so the functional distribution of income can be explained by bargaining power, factor markets institutions, or technological parameters. Thus, factor shares are distributive objects which may or may not reflect the product-elasticity of factors. We do impose that all income is distributed between the factors. In the case of the tradable and non-tradable sectors: $\sum_F \alpha_{F,S'} = 1$. In the case of the natural resource sector: $\sum_F \alpha_{F,R} + \alpha_{E,R} = 1$, where $\alpha_{E,R}$ is the income share received by the owners of the natural resource endowment. That is, the profits $r_E E$ relative to the sectoral revenue $P_R Y_R$.

Setting the price of the tradable sector good as the numeraire, $P_T = 1$, aggregate income (Y) in this economy is given by:

$$Y = P_N Y_N + Y_T + P_R Y_R, \tag{2.4}$$

where P_N and P_R are defined in terms of the traded good's price.

Finally, sector income shares are defined as

$$\alpha_S \equiv \frac{P_S Y_S}{Y} \quad \text{for} \quad S \in \{N, T, R\}, \tag{2.5}$$

while aggregate factor income shares are defined as

$$\alpha_F \equiv \frac{r_F F}{Y} = \frac{r_F\left(F_N + F_T + F_R\right)}{Y} \quad \text{for} \quad F \in \{K, L, H\}. \tag{2.6}$$

In the case of the aggregate natural resource share, we define

$$\alpha_E \equiv \alpha_{E,R} \cdot \frac{P_R Y_R}{Y}. \tag{2.7}$$

Our main interest is to understand how the aggregate factor shares of human capital α_H, raw labor α_L, total labor $\alpha_Z = \alpha_L + \alpha_H$, and physical capital α_K respond to an exogenous change of the commodity price P_R.

2.2 Optimal Consumption Choice

Agents $i \in \{1, ..., L\}$ have identical preferences and maximize the utility of consuming the two goods offered by the tradable and non-tradable sectors, and the commodities. For simplicity, we assume agent's preferences take the form

$$U_i = \ln C_{i,T} + \gamma \ln C_{i,N} + \mu \ln C_{i,R}, \tag{2.8}$$

where γ and μ are taste parameters that capture relative preferences for consumption between the three types of goods.

Agents are endowed with a unit of raw labor which they supply inelastically, and own human capital, physical capital and the natural resource endowment.[5] We take the distribution of these factors as exogenous. Furthermore, an agent i who owns a share ν_i of the natural resource endowment receives a fraction ν_i of its rents $\alpha_{R,E} P_R Y_R$, where $\sum_{i=1}^{L} \nu_i = 1$. Alternatively, we could assume that the natural resource endowment E is owned by the government, so ν_i captures the fraction of the endowment rent transferred to agent i. Regardless, the household's income is described by

$$Y_i = r_H H_i + r_L + r_K K_i + \nu_i \alpha_{E,R} P_R Y_R, \tag{2.9}$$

and the budget constraint is

$$C_{i,T} + P_N C_{i,N} + P_R C_{i,R} = Y_i. \tag{2.10}$$

[5] The size of the population is thus equal to the total endowment of raw labor L.

Given Equations 2.8-2.10, the household's problem is:

$$\max_{C_{i,T},C_{i,N},C_{i,R}} U_i = \ln C_{i,T} + \gamma \ln C_{i,N} + \mu \ln C_{i,R} \;\; \text{s.t.} \;\; C_{i,T} + P_N C_{i,N} + P_R C_{i,R} = Y_i. \tag{2.11}$$

The first-order conditions of this problem satisfy

$$P_N C_{i,N} = \gamma C_{i,T} \qquad P_R C_{i,R} = \mu C_{i,T}, \tag{2.12}$$

so the optimal household's choice is to spend a fixed proportion of their income on each type of consumption good:

$$C_{i,T} = \frac{1}{1+\gamma+\mu} Y_i, \qquad P_N C_{i,N} = \frac{\gamma}{1+\gamma+\mu} Y_i, \qquad P_R C_{i,R} = \frac{\mu}{1+\gamma+\mu} Y_i. \tag{2.13}$$

2.3 General Equilibrium

We define a general equilibrium in this set-up as conditions where all agents are optimizing and markets clear. We allow commodities produced in the domestic economy Y_R to be consumed internally or exported to other countries. This is a milder assumption relative to the common approach in the literature of resource booms, where the natural resources sector is represented as a fully exogenous income flow (Goderis and Malone, 2011; van der Ploeg, 2011).

There are two conditions we need to close the model. First, the market of non-traded goods must clear:

$$C_N = Y_N. \tag{2.14}$$

Second, we assume balanced trade so that trade imbalances in the tradable and commodities sectors are compensated:[6]

$$Y_T - C_T = -P_R \left(Y_R - C_R \right), \tag{2.15}$$

Note that this condition is consistent with reallocation of factors occurring in both net-exporters ($Y_R > C_R$) and net-importers ($Y_R < C_R$) of commodities. For net-exporters, an increase in the price of commodities P_R can discourage the production of tradable goods Y_T, generating a reallocation of factors from T sector to N and R. In this case, the natural resource boom increases the exports-value of natural resources, while

[6] A similar assumption is made by Krugman (1980); Acemoglu and Ventura (2002); Ferraro and Peretto (2018), among others. We provide suggestive evidence of the trade imbalance compensation between tradables and commodity sectors in Appendix Figure A.1.

increasing the imports of tradable goods.[7] In the case of net-importers, the increase in the price of commodities P_R creates incentives to reduce natural resource imports, which can be achieved by reallocating factors from the T sector to the N sector.[8]

Conditions 2.14 and 2.15 imply an aggregate resource constraint of the form

$$C_T + P_N C_N + P_R C_R = Y = Y_T + P_N Y_N + P_R Y_R. \tag{2.16}$$

These conditions hold for each country m, and we assume world-total supply and demand for each type of good clears in equilibrium: $\sum_m C_S = \sum_m aY_S$ for $S \in \{N, T, R\}$.

2.4 Theoretical Prediction: General Equilibrium Factor Shares

From Equations 2.3 and 2.4, expenditure in an specific factor $F \in \{K, L, H\}$ is

$$\begin{aligned} r_F F &= r_F\left(F_N + F_T + F_R\right) \\ &= \alpha_{F,N} P_N Y_N + \alpha_{F,T} Y_T + \alpha_{F,R} P_R Y_R \\ &= \alpha_{F,N} P_N Y_N + \alpha_{F,T}(Y - P_N Y_N - P_R Y_R) + \alpha_{F,R} P_R Y_R \\ &= \left(\alpha_{F,N} - \alpha_{F,T}\right) P_N Y_N + \alpha_{F,T} Y + (\alpha_{F,R} - \alpha_{F,T}) P_R Y_R. \end{aligned} \tag{2.17}$$

Using Equations 2.13 of household's optimality and 2.14 of N market's clearing, and then dividing by total income, we find the general equilibrium factor income shares:

$$\alpha_F = \frac{1}{1+\gamma+\mu}\left[\gamma\alpha_{F,N} + (1+\mu)\alpha_{F,T}\right] + (\alpha_{F,R} - \alpha_{F,T})\frac{P_R Y_R}{Y}. \tag{2.18}$$

This is the key equation of the model. It states that the aggregate income share of factor F can be decomposed into two terms. The first term is a weighted average between the sectoral income shares of F in the tradable and non-tradable sectors, where the weights are given by the preference parameters γ and μ. For example, if consumers have a strong preference for the non-tradable good, and the income share of raw labor in that sector is relatively large, then the aggregate income share of raw labor will also be relatively large.

The second term is of greater interest to us. It states that the aggregate factor income share of F also depends on the income share of the natural resource sector,

[7] The case of the United States illustrates this phenomenon. The commodity price boom induced incentives to increase the exploration and production of natural resources in such a way that in 2015, for instance, the United States was a net exporter of petroleum preparations, petroleum gases, iron, copper, coal, wood, cotton, and soya, according to product-level international trade data from UN Comtrade.

[8] Condition 2.15 can also reflect patterns for international markets in big and small economies. For big economies, a positive exogenous shock to tradable production Y_T -everything else constant- can generate an increase in the relative price of commodities P_R. For small economies, an exogenous rise in the relative price of commodities P_R spurs commodities exports while increasing traded goods imports.

and hence on the commodity price P_R. The magnitude and direction of this relation is determined by two variables. First, the sectoral income share of F in the natural resource sector $\alpha_{F,R}$: if factor F is relatively important in the production of the commodity, a larger natural resource sector will imply a larger aggregate factor income share for F. Second, the sectoral income share of F in the tradable sector $\alpha_{F,T}$, which captures the Dutch disease mechanism: a larger natural resource sector will tend to negatively affect production in the tradable sector, and hence lower the income share of factors that the tradable sector uses more intensively. For instance, if the tradable sector is very intensive in human capital, a natural resource boom, driven by an exogenous rise in commodity prices, will tend to depress the aggregate income share of human capital. The only case in which this does not happen is if the natural resource sector also uses human capital intensively, so the effects balance out.[9]

There is a direct effect of a change of the commodity price on each aggregate factor share, which implies a redistribution of income across factors. Starting from Equation 2.18, we can characterize how the relative share $\alpha_F - \alpha_{F'} \equiv \alpha_{F-F'}$ of two factors, F and F', changes in response to an exogenous change in P_R:

$$\alpha_{F-F'} = \frac{1}{1+\gamma+\mu}\left[\gamma\alpha_{F-F',N} + (1+\mu)\alpha_{F-F',T}\right] + (\alpha_{F-F',R} - \alpha_{F-F',T})\frac{P_R Y_R}{Y}. \quad (2.19)$$

This equation allows us to study the distributional effects of a natural resource boom along different dimensions. One is the relative share between human capital and raw labor, $\alpha_H - \alpha_L \equiv \alpha_{H-L}$, which captures how total labor income is redistributed. The second one is between total labor and physical capital, $\alpha_Z - \alpha_K \equiv \alpha_{Z-K}$.

This theoretical model shows that a natural resource boom affects the functional distribution of income. The magnitude and direction of the effect depends crucially on the intensity in which each factor is used in the different sectors. In particular, factors that are used with the greatest intensity in the tradable sector will tend to lose space relative to the rest. Equations 2.18 and 2.19 will be the point of departure of the empirical analysis described in Section 4.[10]

[9] The model includes both an expenditure effect (Goderis and Malone, 2011; van der Ploeg, 2011) and a resource-movement effect (Corden and Neary, 1982; Ferraro and Peretto, 2018). We focus in a price-induced change in natural resources income as our main force of adjustment, which highlights demand-side features shaping factor shares (Kehrig and Vincent, 2021; Grossman and Oberfield, 2021).

[10] Our theoretical model contains a number of simplifying assumptions, but it is fairly flexible and allows for useful extensions. In Appendix B we present a dynamic extension and discuss the consequences regarding our theoretical results of relaxing the static environment assumption. In general, our theoretical prediction is robust to including dynamics in the model, and its empirical interpretation holds.

3 Factor Income Shares: Estimation and Patterns

In this section we describe the process to construct estimates of the four aggregate factor income shares of our model for an unbalanced panel of 47 countries in the years 1995, 2000, 2005 and 2010.[11] The advantage of this data is that it allows us to address more closely the empirical relevance of our theoretical predictions with direct measures of each factor share, instead of relying on broad measures of inequality. The process has three steps: *i*. estimate the aggregate labor share $\alpha_Z \equiv \alpha_L + \alpha_H$, which also determines the aggregate capital share $\alpha_{\tilde{K}} = 1 - \alpha_Z$; *ii*. separate the aggregate labor share into the raw labor α_L and human capital α_H shares; and *iii*. separate the aggregate capital share into the physical α_K and natural resources α_E shares.[12]

3.1 The Total Labor Share

We use country and year specific information on total employee compensation, GDP, indirect taxes, and Gross Mixed Income from Table 4.1 of the United Nations Yearbook of National Account Statistics. In particular, for each country-year, we estimate

$$\alpha_Z = \left(\frac{\text{Employee Compensation}}{\text{GDP- Indirect Taxes - Gross Mixed Income}} \right). \tag{3.1}$$

Employee Compensation is defined as the total remuneration payable by an employer to an employee in return for work. The labor share is simply the ratio of this compensation to GDP net of indirect taxes and Gross Mixed Income (GMI), the most recent measure of total income of the self-employed.[13] We correct for GMI following Bernanke and Gürkaynak (2001) and Gollin (2002), who argued that using only the reported employee compensation can lead to an underestimation of the labor share because it omits labor income of the self-employed. The correction consists of assuming that the mix of labor and capital income of the self-employed is the same as in the rest of the economy, and then assign the corresponding fraction to the total labor income share.

The aggregate capital income share is the fraction of income that is not going to labor compensation, that is:

[11] In Table A.1 of the Appendix we report the sources of the data we use in the empirical exercises. The list of countries for which there is information includes 30 countries in Europe and North America, 10 countries from Latin America, and 7 countries between Asia, Africa and Oceania. We present a complete list of the countries in Table A.2 of the Appendix.

[12] We thank Brad Sturgill for kindly sharing his data on factor income shares for this study. Most of our work consisted of updating or complementing his original database for the purposes of our analysis. For a description of the original database, see Sturgill (2012).

[13] The United Nations Statistical Division defines GMI as "surplus or deficit accruing from production by unincorporated enterprises owned by households". GMI is the most recent measure of self-employed income, known before as Operating Surplus of Private Unincorporated Enterprises (OSPUE).

$$\alpha_{\tilde{K}} = \alpha_K + \alpha_E = 1 - \alpha_Z. \tag{3.2}$$

3.2 Separating The Human Capital and Raw Labor Shares

The labor income share is affected by the amount of human capital workers possess, so it can be desirable to adjust labor compensation for human capital accumulation. This was pointed out by Krueger (1999), who suggests distinguishing between the raw labor and human capital income shares. This separation also allow us to study the distributional effects of natural resource booms within the aggregate labor share.

