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ABSTRACT

The Natural Resource Boom and the Uneven Fall of the Labor Share*

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 suggests that the response of factor shares to exogenous changes in commodity prices depends on the relative intensity of factors in the tradable and natural resource sectors. We construct estimates of income shares accruing to raw labor, human capital, physical capital, and natural resources, and quantify the effect of the resource boom on factor shares. For identification, we use a two-way fixed effects strategy and a differential exposure design to instrument commodity prices. We find that a 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 25.7 percent of the global decline of the total labor share during the 2000s. We also find a redistribution effect within labor income that indicates that the fall of the labor share was unevenly distributed against human capital.

JEL Classification: D33, F14, J31, O13

Keywords: labor share, factor income shares, natural resource boom, commodity price boom, dutch disease, human capital

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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 raw labor, human capital, physical capital, and natural resources, for a sample of 47 countries between 1995 and 2010. 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 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-resource- 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 three factors of production: physical capital, human capital, and raw labor. The solution of the model provides a set of equations that describe how natural resource windfalls affect equilibrium factor shares. In particular, the theory predicts that an increase in the income share of the natural resource sector deferentially affects factor shares depending on the relative intensity of factors in the tradable and natural resource sectors.

We use the empirical counterparts of the equilibrium factor shares theoretical equations, and the country-level panel of factor shares estimates, to test the predictions of the model. We study 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-sectional variation in the exposure to China's massive increase in demand for commodities in the late 1990s and 2000s, a key developer behind the upswing in commodity prices (Kaplinsky, 2006; Erten and Ocampo, 2013; Costa et al., 2016), to instrument the price of natural resources.

There are two stylized facts that motivate our work. First, the (population weighted) average labor income share declined 5.21 percent between 1995 and 2010, our period of analysis, a fact that has been widely documented (Karabarbounis and Neiman, 2013; International Labour Organization, 2019; Autor et al., 2020). However, the rate at which the labor share fell was not constant: most of the decline (90 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 19 percent, while the human capital share was comparatively more stable. Then, the fall of the labor share is fully accounted by the raw labor share losing ground.

Second, we show that the natural resources share increased by 11.8 percent, fueled by the sharp rise in commodity prices that begun in the early 2000s. Although the physical capital share also grew during this period (by 8.23 percent), it did so in a lesser magnitude. Actually, our estimates show that the factor income share that had the strongest 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 aggregate factor shares and their distribution.

We test if the commodity price boom can explain how income shares were redistributed across factors between 1995 and 2010. Our estimates show that a resource boom impacts negatively the total labor, human capital and physical capital shares, while the raw labor share remains unchanged. We find that the impact of an increase of one standard deviation of the natural resources share on the total labor share is around -4.0 percentage points. This estimate suggests that the natural resource boom explains nearly 25.7 percent of the global decline of total 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 resource share is associated with a 6 percentage point decline of the difference between the human capital and raw labor shares, equivalent to one third of the average gap of 19 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; Fernandez et al., 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 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 resource 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, 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. Third, we highlight important heterogeneities concealed behind the evolution of the income shares of capital and labor. 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). In the theory of Dutch disease, resource revenues lead to an appreciation of the real exchange rate, which harms the competitiveness of the non-resource 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 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.[1] 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 studying the decline of the labor share in recent decades (International Labour Organization, 2019). 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, 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); 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); international trade (Rodríguez and Ortega, 2001; Burstein and Vogel, 2011); changes in the institutional setting (Bentolila and Saint-Paul, 2003; Giammarioli et al., 2002; Berthold et al., 2002; Bental and Demougin, 2010); FDI and offshoring (Dunning, 1988; Elsby et al., 2013); reallocation of value added towards the low end of the labor share distribution (Kehrig and Vincent, 2021); and even measurement issues (Rognlie, 2016, 2018).

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 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, mainly because it affects both in similar magnitudes.