We estimate the fraction of labor remuneration that goes to raw labor using average earnings of workers with little to no human capital in low-skilled occupations. To do so, we use country and year specific microdata from labor and household surveys collected and homogenized by the Luxembourg Income Study (LIS) and the Center of Distributive, Labor, and Social Studies (CEDLAS).[14] In particular, we recover the value of "intercept labor" compensation from regressions of the form:

$$\ln w_i = \beta_0 + \beta_1 S_i^M + \beta_2 S_i^H + \beta_3 O_i^M + \beta_4 O_i^S + \beta_5 E_i + \beta_6 E_i^2 + \varepsilon_i, \tag{3.3}$$

where $\ln w_i$ is the (log) annual wage of worker i; $S_i^M = 1$ for high-school graduates and college drop-outs; $S_i^H = 1$ for college graduates; $O_i^M = 1$ for workers in professional or managerial occupations; $O_i^S = 1$ for workers in other skilled occupations; and E_i is potential experience calculated as age minus years of education minus 6. We estimate Equation 3.3 for each country-year pair using a sample of employed workers between 20 and 60 years of age.[15]

Following Krueger (1999), the raw labor share of wages is defined as

$$\text{Raw Labor Share of Wages} = \frac{L \times e^{\hat{\beta}_0}}{\sum_i w_i} = \frac{e^{\hat{\beta}_0}}{\bar{w}}, \tag{3.4}$$

where L is the total number of workers in the economy and $\bar{w}$ is the average wage. Intuitively, every worker is endowed with a unit of raw labor which is compensated at a rate $e^{\hat{\beta}_0}$. All compensation beyond this level correspond to returns to human capital accumulation.

[14] LIS and CEDLAS make homogenized microdata available to the public after collecting and harmonizing household surveys across countries. The LIS data set contains microdata for about 50 countries, while CEDLAS collects data from all Latin American countries. The public microdata includes information on labor income and individual characteristics.

[15] We present specific details about the construction of the data in Appendix C.1. When the microdata of a country-year pair is insufficient to estimate regression 3.3, we impute the raw labor wage using the corresponding percentile of the estimated values in the wage distribution of workers with low education and low experience. For country-year pairs with no available microdata, we predict the raw labor share of wages using a Gradient Boosting Machines algorithm. We provide details in Appendix C.2 and C.3.

The raw labor income share is defined as:

$$\alpha_L = \text{Raw Labor Share of Wages} \times \underbrace{(\alpha_H + \alpha_L)}_{\alpha_Z}, \tag{3.5}$$

while the human capital income share is

$$\alpha_H = \alpha_Z - \alpha_L. \tag{3.6}$$

Our strategy relies on the assumption that the wage of workers in the lower tail of the skills distribution defines the payment of raw labor. Moreover, we assume that the average size of raw labor compensation depends on educational and occupational attainment, and work experience. Appendix C discuses these assumptions and presents more details on the measurement of the raw labor share of wages.

3.3 Separating The Physical Capital and Natural Resource Shares

We separate the income shares of physical capital and natural resources following Caselli and Feyrer (2007). Conceptually, the main assumption we make is that differences in capital gains from physical capital and natural resources are, on average, negligible, so both units pay approximately the same return. Let $\tilde{K} \equiv K + E$, where K is the value of physical capital stocks, and E is the value of natural resource endowments in the economy. If we define $r_{\tilde{K}}$ as the equalized rent between these two types of capital, we have

$$\alpha_K \approx \frac{r_{\tilde{K}} K}{Y} = \frac{K}{\tilde{K}} \frac{r_{\tilde{K}} \tilde{K}}{Y}. \tag{3.7}$$

But $\frac{r_{\tilde{K}} \tilde{K}}{Y} \approx \alpha_{\tilde{K}} = \alpha_K + \alpha_E$, so

$$\alpha_K \approx \frac{K}{\tilde{K}} \left(\alpha_K + \alpha_E\right). \tag{3.8}$$

Equation 3.8 states that the physical capital's income share is a proportion of the total capital income share. The proportion is determined by the ratio $\frac{K}{K+E}$, that is, the relative value of physical capital stocks to the value of total capital in the economy.

In practice, we use country and year specific measures of both the value of natural resource endowments and the stock of physical capital. We take both measures from the World Bank's Wealth of Nation's Database (WND), a database designed to provide comparable information on total wealth and its components across countries and years. The data is available in 5 year periods between 1995 and 2010.

In the WND, natural resources consist of different types of assets: energy and mineral resources (petroleum, natural gas, coal, metals and minerals), agricultural land (cropland and pasture land), forests (timber and non-timber services), and protected areas (reserves).[16] The general approach is to estimate the value of rents from a particular asset and then capitalize this value using a fixed discount rate. For example, for each asset type classified as non-renewable, The World Bank generates a valuation based on the present value of the stream of expected rents that can be extracted until the resource is exhausted. Rents are calculated based on asset-specific information on revenues (production and prices) and costs, while the lifetime of each resource is calculated based on the size of reserves and extraction rates. The valuation of renewable resources is done in an analogous way, but the estimated lifetime depends both on the rates of extraction and the rates of resource replacement.[17]

Finally, the value of the physical capital stock K, which consists of manufactured or built assets such as machinery, equipment, and physical structures, are also taken from the WND database. The estimates are constructed from historical investment data using the perpetual inventory method.

3.4 Descriptive Patterns of Factor Income Shares

We present estimates of the four aggregate factor income shares for each country in Appendix Table A.2. Pooling all the countries and years in the sample, the GDP-weighted average aggregate labor income share was 59.8 percent, while the physical capital and natural resource income shares were 27.6 and 12.6 percent respectively. Compensation for human capital accumulation accounts for 72.1 percent of the labor share, which implies an average human capital share of 43.1 percent and a raw labor share of 16.9 percent.

There was a significant decline of the global labor share between 1995 and 2010 (see Figure 1). In 1995, the share of income accrued to labor was 62 percent. By 2010 the same number was close to 58.9 percent, a fall of 3.1 percentage points (5 percent).[18] The rate at which the labor share fell, however, was not constant: most of the decline (80.6 percent) over this 15 year period happened between 2000 and 2005. Moreover, this particular trend conceals important heterogeneities: the raw labor share fell continuously since 1995, with an estimated contraction of 20.5 percent, while the human capital share moved up and down, but with a sharp decline of 4.1 percent between 2000 and 2005 (see Panel (a) of Figure 3).

The period when the fall of the labor share accelerated coincides with a rise in

[16] Metals and minerals resources include bauxite, copper, gold, iron, lead, nickel, phosphate, rock, silver, tin, and zink.

[17] Other studies that use similar estimates for the valuation of natural resource include Gylfason (2001); Caselli and Feyrer (2007); Bhattacharyya and Hodler (2010); van der Ploeg (2011); Sturgill (2012). Details on the data sources used for each country and asset are described in The World Bank (2019).

[18] These numbers are consistent, both in levels and changes, with other recent estimates of the evolution of the global labor share during the same period. See, for example, Karabarbounis and Neiman (2013); ILO (2019); Autor et al. (2020).

the natural resources income share (see Figure 1), which went from 11.4 percent in 2000 to 12.1 percent in 2005, a 6.1 percent increase. More generally, our estimates show that since the 2000s, the factor income share that had the strongest proportional growth was that of natural resources, with an upswing of 8.8 percent (see Figure 2), contributing by almost 42 percent to the gains made by non-labor factors in the functional distribution of income (see Figure 3), a fact that has not received much attention in the literature.[19]

This upward trend is mostly explained by the increase in commodity prices, especially those of energy and minerals, the assets that comprise the largest share of output from the natural resources sector. Figure 4 shows the cumulative growth of the price of petroleum, iron, coal, copper, and natural gas related products, indexed so that the baseline year is 2000. In most cases, the prices of these commodities more than doubled in a period of ten years, a massive increase in a very short period of time. The windfall for countries that produce natural resources was then substantial.

From a distributional perspective, the gain of the natural resources income share has to be compensated by loses among the other three factors. Figure 5 shows the cross sectional correlation between the natural resource share and each of the other factor shares. We also report the slope of a linear regression between the two variables. As expected, there is negative correlation, but the magnitudes tend to differ, with the aggregate labor income share having the steepest slope of -0.61 (SE 0.06). These are simple correlations, but they make clear that a natural resource boom can impact factor income shares in a heterogeneous way. We now move to the empirical strategy we use to quantify the effect of the natural resources boom of the 2000s on the functional distribution of income.

4 Empirical Strategy

The econometric models are the empirical counterparts of Equations 2.18 and 2.19. For each index $F \in \{Z, H, L, K, H-L, Z-K\}$, the model takes the form:

$$\alpha_{Fct} = \eta_c + \phi_{gt} + \beta\alpha_{Ect} + \mathbf{x}'_{ct}\gamma + \epsilon_{ct}, \tag{4.1}$$

where $c \in \{1, ..., C\}$ index countries, $g \in \{1,...,G\}$ index groups of countries (grouped either by region or income level), $t \in \{1,...,T\}$ index years, η_c are country fixed effects, ϕ_{gt} are year and group-specific flexible time trends, and $\mathbf{x}_{ct}$ are time-varying covariates, discussed below.[20]

[19] The growth of the natural resources share was 71% larger than that of the physical capital share.

[20] We consider six regions: Africa, Asia, Europe, Latin America and The Caribbean, North America, and Oceania. For the income levels, we use the World Bank's income classification of 2016, which defines three groups according to per capita Gross National Income (GNI): low: \$1,025 or less; middle: between \$1,026 and \$12,475, and high: \$12,476 or more.

The independent variable of interest is α_E, the factor income share of natural resources.[21] This is not the same as the sectoral income share, $\alpha_R \equiv \frac{P_R Y_R}{Y}$, that appears in Equations 2.18 and 2.19. However, $\alpha_E \equiv \alpha_{E,R} \cdot \alpha_R$ (see Equation 2.7), so we use it as a proxy of α_R.[22] The main identification challenge is to isolate the variation in α_E induced by exogenous changes in the price of commodities P_R. Once this is done, we interpret the parameter β as the effect of a price-induced natural resource boom on each factor income share.

Our theoretical model suggests there are two main sources of unobserved heterogeneity that are particularly important for identification: *i*. the intensity in which each factor is used in the tradable and non-tradable sectors, and *ii*. the consumer's relative preferences for non-tradable goods and commodities. A fraction of these and other sources of heterogeneity are absorbed by the fixed effects. First, η_c accounts for cross-sectional heterogeneity at the country level, including all institutional, technological, geographical or cultural factors that are country-specific but constant over the 15 year period. Second, ϕ_{gt} accounts for secular trends or shocks that are common at a region or income group level, including aspects of automation, or technological or demographic change. To address the concern that there may remain relevant omitted variables that vary at the country-year level and to isolate variation coming only from commodity price changes, we also implement an instrumental variables approach.

4.1 The China Shock

The instrument rests on the premise that the commodity price boom of the 2000s was mainly driven by the fast and unexpected rise in China's demand for primary commodities, particularly the demand for energy and mineral resources, in a way that is orthogonal to local conditions of commodity exporting countries. There is extensive evidence showing that China was the main driver behind the price boom (Kaplinsky, 2006; Radetzki, 2006; Erten and Ocampo, 2013; Costa et al., 2016). China's rising demand for commodities was a byproduct of its transition to a market-oriented economy in the early 1990s, and the impressive growth performance that followed. In contrast with other emerging economies that specialized in primary commodities, China's manufacturing sector was at the heart of its growth spurt: China's share of world manufacturing value added went from 6 percent in 1990 to 24 percent in 2010 (The World Bank, 2016). Manufacturing production requires large amounts of primary materials, so there was a massive demand shock to global commodity markets.

Panel (a) of Figure 6 shows the cumulative growth of the value of imports of China between 1992 and 2010 for seven selected commodities: *i*. petroleum oils and crude, *ii*.

[21] When referring to factor shares, we omit country and year indexes to simplify notation.

[22] We can not estimate α_R directly with the data available.

iron ores, *iii*. petroleum preparations, *iv*. refined and unwrought copper, *v*. copper ores, *vi*. coal, and *vii*. natural gases. These commodities were selected based on two criteria: *i*. they are a subset of the energy and mineral resources that are used in the WND database to calculate the natural resources share, and *ii*. they have an important relative weight in China's overall imports during the period, placing at least above the 95th percentile in terms of their aggregate imports value (see Figure 7). To get a sense of the magnitude of the demand shock, China's imports of petroleum preparations nearly quadruple between 1992 and 2010, while coal imports were multiplied by 6. Panel (b) of Figure 6 shows the cumulative growth of import-prices for each commodity. The price of the majority of the products more than doubled since 2000.

There are two features of China's emergence as a global economic power that are relevant for our identification strategy. First, it was unexpected. In the early 1990s, few anticipated how important China would become for the world economy, so countries had no time to adapt to the new global market conditions created by China's rapid opening (Autor et al., 2021). Second, it was not a response to external economic shocks but resulted from internal conditions idiosyncratic to the country, some of which had been developing since the 1970s (Autor et al., 2016, 2021). These two features suggest that the increase in China's demand for commodities was an unanticipated positive exogenous demand shock to exporters of natural resources.

4.2 Shift-share Instrument

We leverage variation in the initial exposure of countries to this common shock by constructing a shift-share instrument using commodity-level international trade data from UN Comtrade. Let j index the seven selected commodities and define X_{jc1995} to be the total value of exports by country c of commodity j in 1995. Let O_{c1995} be the trade-to-GDP ratio in 1995, a measure of the relative importance of international trade in the economy prior to the boom.[23] We adjust for this measure of trade openness to account for countries poorly connected to international trade flows, but where natural resources are an essential part of total exports. We define the exposure s_{jc} of each country-commodity pair as:

$$s_{jc} = \frac{X_{jc1995}}{X_{c1995}} \times O_{c1995}, \tag{4.2}$$

where X_{c1995} is the total value exports of country c in 1995. That is, the relative importance of the commodity in total exports weighted by the relative importance of trade in GDP.

[23] We compute the trade-to-GDP ratio as $O_{c1995} = (X_{c1995} + M_{c1995}) / (Y_{c1995})$, the fraction of total trade value, exports (X_{c1995}) and imports (M_{c1995}), to GDP (Y_{c1995}), all calculated at baseline year 1995. We take this data from World Bank's World Development Indicators.

There is significant variation in the exposure of countries to China's demand shock. Figure 8 shows a map with the exports value share of the seven selected products in 1995. For several countries, the share of the selected commodities in total exports is above 30 percent. The median export value share is 2 percent, while the cross-country standard deviation is 8.6. Figure 9 shows a map with the trade-to-GDP ratio in 1995. Again we see significant variation. A great number of countries in our sample were poorly connected to international markets, but 17 percent of them had a trade-to-GDP above 100 percent.

The instrument is constructed as

$$B_{ct} = \sum\nolimits_{J} s_{jc} \times P_{jt}, \tag{4.3}$$

where P_{jt} is the import-price per kilogram paid by China for the commodity j in year t.[24]

The recent literature on shift-share IV's shows that the instrument is valid if either the exposure shares s_{jc} (Goldsmith-Pinkham et al., 2020) or the common shocks P_{jt} (Borusyak et al., 2022) are exogenous. For the former condition to hold, we need that the relative importance of each of the seven selected commodities in total exports in 1995 is unrelated to the unobserved error in Equation 4.1. The latter condition, on the other hand, requires that relative changes in the price of the selected commodities are as if randomly assigned, and that there are many sufficiently independent shocks, so that a shock-level law of large numbers apply (Borusyak et al., 2022). Fulfilling this last requirement is unlikely in our context since we focus on a small subset of commodities. However, we provide suggestive evidence for the validity of the instrument under both frameworks.

We first reiterate that both identifying assumptions hold conditional on the country and time fixed effects included in Equation 4.1. That is, we are not arguing that the exposure shares are unrelated to the *level* of the factor shares, but that *changes* over time in those factor shares that deviate from group-specific flexible time trends are unrelated to our baseline measures of exposure. One concern is that a country's functional distribution of income can be deferentially affected by China's growing economic importance through channels different from the impact on commodity prices, violating the exclusion restriction. One example is the idiosyncratic effect of China's manufacturing exports on a country's employment structure and industrial production (Autor et al., 2013, 2021). For this reason, we include a vector of additional controls $\mathbf{x}_{ct}$ in the estimation. The vector is composed of four country-specific variables measured at baseline (1995) and interacted with year fixed effects: *i.* each country's manufacturing value added; *ii.* the weight of imports from China on total imports; *iii.* each country's exports' share of the

[24] The price per kilogram is calculated as China's imports value over imported quantities. Petroleum oils and crude prices are transformed from liters to kilograms assuming a gravity coefficient of 0.8, an approximated density of 800 kg/m^3.

main 15 products exported by China, capturing exports' competition; and *iv.* a de jure globalization index that accounts for trade barriers.[25]

The identifying assumptions are not directly testable, but Goldsmith-Pinkham et al. (2020) suggest that if there is a pre-shock period, one can run a test analogous to parallel pretrends. Intuitively, before the shocks occur, the evolution of each factor share should be independent of the baseline exposure shares. We test for the existence of pretrends using the fact that, although China's demand for commodities was growing since the mid 1990s, commodity prices only started to increase after the 2000s (see Figure 6). We then take the period between 1995 and 2000 as a pre-shock period and run regressions of the change in each factor share during this quinquennium on the baseline exposure shares, including the aforementioned controls. Results are presented in Table 1. The estimates suggest there are no pretrends associated with any of the exposure shares individually, nor for the composite shift-share instrument: out of the 48 coefficients, in only three cases we observe statistically significant coefficients at standard levels, this without any adjustment for multiple hypothesis testing.

Alternatively, to test if shocks are plausibly exogenous, Borusyak et al. (2022) recommend regressing future shocks on past outcomes, which are likely correlated with current residuals. In our case, we regress changes in the shift-share instrument over three periods: 2000-1995, 2005-1995, and 2010-1995, on the factor shares at baseline and the controls. Results are presented in Table 2. The estimates show no correlation between the levels of each factor share prior to the increase in commodity prices and the respective posterior (weighted) change in prices. We take this as suggestive evidence that shocks are plausibly exogenous, with the caveat that the number of commodities considered is small.

5 The Natural Resource Boom Effect on Factor Shares

In Tables 3-8 we present the results from estimating Equation 4.1. Each table corresponds to a different factor income share as the dependent variable. We report six specifications: with and without the instrument, and varying the types of fixed effects included. We report summary statistics of the main dependent and independent variables at the bottom of each table. In Appendix Table A.3 we show the results of the first stage of the IV regressions. The instrument has the expected positive relation with the natural resources share, and the F-statistic on the excluded instrument is above 31 in two out of three specifications, and above 11 in the reminder one, which indicates the instrument has

[25] We obtain manufacturing value added from World Bank's World Development Indicators and de jure globalization from the KOF Swiss Economic Institute. We also calculate the weight of China's exports on each country's imports and measure exports competition with trade data from UN Comtrade. For more details see Appendix C.4.

sufficient power.

5.1 Total Labor, Human Capital, and Raw Labor

Results in Table 3 show that a price-induced increase in the natural resource share leads to a decline in the total labor share that is robust to the alternative specifications. The effect is both statistically and economically significant. The point estimates of the IV specifications range between -0.528 (SE 0.185) and -0.660 (SE 0.308). To get a sense of the magnitude, we estimate that the (GDP-weighted) average natural resource share increased 1.02 percentage points between 2000 and 2010 (see Figure 2). Using this change as the benchmark, in our preferred specification (column six of each table), the point estimate suggest the resource boom reduced the labor share by 0.54 percentage points, which is close to 22.07 percent of the actual observed fall (-2.44 percentage points). The point estimates using OLS are larger, with values between -1.062 (0.150) and -1.264 (0.146), but we abstain from giving any causal interpretation to them. These results corroborate the hypothesis that the natural resource boom was an important factor behind the accelerated fall of the labor share after the rise of commodity prices in the 2000s.

Although we estimate a negative effect of a resource boom on the labor share, the impact on its two components is quite different: the human capital share reacts much more strongly than the raw labor share. In our preferred specification, the point estimate is -0.597 (SE 0.186) when the dependent variable is the human capital share (see Table 4), but it is positive although not statistically significant when the dependent variable is the raw labor share (see Table 5). This implies that resource booms also have distributional effects among workers, potentially compressing the labor earnings's distribution. We showed in Panel (a) of Figure 3 that the raw labor share fell continuously between 1995 and 2010, losing participation in the total labor income share. Our results suggest that the commodity price boom did not accentuate this downward trend, slowing the pace of growth of inequality.

We explore this distributional effect further in Table 6, where the dependent variable is the difference between the human capital and the raw labor share α_{H-L}. The point estimate of our preferred specification is -0.682 (SE 0.309). This implies that a one standard deviation increase in the natural resource share is associated with a 6 percentage point decline of the difference between the human capital and raw labor shares, equivalent to one fourth of the GDP-weighted average gap which is 26.2 percentage points. These are non-trivial effects that could help explain cyclical variations in inequality in countries that are heavily reliant on commodity exports, like those observed in Latin American countries over the last three decades (Gasparini and Lustig, 2011; Messina and Silva, 2017; Fernández and Messina, 2018).

The theoretical model suggests that the differential impact of resource booms should reflect different intensities in which raw labor and human capital are used in the tradable and natural resource sectors (see Equation 2.18). For example, our estimates are consistent with a relatively large sectoral income share of human capital in the tradable sector, which, through a Dutch disease mechanism, experiences a slow-down. They are also consistent with an equal or slightly larger sectoral income share of raw labor in the natural resource sector vis-à-vis the tradable sector.

5.2 Physical Capital

Table 7 shows the estimates when we use the physical capital income share as the dependent variable. We find that a price-induced increase in the natural resource share leads to a decline in the physical capital share, with point estimates of the IV specifications in a range between -0.340 (SE 0.308) and -0.472 (SE 0.185). We showed in Panel (b) of Figure 3 that the physical capital share increased during the entire period, gaining close to 1.41 percentage points since 2000 (2.5 since 1995). Using again the 1.02 percentage points increase in the natural resource share as proxy for the size of the boom, we estimate that the physical capital share would have been 0.48 percentage points larger, a sizable difference.

Finally, Table 8 shows the results when the dependent variable is the difference between the total labor and physical capital share α_{Z-K}. In this exercise we are again interested in the distributional impact of the resource boom, but now comparing the relative effects on labor and physical capital. The point estimates of the IV specifications are all negative, but none of them is statistically significant at standard levels, suggesting total labor and physical capital are negatively affected by the resource boom in approximately similar magnitudes.

5.3 Counterfactual Exercise: Quantifying the Boom's Impact

To explore what would have happened with the evolution of factor shares in the absence of the commodity price boom of the 2000s, we perform a counterfactual exercise using the estimated parameters of our preferred specification for each factor share (column VI of tables 3, 4, 5 and 7). The counterfactual is calculated as the predicted change of the factor share if the natural resources share was fixed at the level of 2000 (i.e. in the absence of the boom).[26] Figure 10 summarizes the main findings. Here we report the observed (grey bar) and counterfactual (blue bar) change of each factor income share between 2000 and 2010. The red bar is the change attributed to the natural resource boom, which is

[26] To estimate the counterfactual change, we subtract from the observed change the implied change of factor shares from the product of our estimated impact and the 1.02 percentage points increase of the natural resource share (see Figure 2) we use to benchmark the size of the boom.

the difference between the two.

There are three takeaways. First, in the absence of the resource boom the magnitude of the fall of the total labor share would have been 0.54 percentage points smaller. Therefore, we quantify that the commodity price boom explains 22.07 percent of the global decline of the labor share during the 2000s. Second, the distributional effect of the boom within labor income contracted the human capital share while leaving the raw labor share relatively unaffected. In the counterfactual scenario, the human capital share would have remain practically unchanged, it would have fall only in 0.03 percentage points, while we observe an average fall of 0.64 percentage points. The natural resource boom redistributed the total labor share in favor of raw labor compensation, causing an uneven fall of the labor share against human capital. Finally, the physical capital share would have grown 0.48 percentage points more without the effect of the boom, implying an attenuation effect of 34.04 percent in the observed increasing trend.

We further decompose the estimated change attributed to the natural resource boom into a factor-neutral and a redistribution effect (see Figure 11). The factor-neutral effect comes from the fact that changes in factor shares must add-up to zero: if one factor share raises, at least one of the the other factor shares must fall. We then define the factor-neutral effect as the change we would observe if the gains of the natural resources share were compensated by losses in the other factor shares in a uniform-homogeneous way. The redistribution effect is defined as the difference between the estimated change attributable to the resource boom and the factor-neutral effect.

We highlight three findings from this decomposition. First, the impact of the natural resource boom on the total labor share can be more than fully explained by the factor-neutral effect, but the redistribution effect mitigated the fall: in the absence of redistributional forces, the global decline of the labor share explained by the commodity boom would have been 26 percent larger. Second, in the case of reproducible factors -human capital and physical capital- both the factor-neutral and redistribution effects go in the same direction, inducing a larger fall in the respective factor share. We quantify that the redistribution component deepens the factor-neutral effects by 44 percent for the human capital share and by 29 percent for the physical capital share. Finally, we find that redistribution forces soaked the factor-neutral effect of the rise in natural resources income on raw labor compensation, leaving it comparatively unchanged. Our findings suggest that the redistributive component of the natural resource boom impact played a crucial role shaping the observed dynamics of factor shares.

6 Conclusions

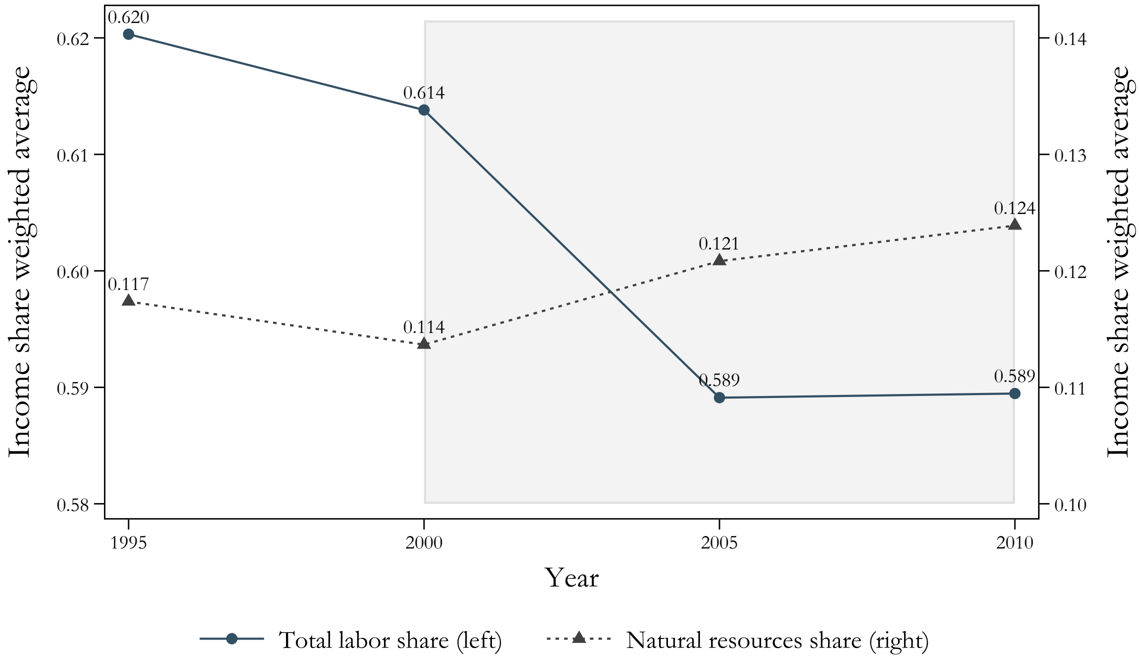
We analyze the effect of a natural resource boom on the functional distribution of income. To do so, we develop a Dutch disease theoretical framework that characterizes how natural resource windfalls, driven by an exogenous increase of commodity prices, affect equilibrium factor shares. The theory predicts that an increase in the income share of the natural resource sector differentially affects factor shares depending on the factors' relative intensity between the tradable and natural resource sectors. We then estimate the parameters that shape the theoretical relationship of a price-induced increase in natural resources income with aggregate and relative factor income shares.

To estimate the main elasticities, we use a two-way fixed effects strategy and a differential exposure design. In particular, we leverage cross-sectional variation in the exposure to China's massive increase in demand for commodities in the late 1990s and 2000s to instrument the price of natural resources. Our estimates show that a resource boom negatively impacts the total labor, human capital, and physical capital shares, while the raw labor share remains unchanged. These results suggest that the tradable sector is relatively more intensive in labor, human capital, and physical capital than the natural resources sector, while both sectors are equally intensive in raw labor.