Finally, 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; Zuleta and Sturgill, 2015). 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.[2] 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-

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

[2] 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.

reproducible factors (natural resources and raw labor) is negatively correlated with income per capita (Blanchard et al., 1997; Krueger, 1999; Acemoglu, 2002; Caselli and Feyrer, 2007; Zuleta, 2008b; Sturgill, 2012; Zuleta et al., 2010; Zuleta and Sturgill, 2015). Moreover, even if the relative income share of capital to labor was stable, it can conceal important heterogeneities. For example, we show that the decline of the labor share is fully accounted by the declined 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 some heterogeneities across countries.

This paper is organized in six sections. In Section 2, we present the theoretical model and derive the testable hypotheses. In Section 3 we explain how we construct our measures of factor shares and present the main descriptive patterns in the data. In Section 4, we explain the empirical strategy. In Section 5 we present the main results and some robustness checks. Finally, we conclude in section 6.

2 Theory: Natural Resource Booms and Factor Shares

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

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). Thus, production in the tradable and non-tradable sectors is:

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

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.) that is produced using the same three factors, plus an exogenous and fixed natural resource endowment E (e.g. petroleum reservoirs, coal mines, forest land, etc.):

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

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

Therefore, there is a maximum possible level of the commodity Y_R that can be produced, determined either by the size of the endowment or by regulation about its use.

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 factor $F \in \{K, L, H\}$ 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. We do impose that all income is distributed between the factors. In the case of the tradable and non-tradable sectors: $\sum_F \alpha_{F,S'} = 1$ for $S' \in \{N, T\}$. 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 relative to the sectoral revenue.

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

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

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

2.2 Consumption and General Equilibrium

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.[3] We assume that the demand for the natural resource sector output comes from external markets only. That is, there is no local consumption of the commodity Y_R. This is a milder assumption relative to the common approach in the literature of resource booms, where the resource sector is represented as a fully exogenous income flow (Goderis and Malone, 2011; van der Ploeg, 2011). We can rationalize this assumption in the context of a small open economy with a relatively large natural resource endowment, or if a large shift in external demand unrelated to local conditions triggers the resource boom, as we claim was the case with the increase of commodity prices of the 2000s.

For simplicity, we assume agent's preferences take the form

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

where γ is the relative preference for non-tradable goods of the household.

Agents are endowed with a unit of raw labor, which they supply inelastically, and own human capital, physical capital and the natural resource endowment. 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

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

and the budget constraint is

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

[3] Each agent is endowed with an unit of raw labor, so the size of the population is equal to the total endowment of raw labor L.

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

$$\max_{C_{i,T},C_{i,N}} U_i = \ln C_{i,T} + \gamma \ln C_{i,N} \quad s.t. \quad C_{i,T} + P_N C_{i,N} = Y_i. \tag{2.11}$$

The first-order conditions of this problem satisfy

$$\frac{C_{i,N}}{C_{i,T}} = \frac{\gamma}{P_N}, \tag{2.12}$$

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

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

A general equilibrium in this set-up is defined as conditions where all agents are optimizing and markets clear. This implies an aggregate constraint of the form

$$C_T + P_N C_N = r_H H + r_L L + r_K K + \alpha_{R,E} P_R Y_R = Y. \tag{2.14}$$

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

$$C_N = Y_N. \tag{2.15}$$

Second, we assume the commodity price is determined in the international markets and is not affected by local production, so P_R is exogenosuly given. Due to Walras Law, we can omit the market equilibrium for traded goods. These conditions and the optimality of the household's decision characterize the general equilibrium of this economy.

2.3 Theoretical Prediction: The Effect of a Natural Resource Boom on Factor Shares

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

$$
\begin{aligned}
r_F F &= r_F \left(F_N + F_T + F_R\right) \\
&= \alpha_{F,N} P_N Y_N + \alpha_{F,T} Y_T + \alpha_{F,R} P_R Y_R \\
&= \alpha_{F,N} P_N Y_N + \alpha_{F,T}(Y - P_N Y_N - P_R Y_R) + \alpha_{F,R} P_R Y_R \\
&= \left(\alpha_{F,N} - \alpha_{F,T}\right) P_N Y_N + \alpha_{F,T} Y + (\alpha_{F,R} - \alpha_{F,T}) P_R Y_R.
\end{aligned}
\tag{2.16}
$$

Using Equations 2.13, of household's optimality, and 2.15, of market's clearing, and then dividing by total income, we find the general equilibrium factor income shares:

$$
\alpha_F = \frac{1}{1+\gamma}\left(\gamma \alpha_{F,N} + \alpha_{F,T}\right) + (\alpha_{F,R} - \alpha_{F,T}) \frac{P_R Y_R}{Y}. \tag{2.17}
$$

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 parameter γ. 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. This is intuitive and not particularly surprising.

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, 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 $\alpha_{F,R}$. Again, this is an intuitive result: 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 $\alpha_{F,T}$ 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 cancel each other.

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 2.17, we can characterize how the relative share of two factors, F and F', changes in response to an exogenous change in P_R:

$$\alpha_F - \alpha_{F'} \equiv \alpha_{F-F'} = \frac{1}{1+\gamma}\left(\gamma\alpha_{F-F',N} + \alpha_{F-F',T}\right) + \left(\alpha_{F-F',R} - \alpha_{F-F',T}\right)\frac{P_R Y_R}{Y}. \quad (2.18)$$

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 2.17 and 2.18 will be the point of departure of the empirical analysis described in Section 4.[4]

3 Factor Income Shares: Estimation and Patterns

In this section we describe the process to construct estimates of the four aggregate factor income shares for an unbalanced panel of 47 countries in the years 1995, 2000, 2005 and 2010.[5] 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.[6]

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

[4]The theoretical model that we present in this article contains a number of simplifying assumptions. However, it is also a fairly flexible model that allows for useful extensions for future research. As we mentioned earlier, we do not assume a specific structure of the labor market. Thus, factor shares must be understood as distributive parameters that may or may not reflect the elasticity of the product with respect to the factors. Second, although we present a static model, it is possible to do a simple extension to include dynamics. This extension would allow us to analyze the effects of natural resource booms on the accumulation of physical and human capital, and study the effects on growth and on the dynamics of inequality. However, the theoretical result presented in Equation 2.17 holds in a dynamic environment. For this reason, to maintain the simplicity of the theory, in this paper we present the static version of the model.

[5]The list of countries includes 30 countries in Europe and North America, 10 countries from Latin America, and 7 countries between Asia, Africa and Oceania. A complete list is presented in Table A.1 of the Appendix.

[6]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).

of National Account Statistics. In particular, for each country-year, we estimate

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

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.[7] 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:

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

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).[8] In particular, we recover the value of "intercept labor" compensation from regressions of the form:

[7] 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).

[8] 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.

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

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.[9]

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

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

where L is the total number of workers in the economy and $\bar{w}_i$ 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.[10]

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 B discuses these assumptions and presents more details on the measurement of the raw labor share of wages.

[9] We present specific details about the cleaning and construction of the data in Appendix B.1.

[10] 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 B.2 and B.3.

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 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 need 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).[11] 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.[12].

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

[12] 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).

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.1. Pooling all the countries and years in the sample, the (population-weighted) average aggregate labor income share was 57.3 percent, while the physical capital and natural resource income shares were 26.8 and 15.9 percent respectively. Compensation for human capital accumulation accounts for 71.1 percent of the labor share, which implies a human capital share of 40.7 percent and a raw labor share of 16.6 percent.

There was a significant decline of the aggregate labor share between 1995 and 2010 (see Figure 1). In 1995, the share of income accrued to labor was 59.4 percent. By 2010 the same number was close to 56.3, a fall of 3.1 percentage points (5 percent).[13] The rate at which the labor share fell, however, was not constant: most of the decline (90 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 19 percent, while the human capital share moved up and down, but with a sharp decline of 5 percent between 2000 and 2005 (see Panel (a) of Figure 2).