We find that an increase of one standard deviation of the natural resource share impacts the total labor share in about -5.0 percentage points. This estimate suggests that the natural resource boom explains nearly 22.1 percent of the global decline of the total labor share during the 2000s. Moreover, we find that the natural resource boom has a negative effect on the human capital to raw labor relative share, but not on the total labor to physical capital relative share. These findings indicate a redistribution effect of income within the labor share, but not between labor and capital. In this sense, the commodity price boom hindered the pace of growth of inequality through its global and redistribution effects on factor income shares.

Figures and Tables

Figure 1: Declining Total Labor Share and the Rise of Natural Resources



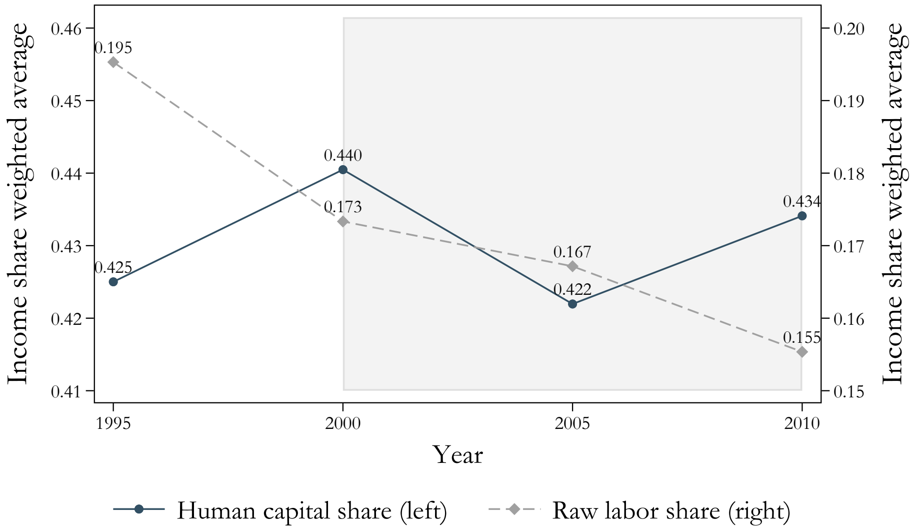
Note: The figure shows the (GDP-weighted) average total labor (α_{Zct}) and natural resources (α_{Ect}) factor income shares. Each series corresponds to the year fixed effects from a regression of the factor share on country and year fixed effects. Regressions are weighted by GDP size. We normalize the year fixed effects to equal the weighted average of the corresponding factor share in 1995. The shaded region highlights the years of the natural resource boom.

Figure 2: Changes in Factor Shares Between 2000 and 2010

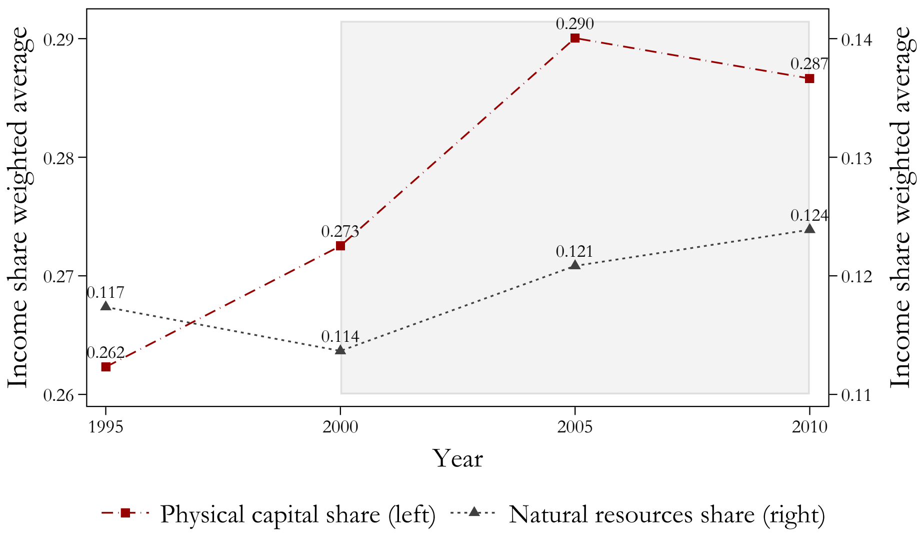
Note: The figure shows the difference in the (GDP-weighted) average factor income shares between 2000 and 2010. Each bar corresponds to the 2010 year fixed effect from a regression of the factor share on country and year fixed effects. Regressions are weighted by GDP size.

Figure 3: Evolution of Factor Income Shares

(a) Labor related factor shares

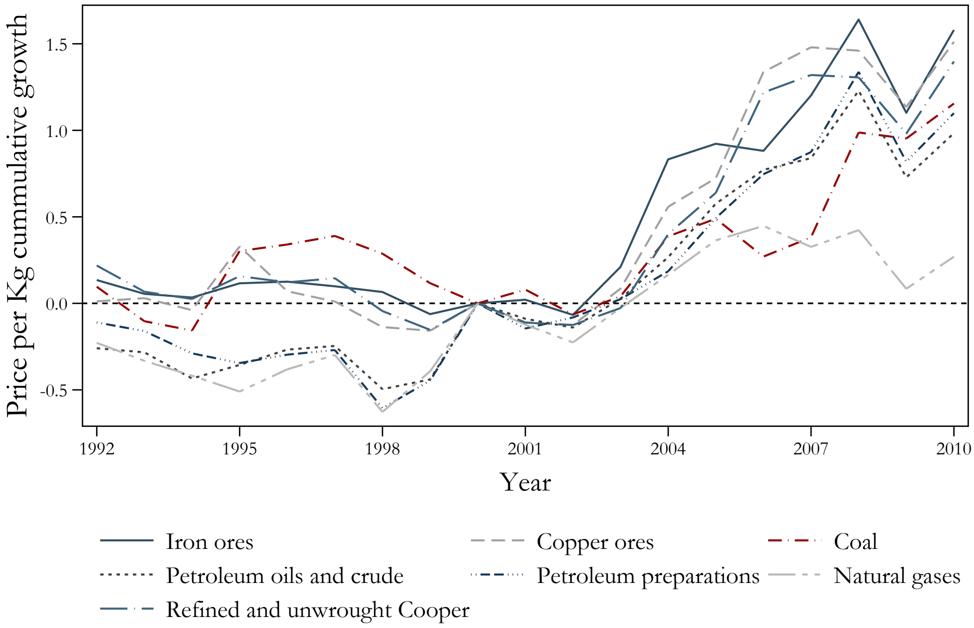


(b) Capital related factor shares



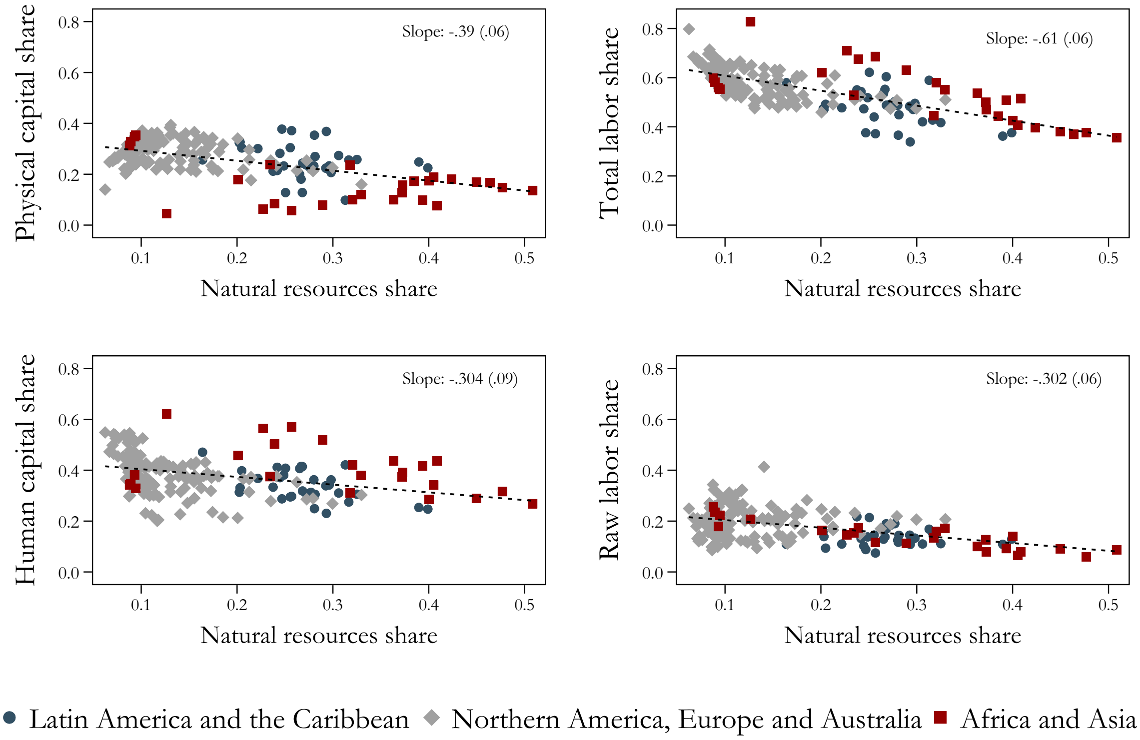
Note: The figure shows the (GDP-weighted) average factor income share of human capital (α_{Hct}), raw labor (α_{Lct}), physical capital (α_{Kct}), and natural resources (α_{Ect}). Each series corresponds to the year fixed effects from a regression of the factor share on country and year fixed effects. Regressions are weighted by GDP size. We normalize the year fixed effects to equal the weighted average of the corresponding factor share in 1995. The shaded region highlights the years of the natural resource boom.

Figure 4: Change in the Price of Energy and Mineral Commodities



Note: The figure shows the cumulative growth of the price of petroleum, iron, coal, copper, and natural gas related products between 1992 and 2010. We use commodity-level international trade data from UN Comtrade. Price per Kg is calculated as China's imports value over imported quantities. Petroleum oils and crude prices are transformed from litres to Kg assuming a gravity coefficient of 0.8, an approximated density of 800 kg/m^3.

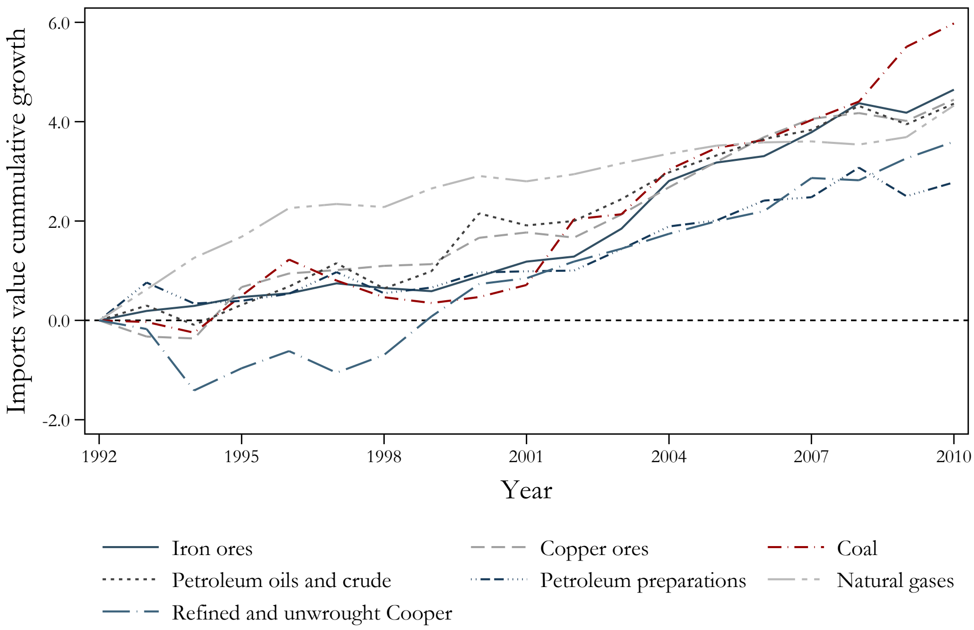
Figure 5: Correlation of the Natural Resources Share with Factor Shares



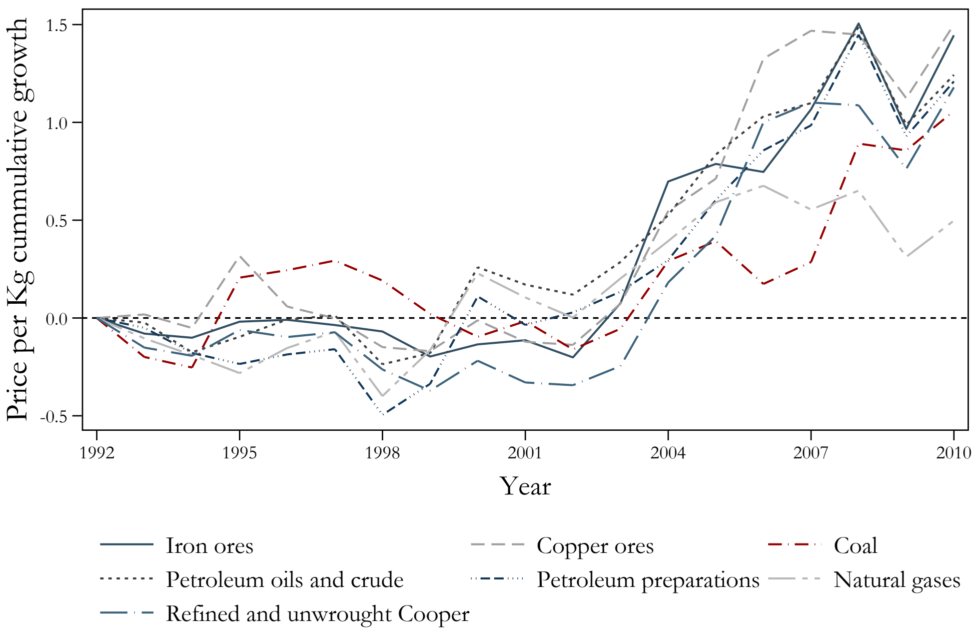
Note: The figure shows the relation between the natural resources share (α_{Ect}) and the factor income shares of physical capital (α_{Kct}), total labor (α_{Zct}), human capital (α_{Hct}), and raw labor (α_{Lct}). Each symbol corresponds to a country-year pair. The dotted line shows the slope of a linear regression between the two variables.