The period when the fall of the labor share accelerated coincides with a sharp rise in the natural resource income share (see Figure 1), which went from 14.4 percent in 2000 to 15.6 percent in 2005, an 8 percent increase. More generally, our estimates show that since the 2000s, the factor income share that had the strongest growth was that of natural resources (see Figure 3), a fact that has not received much attention in the literature. 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 resource 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 resource 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

[13] 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); International Labour Organization (2019); Autor et al. (2020).

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 (-0.61 (se 0.06)). These are simple correlations, so we cannot claim any causal relation, but they clarify 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 2.17 and 2.18. For each index $F \in \{Z, H, L, H-L, K, Z-K\}$, the model takes the form:

$$\alpha_{F,c,t} = \eta_c + \phi_{g,t} + \beta\alpha_{E,c,t} + \mathbf{x}_{c,t}\gamma + \epsilon_{c,t}, \tag{4.1}$$

where $c \in \{1, ..., C\}$ index countries, $g \in$ {1,...,G} index groups of countries (grouped either by region or income level)[14]; $t \in$ {1,...,T} index years; η_c are country fixed effects; $\phi_{g,t}$ are year and group-specific flexible time trends; and $\mathbf{x}_{c,t}$ are time-varying covariates, discussed below.

The independent variable of interest is α_E, the factor income share of natural resources.[15] This is not the same as the sectoral income share $\alpha_R \equiv \frac{P_R Y_R}{Y}$, that appears in Equations 2.17 and 2.18. However, by definition, $\alpha_E \equiv \alpha_{R,E} \cdot \alpha_R$, according to Equation 2.7. Thus, we use α_E as a proxy of α_R. 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 of interest.

Our model suggests there are two main sources of unobserved heterogeneity that are particularly important: *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. A fraction of these and other sources of heterogeneity is captured in 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, $\phi_{g,t}$ accounts for secular trends or shocks that are common at a region or income group level, including aspects of automation or

[14] We consider six regions: Africa, Asia, Europe, Latin America and The Caribbean, Northern 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.

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

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 use 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 for the claim 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: Chinas's share of world manufacturing value added went from 6 percent in 1990 to 24 percent in 2010 (WDI, 2016). Manufacturing production required 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. iron ores, iii. petroleum preparations, iv. refined and unwrought copper, v. copper ores, vi. coal, and vii. natural gases.[16] 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 quadruple between 1992 and 2010, while imports of coal were multiplied by 6. Panel (b) of Figure 6 shows the cumulative growth of prices for each selected commodity. The price of the majority of the products more than doubled over the period.

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 experts anticipated how important China would become for the world economy, so countries had no time to adapt to the new global market conditions. 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). These two features suggest that the increase in China's demand for commodities was an

[16] We use commodity-level international trade data from UN Comtrade.

unanticipated positive exogenous 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. Let j index the seven selected commodities and define $X_{j,c,1995}$ to be the total value of exports by country c of commodity j in 1995. Let $O_{c,1995}$ be the trade-to-GDP ratio, a measure of the relative importance of international trade in the economy.[17] 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 $s_{j,c}$ of each country-commodity pair as:

$$s_{j,c} = \frac{X_{j,c,1995}}{X_{c,1995}} \times O_{c,1995}, \tag{4.2}$$

where $X_{c,1995}$ is the total value exports of country c in 1995.

There is significant variation in the exposure of countries to China's demand shock. Figure 8 shows a map with the export value share of the seven selected products in 1995.[18] 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 then constructed as

$$B_{c,t} = \sum\nolimits_J s_{j,c} \times P_{j,t}, \tag{4.3}$$

where $P_{j,t}$ is the price per kilogram paid by China for the commodity j in year t.[19] The recent literature on shift-share IV's clarifies that the validity of the instrument can be argued in terms of the exposure variables ($s_{j,c}$) (Goldsmith-Pinkham et al., 2020), or the aggregate shocks ($P_{j,t}$) (Borusyak et al., 2021). As we discussed in the previous paragraphs, we argue that the demand shock (i.e. the variation in prices) provides the exogenous variation used for identification.