Figure 6: China's Demand Shock

(a) Cumulative Growth of Imports by China

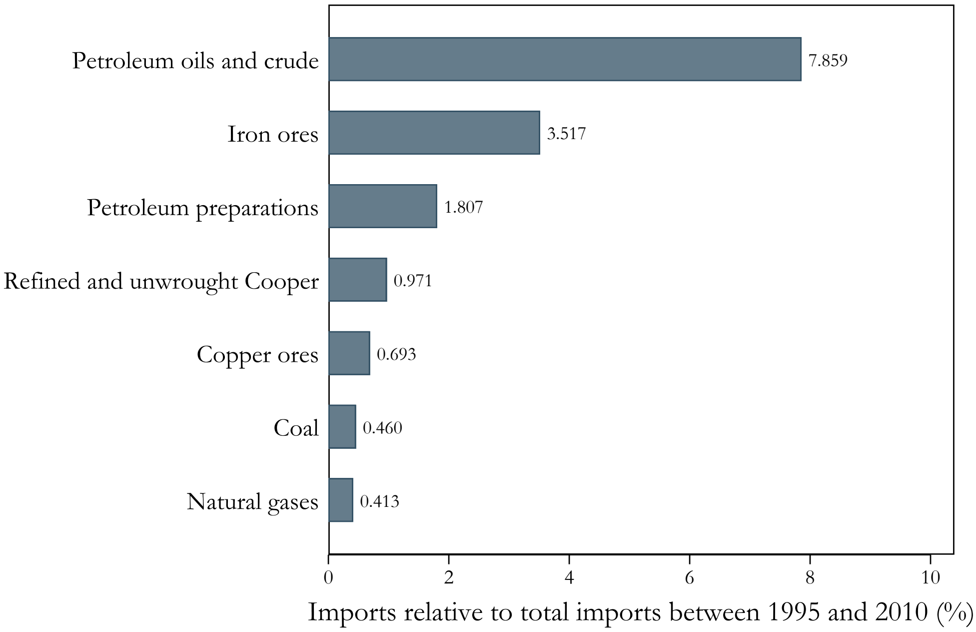


(b) Commodities Prices



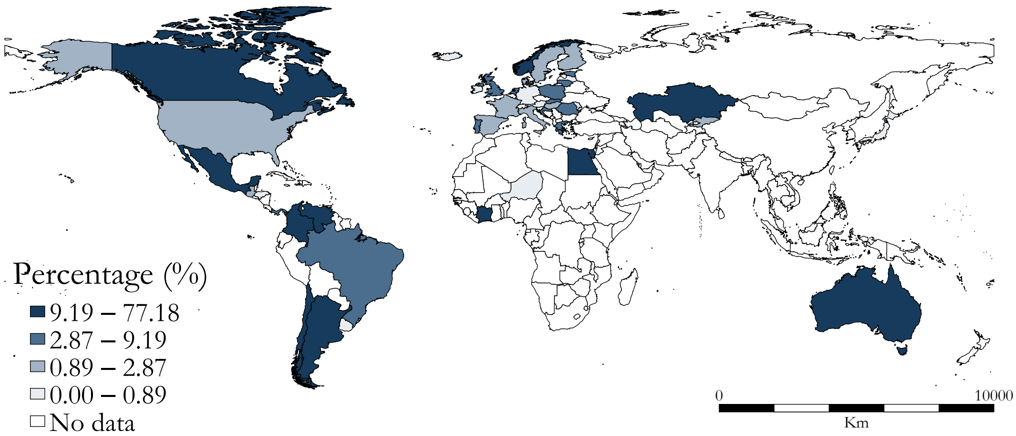
Note: Panel (a) shows the cumulative growth of the value of imports of China between 1992 and 2010 for the seven selected commodities. Panel (b) reports the cumulative growth of the price of each commodity between 1992 and 2010. All series are indexed so that the baseline year is 1992. We use commodity-level international trade data from UN Comtrade. Price per Kg is calculated as China's imports value over imported quantities. Petroleum oils and crude prices are transformed from litres to Kg assuming a gravity coefficient of 0.8, an approximated density of 800 kg/m^3.

Figure 7: Imports Share of Leading China's Commodities Imports



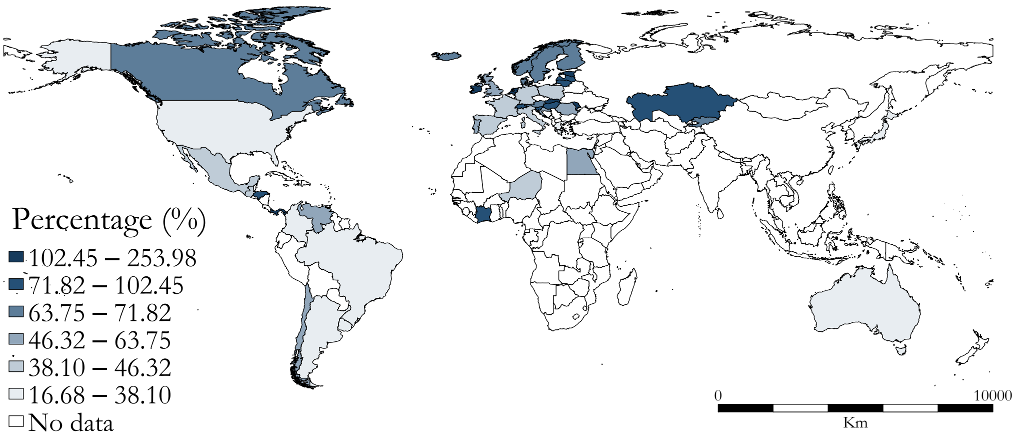
Note: The figure reports the relative importance of each commodity on China's total imports between 1995 and 2010. We measure the relative importance as the specific commodity imports value between 1995 and 2010 over the total imports value. The selected commodities belong to a subset of natural resources products imported by China that are in the top 5 percent of products in terms of their aggregate imported value. We use commodity-level international trade data from UN Comtrade.

Figure 8: Commodities' Share of Exports on Total Value of Exports in 1995



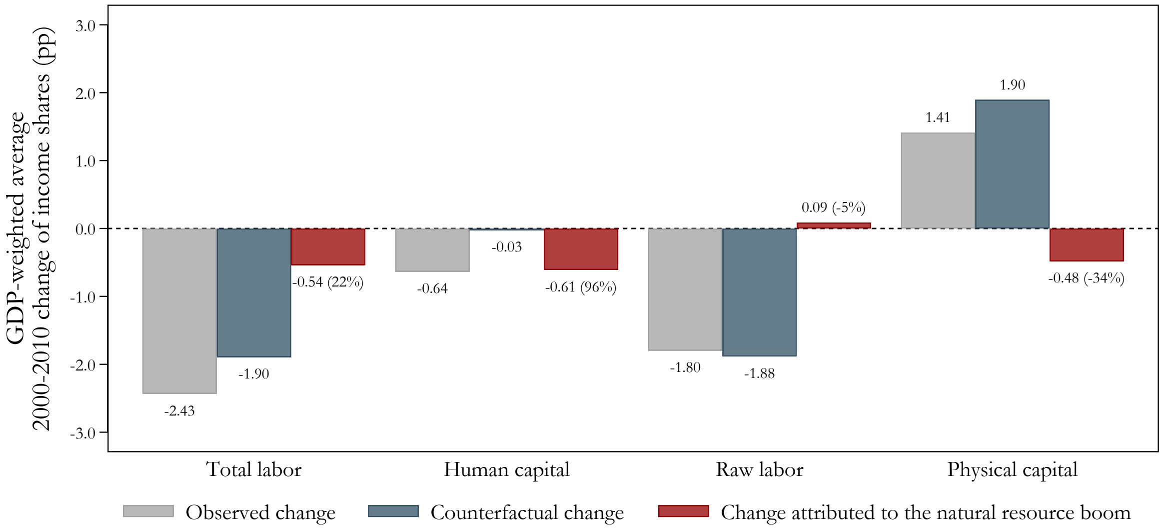
Note: The map shows the share of exports of the seven selected commodities on total exports value in 1995 for the countries in the sample. We measure the exports value share as the sum of the commodities exports value in 1995 over the total exports value across products in the same year. The ranges correspond to quartiles of the export-share distribution across countries. We use commodity-level international trade data from UN Comtrade.

Figure 9: Trade-to-GDP ratio in 1995



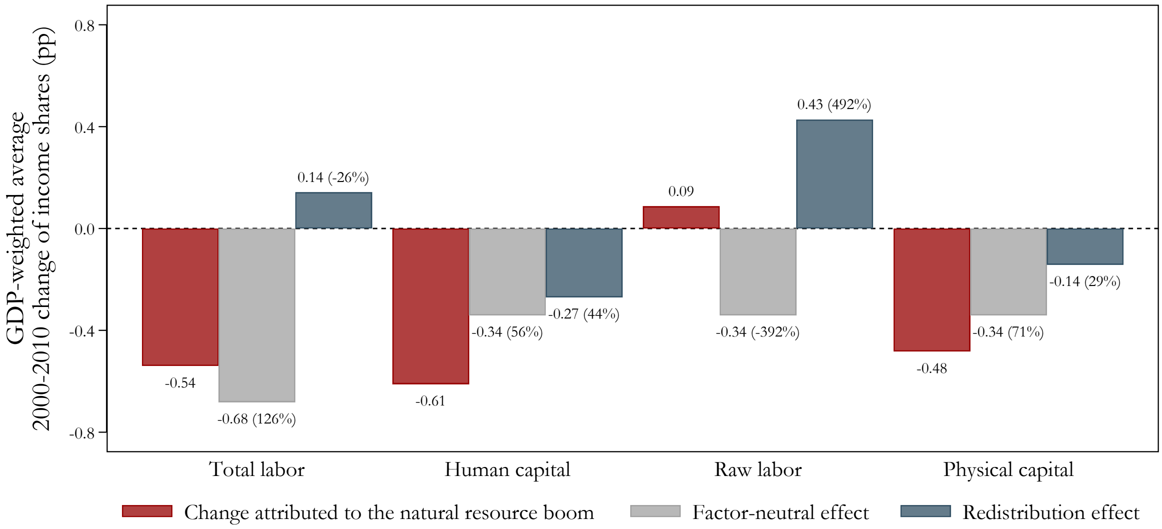
Note: The map shows the trade-to-GDP ratio in 1995 for the countries in the sample. The ratio is calculated as the sum of exports and imports value over GDP. The ranges correspond to 6-quantiles of the trade-to-GDP ratio distribution across countries. We use country-level measures from World Bank's World Development Indicators.

Figure 10: Observed and Counterfactual Changes of Factor Shares



Note: The figure shows the observed and counterfactual change in the (GDP-weighted) average factor income shares between 2000 and 2010. The observed change corresponds to the 2010 year fixed effect from a regression of the factor share on country and year fixed effects. Regressions are weighted by GDP size. The counterfactual is calculated as the predicted change of the factor share if the natural resources share was fixed at the level of 2000. We compute this change using the estimated parameters of our preferred specification (column VI of tables 3, 4, 5 and 7). The red bar is the difference between observed and counterfactual change, our measure of the impact of the boom. We report in parenthesis the proportion of the observed change that is attributed to the natural resource boom.

Figure 11: Decomposition of the Boom's Impact



Note: The figure shows the change in factor shares attributed to the natural resource boom, our measure of the impact of the boom, which is the difference between observed and counterfactual change of Figure 10. We decompose this effect in two components. First, we measure factor-neutral forces as the change we should observe if the gains of the natural resources share were compensated by losses in the other factor shares in a uniform-homogeneous way. Second, we quantify changes caused by redistribution as the difference between the estimated impact and the factor-neutral component. We report in parenthesis the proportion of the change attributed to the natural resource boom that is explained by each component.

Table 1: Shift-share Instrument Pretrends Diagnostic Test for Exposure Shares Exogeneity

	1995-2000 changes in outcomes:					
Commodities	Total Labor α_{Zct}	Human Capital α_{Hct}	Raw Labor α_{Lct}	Relative α_{H-Lct}	Physical Capital α_{Kct}	Relative α_{Z-Kct}
Exposure Shares:	I	II	III	IV	V	VI
Iron ores	2.781	0.259	2.523*	-2.264	-0.633	3.414
	(2.252)	(2.237)	(1.033)	(2.660)	(1.335)	(3.517)
Observations	37	37	37	37	37	37
Copper ores	0.737**	0.146	0.592*	-0.446	0.078	0.660
	(0.251)	(0.376)	(0.252)	(0.589)	(0.189)	(0.426)
Observations	37	37	37	37	37	37
Coal	-0.645	-0.144	-0.501	0.357	0.433	-1.078
	(0.646)	(1.228)	(0.896)	(2.051)	(0.368)	(0.993)
Observations	37	37	37	37	37	37
Petroleum crude	-0.191	-0.244	0.052	-0.296	0.098	-0.289
	(0.130)	(0.155)	(0.063)	(0.197)	(0.075)	(0.199)
Observations	37	37	37	37	37	37
Petroleum preparations	0.123	-0.269	0.391	-0.660	-0.071	0.193
	(0.317)	(0.338)	(0.274)	(0.528)	(0.274)	(0.557)
Observations	37	37	37	37	37	37
Natural gas	0.034	-0.512	0.546	-1.059	0.026	0.008
	(0.580)	(0.597)	(0.414)	(0.847)	(0.309)	(0.864)
Observations	37	37	37	37	37	37
Refined cooper	-0.022	-0.195	0.173	-0.368	0.221	-0.243
	(0.347)	(0.341)	(0.120)	(0.375)	(0.171)	(0.513)
Observations	37	37	37	37	37	37
Baseline shift-share IV	-0.008	-0.091	0.083	-0.174	0.088	-0.096
	(0.140)	(0.138)	(0.043)	(0.148)	(0.068)	(0.206)
Observations	37	37	37	37	37	37

Note: Regression coefficients represent the correlation between exposure shares for each commodity used in the instrument plus the shift-share instrument at baseline with the change of each outcome between 1995 and 2000, before the commodities demand shock turns on. These coefficients test for pre-trends in each outcome across exposure levels to the commodity boom. All regressions include controls at baseline 1995 for: the weight of China exports in total imports, manufacturing value added, the exports share of China's top 15 exported products between 2000-2010 for each country, and De Jure trade globalization. Robust standard errors in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 2: Shift-share Instrument Diagnostic Test for Shocks Exogeneity

	Shift-share instrument changes:		
	2000-1995	2005-1995	2010-1995
Outcomes at baseline in 1995:	I	II	III
Total Labor α_{Zct}	0.005	-0.133	-0.050
	(0.028)	(0.102)	(0.115)
Observations	37	37	36
Human Capital α_{Hct}	-0.010	-0.055	-0.026
	(0.015)	(0.065)	(0.139)
Observations	37	37	36
Raw Labor α_{Lct}	0.020	-0.060	-0.014
	(0.023)	(0.079)	(0.153)
Observations	37	37	36
Relative Factor Share α_{H-Lct}	-0.009	-0.004	-0.006
	(0.009)	(0.035)	(0.087)
Observations	37	37	36
Physical Capital α_{Kct}	0.025	-0.005	-0.186
	(0.021)	(0.103)	(0.292)
Observations	37	37	36
Relative Factor Share α_{Z-Kct}	-0.003	-0.050	0.021
	(0.014)	(0.057)	(0.098)
Observations	37	37	36

Note: Regression coefficients represent the correlation between outcomes at baseline with the change of the Shift-share instrument between 1995 and 2000, 2005 and 2010. Changes in the Shift-share instrument quatify shock's changes during the periods of the difference. All regressions include controls at baseline 1995 for: the weight of China exports in total imports, manufacturing value added, the exports share of China's top 15 exported products between 2000-2010 for each country, and De Jure trade globalization. Robust standard errors in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 3: Natural Resources Boom Impact on the Total Labor Share

	Total Labor Share α_{Zct}					
	OLS	IV	OLS	IV	OLS	IV
	I	II	III	IV	V	VI
Natural resources share α_{Ect}	-1.098***	-0.601***	-1.264***	-0.660**	-1.062***	-0.528***
	(0.132)	(0.132)	(0.146)	(0.308)	(0.150)	(0.185)
F on the excluded instrument		31.646		11.110		36.270
Observations	171	171	167	167	167	167
Countries	46	46	45	45	45	45
Country fixed effects	✓	✓	✓	✓	✓	✓
Year fixed effects	✓	✓				
Region specific time trend			✓	✓		
Income group specific time trend					✓	✓
Controls	✓	✓	✓	✓	✓	✓
Total labor share α_{Zct} mean	0.56	0.56	0.56	0.56	0.56	0.56
Total labor share α_{Zct} SD	0.09	0.09	0.09	0.09	0.09	0.09
Natural resources share α_{Ect} mean	0.17	0.17	0.17	0.17	0.17	0.17
Natural resources share α_{Ect} SD	0.10	0.10	0.10	0.10	0.09	0.09
Standardized coefficient	-0.10	-0.06	-0.12	-0.06	-0.10	-0.05

Note: Standardized coefficient is calculated as $\hat{\beta} \times \sigma_x$, where σ_x is the standard deviation of the independent variable. All regressions include controls at baseline multiplied by year fixed effects for: the weight of China exports in total imports, manufacturing value added, the exports share of China's top 15 exported products between 2000-2010 for each country, and De Jure trade globalization. We cluster the standard errors at the country level. Clustered standard errors in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 4: Natural Resources Boom Impact on the Human Capital Share

	Human Capital Share α_{Hct}					
	OLS	IV	OLS	IV	OLS	IV
	I	II	III	IV	V	VI
Natural resources share α_{Ect}	-0.784***	-0.704***	-0.869***	-0.896**	-0.734***	-0.597***
	(0.095)	(0.123)	(0.161)	(0.360)	(0.121)	(0.186)
F on the excluded instrument		30.168		11.220		32.926
Observations	168	168	164	164	164	164
Countries	45	45	44	44	44	44
Country fixed effects	✓	✓	✓	✓	✓	✓
Year fixed effects	✓	✓				
Region specific time trend			✓	✓		
Income group specific time trend					✓	✓
Controls	✓	✓	✓	✓	✓	✓
Human capital share α_{Hct} mean	0.38	0.38	0.38	0.38	0.38	0.38
Human capital share α_{Hct} SD	0.08	0.08	0.08	0.08	0.08	0.08
Natural resources share α_{Ect} mean	0.17	0.17	0.17	0.17	0.16	0.16
Natural resources share α_{Ect} SD	0.09	0.09	0.09	0.09	0.09	0.09
Standardized coefficient	-0.07	-0.06	-0.08	-0.08	-0.06	-0.05

Note: Standardized coefficient is calculated as $\hat{\beta} \times \sigma_x$, where σ_x is the standard deviation of the independent variable. All regressions include controls at baseline multiplied by year fixed effects for: the weight of China exports in total imports, manufacturing value added, the exports share of China's top 15 exported products between 2000-2010 for each country, and De Jure trade globalization. We cluster the standard errors at the country level. Clustered standard errors in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 5: Natural Resources Boom Impact on the Raw Labor Share

	Raw Labor Share α_{Lct}					
	OLS	IV	OLS	IV	OLS	IV
	I	II	III	IV	V	VI
Natural resources share α_{Ect}	-0.324***	0.103	-0.407***	0.242	-0.333***	0.085
	(0.101)	(0.155)	(0.122)	(0.330)	(0.092)	(0.179)
F on the excluded instrument		30.168		11.220		32.926
Observations	168	168	164	164	164	164
Countries	45	45	44	44	44	44
Country fixed effects	✓	✓	✓	✓	✓	✓
Year fixed effects	✓	✓				
Region specific time trend			✓	✓		
Income group specific time trend					✓	✓
Controls	✓	✓	✓	✓	✓	✓
Raw labor share α_{Lct} mean	0.18	0.18	0.18	0.18	0.19	0.19
Raw labor share α_{Lct} SD	0.06	0.06	0.06	0.06	0.06	0.06
Natural resources share α_{Ect} mean	0.17	0.17	0.17	0.17	0.16	0.16
Natural resources share α_{Ect} SD	0.09	0.09	0.09	0.09	0.09	0.09
Standardized coefficient	-0.03	0.01	-0.04	0.02	-0.03	0.01

Note: Standardized coefficient is calculated as $\hat{\beta} \times \sigma_x$, where σ_x is the standard deviation of the independent variable. All regressions include controls at baseline multiplied by year fixed effects for: the weight of China exports in total imports, manufacturing value added, the exports share of China's top 15 exported products between 2000-2010 for each country, and De Jure trade globalization. We cluster the standard errors at the country level. Clustered standard errors in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 6: Natural Resources Boom Impact on α_{H-Lct} Relative Share

	Human Capital to Raw Labor Relative Share α_{H-Lct}					
	OLS	IV	OLS	IV	OLS	IV
	I	II	III	IV	V	VI
Natural resources share α_{Ect}	-0.460***	-0.806***	-0.462*	-1.138*	-0.401***	-0.682**
	(0.142)	(0.247)	(0.243)	(0.620)	(0.148)	(0.309)
F on the excluded instrument		30.168		11.220		32.926
Observations	168	168	164	164	164	164
Countries	45	45	44	44	44	44
Country fixed effects	✓	✓	✓	✓	✓	✓
Year fixed effects	✓	✓				
Region specific time trend			✓	✓		
Income group specific time trend					✓	✓
Controls	✓	✓	✓	✓	✓	✓
Relative factor share α_{H-Lct} mean	0.20	0.20	0.20	0.20	0.19	0.19
Relative factor share α_{H-Lct} SD	0.12	0.12	0.12	0.12	0.12	0.12
Natural resources share α_{Ect} mean	0.17	0.17	0.17	0.17	0.16	0.16
Natural resources share α_{Ect} SD	0.09	0.09	0.09	0.09	0.09	0.09
Standardized coefficient	-0.04	-0.07	-0.04	-0.10	-0.04	-0.06

Note: Standardized coefficient is calculated as $\hat{\beta} \times \sigma_x$, where σ_x is the standard deviation of the independent variable. All regressions include controls at baseline multiplied by year fixed effects for: the weight of China exports in total imports, manufacturing value added, the exports share of China's top 15 exported products between 2000-2010 for each country, and De Jure trade globalization. We cluster the standard errors at the country level. Clustered standard errors in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 7: Natural Resources Boom Impact on the Physical Capital Share

	Physical Capital Share α_{Kct}					
	OLS	IV	OLS	IV	OLS	IV
	I	II	III	IV	V	VI
Natural resources share α_{Ect}	0.098	-0.399***	0.264*	-0.340	0.062	-0.472**
	(0.132)	(0.132)	(0.146)	(0.308)	(0.150)	(0.185)
F on the excluded instrument		31.646		11.110		36.270
Observations	171	171	167	167	167	167
Countries	46	46	45	45	45	45
Country fixed effects	✓	✓	✓	✓	✓	✓
Year fixed effects	✓	✓				
Region specific time trend			✓	✓		
Income group specific time trend					✓	✓
Controls	✓	✓	✓	✓	✓	✓
Physical capital share α_{Kct} mean	0.26	0.26	0.26	0.26	0.27	0.27
Physical capital share α_{Kct} SD	0.07	0.07	0.07	0.07	0.06	0.06
Natural resources share α_{Ect} mean	0.17	0.17	0.17	0.17	0.17	0.17
Natural resources share α_{Ect} SD	0.10	0.10	0.10	0.10	0.09	0.09
Standardized coefficient	0.01	-0.04	0.03	-0.03	0.01	-0.04

Note: Standardized coefficient is calculated as $\hat{\beta} \times \sigma_x$, where σ_x is the standard deviation of the independent variable. All regressions include controls at baseline multiplied by year fixed effects for: the weight of China exports in total imports, manufacturing value added, the exports share of China's top 15 exported products between 2000-2010 for each country, and De Jure trade globalization. We cluster the standard errors at the country level. Clustered standard errors in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 8: Natural Resources Boom Impact on α_{Z-Kct} Relative Share

	Total Labor to Physical Capital Relative Share α_{Z-Kct}					
	OLS	IV	OLS	IV	OLS	IV
	I	II	III	IV	V	VI
Natural resources share α_{Ect}	-1.196***	-0.201	-1.529***	-0.321	-1.124***	-0.055
	(0.265)	(0.264)	(0.291)	(0.615)	(0.300)	(0.370)
F on the excluded instrument		31.646		11.110		36.270
Observations	171	171	167	167	167	167
Countries	46	46	45	45	45	45
Country fixed effects	✓	✓	✓	✓	✓	✓
Year fixed effects	✓	✓				
Region specific time trend			✓	✓		
Income group specific time trend					✓	✓
Controls	✓	✓	✓	✓	✓	✓
Relative share α_{Z-Kct} mean	0.30	0.30	0.30	0.30	0.29	0.29
Relative share α_{Z-Kct} SD	0.13	0.13	0.13	0.13	0.12	0.12
Natural resources share α_{Ect} mean	0.17	0.17	0.17	0.17	0.17	0.17
Natural resources share α_{Ect} SD	0.10	0.10	0.10	0.10	0.09	0.09
Standardized coefficient	-0.11	-0.02	-0.15	-0.03	-0.11	-0.01

Note: Standardized coefficient is calculated as $\hat{\beta} \times \sigma_x$, where σ_x is the standard deviation of the independent variable. All regressions include controls at baseline multiplied by year fixed effects for: the weight of China exports in total imports, manufacturing value added, the exports share of China's top 15 exported products between 2000-2010 for each country, and De Jure trade globalization. We cluster the standard errors at the country level. Clustered standard errors in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

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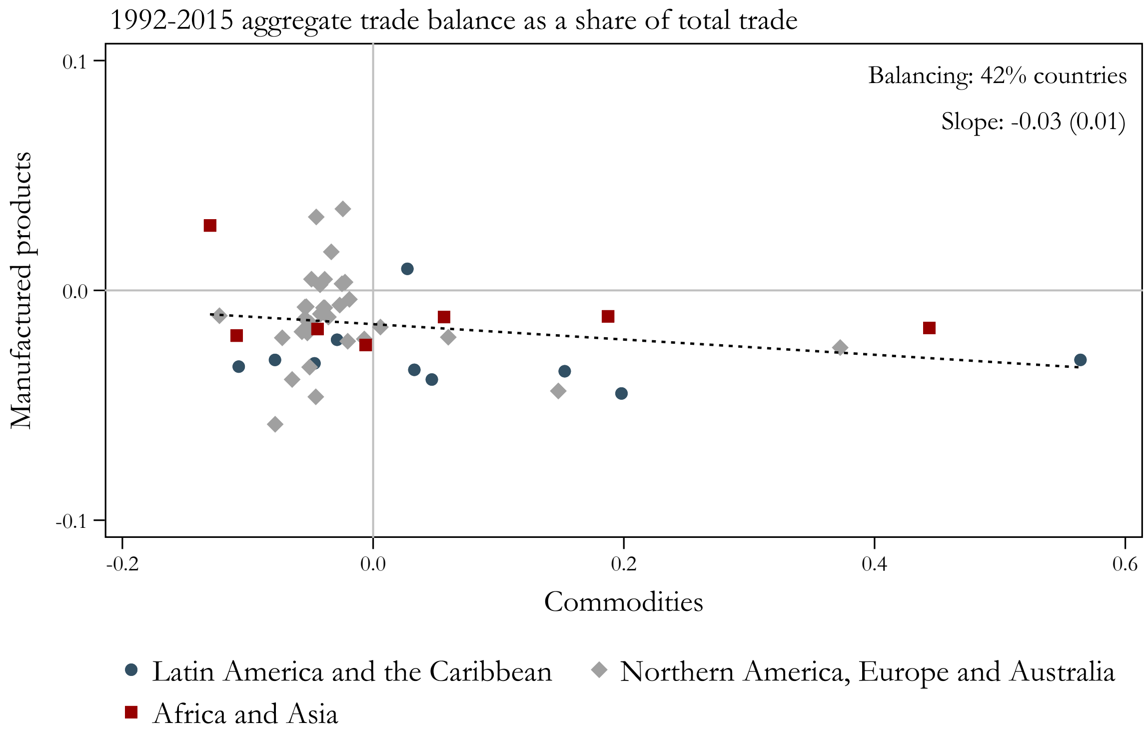
Appendix

A Complementary Figures and Tables

Figure A.1: Manufactured Products and Commodities Trade Balances



Note: The figure shows the relation of the aggregate trade balances for manufactured products and commodities. We calculate aggregate trade balances using total imports and exports between 1992 and 2015, i.e. the sum over all the years of trade values. We define manufactured products as the top 12 products exported by China during the natural resource boom 2000-2010, and commodities as the list of products we use in our Shift-share instrument. Each point represents a country in the factor shares sample. We use product-level international trade data from UN Comtrade.

Table A.1: Data Sources, Levels and Description

Data set source	Observation level	Description	Variables
UN Yearbook of National Account Statistics	Country and year	Section 3.1	Total labor share
LIS and CEDLAS Labor Force Surveys	Workers for each country-year pair	Section 3.2	Human capital and raw labor share
World Bank's Wealth of Nation's Database	Country and year	Section 3.3	Physical capital and natural resources share
UN Comtrade	Product, country and year	Section 4.2	Commodity prices, China's imports and exports value, and country's imports and exports value
World Bank's World Development Indicators	Country and year	Section 4.2	Trade-to-GDP ratio and manufacturing value added
KOF Swiss Economic Institute	Country and year	Section 4.2	De Jure globalization index for trade barriers

Note: The table reports all the data sources used to calculate the variables needed for the empirical exercises, and the observation level of each data set.

Table A.2: Changes in The Functional Distribution of Income from 2000 to 2010

	Factor Income Shares											
	Human Capital Share α_{Hct}			Raw Labor Share α_{Lct}			Physical Capital Share α_{Kct}			Natural Resources Share α_{Rct}		
Country	2000	2010	Change (pp)	2000	2010	Change (pp)	2000	2010	Change (pp)	2000	2010	Change (pp)
Argentina	0.33	0.30	-0.04	0.14	0.15	0.01	0.33	0.30	-0.02	0.20	0.26	0.05
Australia	0.38	0.37	-0.01	0.23	0.21	-0.02	0.22	0.22	0.00	0.17	0.21	0.03
Austria	0.44	0.46	0.02	0.17	0.13	-0.04	0.29	0.31	0.02	0.10	0.10	0.00
Belgium	0.37	0.44	0.08	0.25	0.16	-0.09	0.30	0.32	0.02	0.08	0.09	0.00
Bulgaria	0.30	0.29	-0.02	0.21	0.19	-0.02	0.16	0.25	0.09	0.33	0.27	-0.06
Brazil	0.41	0.41	0.00	0.13	0.14	0.01	0.21	0.18	-0.03	0.24	0.27	0.02
Canada	0.42	0.41	-0.01	0.20	0.24	0.04	0.26	0.22	-0.04	0.13	0.13	0.00
Switzerland	0.53	0.54	0.01	0.14	0.12	-0.02	0.26	0.27	0.01	0.07	0.07	0.00
Côte d'Ivore	0.39	0.32	-0.08	0.08	0.06	-0.02	0.16	0.15	-0.01	0.37	0.48	0.10
Colombia	0.31	0.32	0.01	0.19	0.17	-0.02	0.22	0.24	0.02	0.28	0.27	-0.01
Germany	0.53	0.52	-0.01	0.13	0.09	-0.04	0.27	0.31	0.04	0.08	0.09	0.01
Denmark	0.30	0.44	0.14	0.32	0.20	-0.13	0.29	0.27	-0.02	0.09	0.09	0.00
Spain	0.51	0.44	-0.06	0.14	0.16	0.03	0.26	0.30	0.04	0.09	0.09	0.00
Estonia	0.35	0.38	0.02	0.24	0.21	-0.03	0.25	0.27	0.02	0.16	0.14	-0.02
Finland	0.30	0.41	0.11	0.26	0.18	-0.08	0.33	0.31	-0.02	0.11	0.10	-0.01
France	0.48	0.42	-0.06	0.16	0.22	0.06	0.28	0.28	0.00	0.09	0.08	0.00
United Kingdom	0.44	0.45	0.01	0.16	0.18	0.02	0.31	0.29	-0.02	0.09	0.08	-0.01

Greece	0.41	0.43	0.01	0.09	0.12	0.03	0.36	0.33	-0.03	0.13	0.12	-0.02
Honduras	0.42	0.41	-0.01	0.17	0.21	0.05	0.10	0.13	0.03	0.31	0.25	-0.06
Croatia	0.55	0.43	-0.12	0.25	0.23	-0.02	0.14	0.24	0.10	0.06	0.11	0.04
Hungary	0.34	0.31	-0.04	0.25	0.26	0.00	0.29	0.32	0.03	0.11	0.12	0.00
Ireland	0.29	0.37	0.08	0.19	0.12	-0.07	0.37	0.38	0.02	0.16	0.13	-0.03
Iceland	0.46	0.41	-0.06	0.21	0.15	-0.06	0.25	0.35	0.10	0.07	0.09	0.02
Italy	0.20	0.23	0.03	0.32	0.31	-0.01	0.36	0.35	-0.01	0.12	0.10	-0.01
Japan	0.35	0.38	0.03	0.24	0.18	-0.06	0.33	0.35	0.02	0.09	0.09	0.00
Kazakhstan	0.37	0.29	-0.09	0.15	0.14	-0.01	0.24	0.17	-0.06	0.23	0.40	0.17
Kyrgyzstan	0.50	0.38	-0.12	0.17	0.17	0.00	0.08	0.12	0.04	0.24	0.33	0.09
Lithuania	0.39	0.38	-0.01	0.14	0.11	-0.03	0.30	0.35	0.04	0.17	0.17	0.00
Luxembourg	0.42	0.47	0.06	0.13	0.10	-0.03	0.35	0.33	-0.01	0.11	0.09	-0.01
Latvia	0.38	0.42	0.04	0.15	0.13	-0.02	0.29	0.31	0.02	0.18	0.14	-0.04
Moldova	0.37	0.42	0.06	0.16	0.21	0.04	0.26	0.22	-0.04	0.21	0.15	-0.06
Mexico	0.37	0.30	-0.07	0.11	0.07	-0.04	0.30	0.37	0.07	0.22	0.26	0.04
Mongolia	0.44	0.27	-0.17	0.1	0.09	-0.01	0.10	0.14	0.04	0.36	0.51	0.15
Niger	0.52	0.44	-0.08	0.11	0.08	-0.03	0.08	0.08	0.00	0.29	0.41	0.12
Netherlands	0.45	0.45	0.00	0.18	0.15	-0.03	0.29	0.31	0.02	0.08	0.09	0.00
Norway	0.24	0.21	-0.02	0.25	0.28	0.03	0.34	0.32	-0.03	0.17	0.19	0.01
Panama	0.34	0.25	-0.09	0.13	0.12	-0.01	0.23	0.35	0.12	0.30	0.28	-0.02
Poland	0.40	0.36	-0.04	0.24	0.21	-0.03	0.24	0.28	0.03	0.12	0.15	0.03
Portugal	0.35	0.44	0.09	0.30	0.18	-0.13	0.26	0.29	0.03	0.09	0.10	0.00

Romania	0.35	0.31	-0.04	0.17	0.18	0.01	0.21	0.3	0.08	0.26	0.21	-0.05
Slovakia	0.33	0.31	-0.02	0.21	0.20	-0.01	0.31	0.35	0.04	0.15	0.13	-0.01
Slovenia	0.39	0.41	0.01	0.27	0.26	-0.02	0.24	0.24	0.01	0.09	0.09	0.00
Sweden	0.33	0.31	-0.02	0.27	0.29	0.02	0.30	0.30	0.00	0.11	0.11	0.00
United States	0.53	0.53	-0.01	0.14	0.11	-0.03	0.24	0.26	0.03	0.09	0.10	0.01
Venezuela	0.31	0.25	-0.06	0.11	0.13	0.02	0.26	0.23	-0.03	0.33	0.40	0.07

Table A.3: First Stage: Natural Resources Share and Shift-share Instrument

	Natural Resources Share α_{Ect}		
	I	II	III
Commodity prices shift-share instrument B_{ct}	0.245***	0.222***	0.256***
	(0.046)	(0.074)	(0.042)
F on the excluded instrument	31.646	11.110	36.270
Observations	171	167	167
Countries	46	45	45
Country fixed effects	✓	✓	✓
Year fixed effects	✓		
Region specific time trend		✓	
Income group specific time trend			✓
Controls	✓	✓	✓
Natural resources share α_{Ect} mean	0.17	0.17	0.17
Natural resources share α_{Ect} SD	0.10	0.10	0.09
Commodity prices shift-share instrument B_{ct} mean	0.03	0.03	0.03
Commodity prices shift-share instrument B_{ct} SD	0.09	0.09	0.09
Standardized coefficient	0.02	0.02	0.02

Note: Standardized coefficient is calculated as $\hat{\beta} \times \sigma_x$, where σ_x is the standard deviation of the independent variable. All regressions include controls at baseline multiplied by year fixed effects for: the weight of China exports in total imports, manufacturing value added, the exports share of China's top 15 exported products between 2000-2010 for each country, and De Jure trade globalization. We cluster the standard errors at the country level. Clustered standard errors in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

B Dutch Disease in a Dynamic Environment

Although we present the original model in a static setting, it is possible to do a simple extension to include dynamics in our Dutch disease theory. This extension allows us to analyze the effects of natural resource booms on the accumulation of reproducible factors, physical and human capital, and study the effects on growth and on the dynamics of inequality. Furthermore, we show that the theoretical result of Equation 2.18 holds in the dynamic environment.

To account for dynamics in the model, we introduce an infinite-horizon intertemporal utility function and assets' accumulation in the household's problem, while the production side of the model remains equal to the original version. We now assume that consumers maximize lifetime utility subject to a dynamic budget constraint:

$$\begin{aligned} \max_{C_{i,T,t};C_{i,N,t};C_{i,R,t};a_{i,t+1}} U_i = \sum\nolimits_{t=0}^{\infty} \beta^t \left[\ln C_{i,T,t} + \gamma \ln C_{i,N,t} + \mu \ln C_{i,R,t}\right] \quad \text{s.t.} \\ a_{i,t+1} = a_{i,t} + Y_{i,t} - \left(C_{i,T,t} + P_{N,t}C_{i,N,t} + P_{R,t}C_{i,R,t}\right), \end{aligned} \tag{B.1}$$

where t index time, β is the discount factor, and $a_{i,t}$ are household's assets. The rest of the notation is the same as in the original version of the model. Recall $Y_{i,t}$ is household's total income from the stock of factors at period t:

$$Y_{i,t} = r_{H,t}H_{i,t} + r_{K,t}K_{i,t} + r_{L,t} + \nu_{i,t}\alpha_{R,E,t}P_{R,t}Y_{R,t}. \tag{B.2}$$

We assume that reproducible factors $K_{i,t}$ and $H_{i,t}$ are produced with the same technology, so $a_{i,t} = H_{i,t}+K_{i,t}$ and returns on reproducible factors equalized in equilibrium $r_t = r_{H,t} = r_{K,t}$.

In the long-run, the economy grows in a Balance Growth Path (henceforth BGP) equilibrium, where the first-order conditions of the problem satisfy

$$\begin{gathered} P_{N,t}C_{i,N,t} = \gamma C_{i,T,t}, \qquad\qquad P_{R,t}C_{i,R,t} = \mu C_{i,T,t}, \\ \frac{C_{i,T,t+1}}{C_{i,T,t}} = \beta\left(1+r\right), \quad \frac{C_{i,N,t+1}}{C_{i,N,t}} = \frac{P_{N,t}}{P_{N,t+1}}\beta\left(1+r\right), \quad \frac{C_{i,R,t+1}}{C_{i,R,t}} = \frac{P_{R,t}}{P_{R,t+1}}\beta\left(1+r\right). \end{gathered} \tag{B.3}$$

Under the BGP condition for tradable consumption $\frac{a_{i,t+1}}{a_{i,t}} = \frac{C_{i,T,t+1}}{C_{i,T,t}}$, assumption $a_{i,t} = H_{i,t} + K_{i,t}$, household's income Equation B.2, and the first-order conditions B.3, we find the optimal household's choice for each type of consumption

$$\begin{aligned}
C_{i,T,t} =& \frac{1}{1+\gamma+\mu}\left[a_{i,t}\left(1-\beta\left(1+r\right)\right)+Y_{i,t}\right], \\
P_{N,t}C_{i,N,t} =& \frac{\gamma}{1+\gamma+\mu}\left[a_{i,t}\left(1-\beta\left(1+r\right)\right)+Y_{i,t}\right], \\
P_{R,t}C_{i,R,t} =& \frac{\mu}{1+\gamma+\mu}\left[a_{i,t}\left(1-\beta\left(1+r\right)\right)+Y_{i,t}\right].
\end{aligned} \tag{B.4}$$

Using Equations B.3 and B.4, production side definitions of Section 2.1, and the market clearing condition of non-tradable goods $C_{N,t} = Y_{N,t}$, we find that general equilibrium factor income shares in the dynamic scenario are given by:

$$\alpha_{F,t} = \underbrace{\frac{\gamma\left(\alpha_{F,N}-\alpha_{F,T}\right)}{1+\gamma+\mu}\frac{a_t}{Y_t}\left(1-\beta\left(1+r\right)\right)}_{\text{New term in the dynamic scenario}} + \underbrace{\frac{\gamma\alpha_{F,N}+(1+\mu)\alpha_{F,T}}{1+\gamma+\mu}+\left(\alpha_{F,R}-\alpha_{F,T}\right)\frac{P_{R,t}Y_{R,t}}{Y_t}}_{\text{Right-hand side of Equation 2.18}}. \tag{B.5}$$

Note that equations 2.18 of the original model and B.5 of the dynamic extension are similar. The only difference is the first term of Equation B.5, highlighted with underbraces as a new term. Allowing for dynamics in the model introduces a new feature to our theoretical prediction, but it does not change the elements of the original equation. In particular, the term that captures the effect of the resource boom remains equal. Therefore, our theoretical prediction is robust to including dynamics in the model.

Regarding the empirical interpretation of the equation, our parameter of interest captured by $(\alpha_{F,R} - \alpha_{F,T})$ is exactly the same in both Equations 2.18 and B.5, regardless of the assumptions about dynamics. Moreover, the only term that differs between the two equations is plausibly captured by fixed effects, as it comprises constant parameters or relatively stable variables across regions or income groups. For instance, the ratio between assets and production $\frac{a_t}{Y_t}$ should be constant in a BGP. In the case that this term is not completely soaked up by fixed effects, the instrumental variables approach of our preferred specification would clean our parameter of interest from potential omitted variable bias.

C Details on Data and Measurement

This Appendix presents and discusses more details on our data sources and measurement procedures. We explain the measurement of the raw labor share of wages used to separate the total labor income share in human capital and raw labor shares. We describe the estimation, imputation, and prediction methods of Section 3.2. We also provide details on how we build each of the control variables we present in Section 4.2.

C.1 The Estimation of the Raw Labor Share of Wages

We define raw labor as labor in the absence of human capital. The idea is that the value of labor supply is divided in two components. First, raw labor, the intrinsic value of labor that all workers enjoy due to the possibility of offering their work-force. Second, the compensation for human capital, that enhances the skill level of workers and improves labor value through education, experience, training, and the ability to perform non-routine specialized tasks. Therefore, all the workers in the labor force receive the compensation for their supply of raw labor, while the accumulation of human capital increases earnings through skills' returns.

Our main purpose in this stage of the research is to identify the fraction of wages that accrues to raw labor. To do so, we capture the expected wage of workers with little to no human capital. Using the wage rate of raw labor and the average wage of workers, we calculate the share of wages associated to earnings of raw labor, as explained in section 3. This is a measure of the relative importance of raw labor in earnings.

Our strategy relies in the assumption that the wage of workers in the lower tail of the skills distribution comes mainly from the payment of raw labor. Therefore, we need to estimate the average wage of workers which human capital is relatively close to 0. We assume that human capital is increasing in three main drivers: education, experience, and the ability to perform non-elementary tasks. We then use Mincerian regressions to estimate the expected wage of workers which education, experience and abilities demanded by their occupations are the lowest. In particular, we built different groups of workers that differentiate in their level of human capital, and use these groups to control for the accumulation of skills when estimating the raw labor wage.

First, lets focus in the educational component of human capital. We classify education in three categories: high education for college graduates and more educated workers, medium education for high-school graduates and college drop-outs, and low education for workers with less than a high-school diploma: those that never attended, with only complete primary, or high-school drop-outs. We concentrate in the low education category, as this is the group that contains workers which labor supply value is that of raw labor.

However, within the low educated workers category there is accumulation of human capital. Those workers that receive some high-school education have a higher human capital than those that never attended, or that at best achieve to complete primary. Therefore, in order to accurately measure the wage of workers with the lowest level of human capital, we need to separate workers in the low education category in two groups: *i*. raw labor identified by workers which human capital is negligible, and *ii*. unskilled workers that have some human capital, for instance due to a greater exposure to high-school education.

The main challenge of our strategy is how to assign low educated workers in raw labor or unskilled labor. This is not trivial as human capital is a continuum that results from skills formation and -usually unobserved- abilities. Moreover, the information we can capture from our microdata to approximate human capital is limited, even more within the low educated group of workers. Thus, to correctly classify workers in the raw labor category, we need to find a way to group workers with low education in an upper and lower stage of human capital accumulation.

The methodology we use to perform this classification relies in the matching between the level of skills and the tasks performed by a worker. When possible, we use homogenized data on occupations to classify raw labor as those workers with low education that perform elementary and routine tasks, which are presumably those with the lower level of human capital within the group of low educated workers. On the other side, unskilled workers are those in the low education category that work in more specialized tasks -as managers, professionals, technicians, machine operators, and services or agricultural workers- so that is plausible that their type of work requires a higher intensity of human capital relative to purely raw labor. This method relies in the assumption that raw labor comprises occupations where there is no demand for human capital, education and experience are not necessary to perform the job tasks, and earnings are at the lower tail of the wage distribution due to low labor productivity of employees.

Once we have separate low educated workers between raw and unskilled labor, we count with four groups of workers ordered by their educational-skill level: raw labor, unskilled labor, medium educated labor, and highly educated labor. Clearly, the amount of human capital that workers have is higher towards highly educated labor. Using this 4 groups of workers, we can estimate a Mincerian regression that allows us to capture the average wage of a base category defined as raw labor after controlling for education, experience and the skills content of performed tasks. We employ data from LFS of LIS and CEDLAS to estimate the Mincerian regression of Equation 3.3. Using education, experience and occupations data as inputs, we separate yearly labor income between returns on human capital and the basic value of raw labor.

We use this strategy to estimate the raw labor wage and subsequently compute the raw labor share of wages. We estimate the Mincerian regressions in a sample of employed workers between 20 and 60 years of age. We use this sample in order to improve the probability of observing workers that represent raw labor, in contrast to a more restricted one. To assure that the estimates of the raw wage are comparable across countries and over time, we deflate the yearly wage to 2017 Purchasing Power Parity dollars.[27] Furthermore, due to potential measurement error in earnings data, we trim the log wage if the observed rate is higher than the 90th percentile of the wages distribution in 2 SD or lower than the 10th percentile in 2 SD. Lastly, we employ population individual cross-sectional weights to reflect the size of the labor force covered by each data set.

C.2 Imputation: Insufficient Microdata

When estimating the regression of Equation 3.3, we lose every country-year pair in the data set where occupations are not homogenized and well defined. Moreover, within the LFS cross-sections, we lose all the workers which occupation is indistinguishable or not reported. Therefore, in order to overcome the challenging lack of information in a fraction of the microdata, and maximize the sample size of our cross-country data set, we impute the missing country-year pairs with the percentile of the log wage distribution that accrues to raw labor according to the estimated values.

To do so, we first estimate regression 3.3 in all the country-year pairs with available information for education, experience and tasks. Second, we focus on the wage distribution of workers with an educational attainment lower than high-school graduation (low education) and which value of potential experience is below the median. We then recover the percentile of the distribution corresponding to the estimated raw labor wage. Finally, we calculate the average percentile that identifies the raw labor log wage.

We obtain that, on average, the raw wage is located in the 15th percentile of the low-educated and low-experienced workers wage distribution. We recover this value in the missing country-year pairs with available, but insufficient, microdata and use it to proxy for the raw labor compensation. We then calculate the ratio between this approximated value of the raw wage and the average wage of the complete wage distribution, and impute the raw labor share of wages in the missing observations of the cross-country data set.

C.3 Prediction: No Available Microdata

The match between country-year pairs of the raw labor share of wages estimates and the cross-country aggregate labor share is not perfect. Therefore, we must approximate the raw labor share of wages of countries with no microdata in 1995, 2000, 2005 and 2010, and try to compute the raw labor share of wages for countries without available microdata. To overcome this challenge, we employ a Machine Learning algorithm to predict the raw labor share of wages in the missing years and countries. In particular, we predict the

[27] We adjust the wages by taking the ratio of the nominal yearly wage and a deflator from the product of Consumer Price Index and Purchasing Power Parity values. The result is a real wage measured in the same currency value, an adjustment that accounts for differences in inflation and the exchange rate.

missing raw labor share of wages with a Gradient Boosting Machines (GBM) algorithm (James et al., 2000) using the estimated and imputed values, and a set of predictors with information on labor markets, education, and the sectoral distribution of value added and employment.

In particular, we build a data set with the following predictors: country fixed effects; year fixed effects; the income level of the country; regional fixed effects; agriculture, services, and industry value added and employment; the share of high technologies industry in manufacturing value added; total expenditure in education; years of compulsory education; the share of self employment in total employment; the employment to population ratio; the ratio of female to male labor force participation; the youth labor force (15-24) employment to population ratio; labor force participation and unemployment rate; the gross domestic savings as a percentage of GDP; and the gross value added.

The prediction is done in two steps. First, we predict the missing years within the countries with at least three estimated values of the raw labor share of wages. With this first prediction, we assure the matching between the total labor share estimates and the raw labor share of wages (for countries with estimated values) in 1995, 2000, 2005 and 2010. Second, we use the complete data set, including the predicted values within countries, and predict the missing values of countries with no estimates of raw labor wages, i.e. the countries without available microdata. This last prediction allows us to have a raw labor share of wages for all the country and year pairs needed to separate the total labor share in human capital and raw labor shares.

To calibrate the parameters of the GBM algorithm -the learning rate, the deepness of each regression tree, and the size of the trees ensemble- we perform a grid search over 360,000 alternatives of parameters combinations for the within country prediction, and 600,000 for the between countries predictions. To find the optimal combination of parameters, we evaluate the GBM Root Mean Square Error (RMSE) of each combination with a 3 folds cross validation in each of the steps of the prediction.

The tuned parameters for the within country prediction are a learning rate of 0.001, an interaction deepness of 8 splits, and an ensemble size of 9302 trees. With this combination of parameters, we obtain a RMSE of 0.0517, approximately 5 percentage points of the raw labor share of wages. For the between countries prediction, we obtain an optimal combination of parameters of 0.10 for the learning rate, 10 splits for the deepness of the trees, and an ensemble size of 486 trees. In this prediction we get a RMSE of 0.0366, approximately 4 percentage points. Overall, the prediction accuracy is high relative to the standard deviation of the raw labor share of wages (0.1106). Moreovoer, the GBM outperforms the OLS predictive capacity in both exercises.

C.4 Control Variables

We use four country-specific controls measured at baseline (1995) and interacted with year fixed effects. We now describe how we build each of the controls.

C.4.1 Manufacturing Value Added

We first control for each country's manufacturing value added as a percentage of GDP. We obtain this variable from World Bank's World Development Indicators. The World Bank defines the manufacturing sector as industries belonging to divisions 15-37 of ISIC revision 3. Value added is calculated as the aggregate output of the sector net of intermediate inputs. For more details, see World Development Indicators metadada.

C.4.2 Share of Imports from China on Total Imports

We control for the weight of China's exports on each country's imports. To do so, We use bilateral trade data from UN Comtrade and calculate the share accounted by China-specific imports on each countries total imports. In the cases where we do not observe a country's total or China-specific imports in 1995, we impute the value of the control to equal the regional average among observed countries. With this imputation, we recover 9 countries and 24 observations in our preferred specification: Egypt, Guatemala, Honduras, Croatia, Iceland, Malta, Panama, Uruguay, and Venezuela.

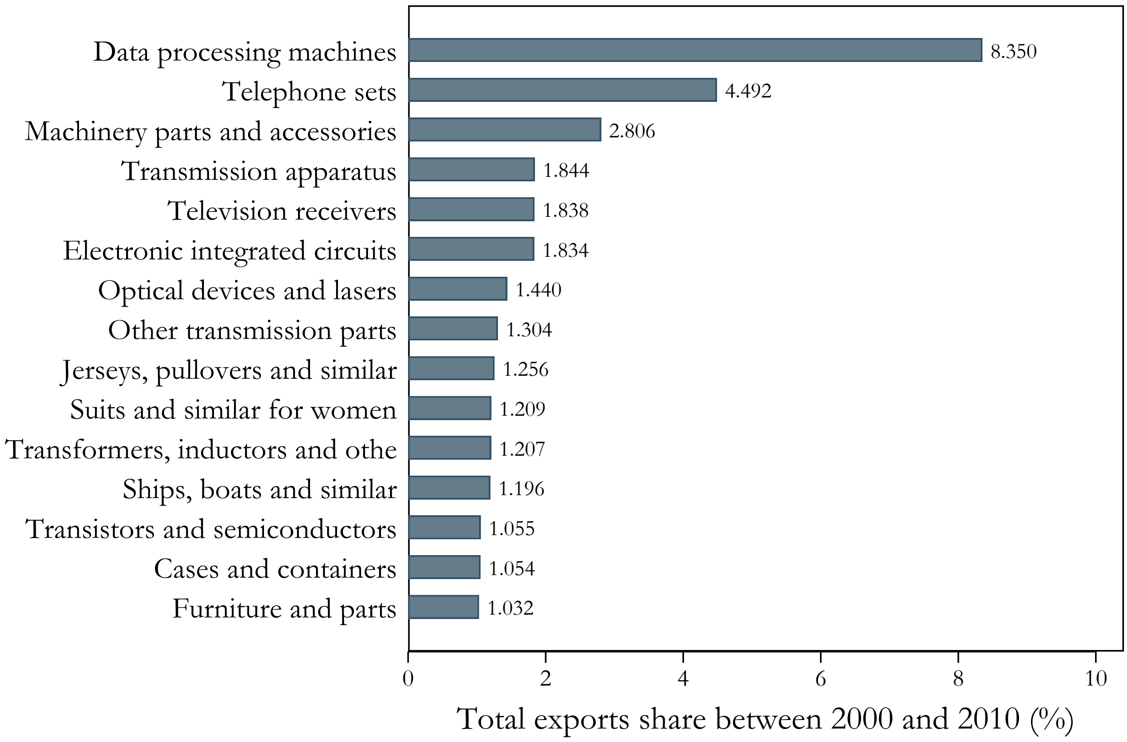
C.4.3 Exports' Competition with China

To measure exports competition with China we first identify the main 15 products exported by China between 2000 and 2010, the period of the shock, using UN Comtrade data (see Figure C.1). We then calculate each country's exports' share in 1995 of the 15 products we identify. This variable allows us to control for baseline trade-competition in the products in which China would lead during the shock.

C.4.4 De Jure Globalization: Trade Barriers

Finally, we control for a measure of de jure trade globalization that accounts for trade barriers from the KOF Swiss Economic Institute Globalization Index (Gygli et al., 2019; Dreher, 2006). This variable measures the relative globalization of each country in terms of its trade regulations, taxes, tariffs, and agreements. In particular, the index aggregates information from: the prevalence of non-tariff trade barriers, compliance costs of importing and exporting orders, income from taxes on international trade as a percentage of revenue, the unweighted mean of tariff rates, and the number of bilateral and multilateral free trade agreements. For more details, see the KOF Globalization Index website.

Figure C.1: Exports Share of Leading China's Exports



Note: The figure reports the exports' share on total China's exports for the main 15 exported products between 2000 and 2010. We measure the exports' share as the specific product exports' value over the total exports value during the complete period. We use product-level international trade data from UN Comtrade.