[17] We compute the trade-to-GDP ratio as $O_{c,1995} = \frac{X_{c,1995}+M_{c,1995}}{Y_{c,1995}}$, the fraction of total trade value: exports ($X_{c,1995}$) and imports ($M_{c,1995}$), to GDP ($Y_{c,1995}$), all calculated at baseline year 1995.

[18] That is, $\sum_j \frac{X_{j,c,1995}}{X_{c,1995}}$.

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

One final concern is that countries might be affected by China's growing economic importance through channels different from the impact on commodity prices. One example is the effect of China's manufacturing exports on local employment and industrial production (Autor et al., 2013). Part of this effect is captured by the fixed effects. Nonetheless, we also include two variables in the vector of controls $\mathbf{x}_{c,t}$: each country's baseline (1995) manufacturing value added times year fixed effects, and the weight of China's exports on each country's imports.

5 The Natural Resource Boom Effect on Factor Shares

The estimates are presented in Tables 1-6, each using 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. Results of the first stage of the IV regressions are shown in Appendix Table A.2. The instrument has the expected positive relation with the natural resources share, and the F-statistic on the excluded instrument is above 19 in all cases.

5.1 Total Labor, Human Capital, and Raw Labor

Results of Table 1 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. It is both statistically significant and meaningful. The point estimates of the IV specifications range between -0.413 (se 0.241) and -0.468 (se 0.097). To get a sense of magnitude, we estimate that the (population-weighted) average natural resource share increased 1.7 percentage points between 2000 and 2010, from 14.4 percent to 16.1 percent (see Figure 1). In our preferred specification (column six of each table), the point estimate suggest this resource boom translated into an additional 0.79 percentage points decline of the labor share, or close to 25.7 percent of the fall (-3.1 percentage points). The point estimates using OLS are significantly larger, with values between -1.099 (0.159) and -1.235 (0.154), but we abstain from giving any causal interpretation to them.[20] 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.

[20]There are two reasons for this. First we are primarily interested in price-induced natural resource booms, but variation in α_E can come from changes in the amount produced of commodities Y_R, or in the rents perceived by the owners of natural resources $\alpha_{R,E} \cdot \frac{P_R Y_R}{Y}$. Both of these can be endogenous generating an spurious correlation. Second, The share of revenue that corresponds to profits $\alpha_{R,E}$ necessarily depends on how each factor is remunerated in the natural resource sector. But, by definition, sectoral factor remuneration determines each factor income share. Without instrumenting, there could be a mechanical negative correlation between the dependent and independent variables.

Although we estimate a negative effect of a resource boom on the labor share, the impact on its two components are quite different: the human capital share reacts much more strongly than the raw labor share. In our preferred specification, the point estimate is -0.541 (se 0.191) when the dependent variable is the human capital share (see Table 2), but it is positive although not statistically significant when the dependent variable is the raw labor share (see Table 3). This implies that resource booms also have distributional effects among workers, potentially compressing the labor earning's distribution. We showed in Panel (a) of Figure 2 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 attenuated this trend, slowing the pace of growth of inequality.

We explore this distributional effect further in Table 4, where the dependent variable is the human capital to raw labor relative share α_{H-L}. The point estimate of our preferred specification is -0.694 (se 0.307). 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 third of the average gap which is 19 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; Fernandez et al., 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 Equations 2.17). 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. We do not have the data to corroborate if this is in fact the case, but the results open an avenue for future research.

5.2 Physical Capital

Table 5 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 -0.532 (se 0.097) and -0.587 (se 0.241). We showed in Panel (b) of Figure 2 that the physical capital share increased during the entire period, gaining close to 2.1 percentage points since 1995 (1.1 pp since 2000). Using again the 1.7 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 0.94 percentage points larger.

Finally, Table 6 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 positive, 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, so the relative effect cancels out. From the theoretical model, this result suggests there is balance in the relative intensity in which each factor is used in the tradable and natural resource sectors.

Counterfactual Exercises Figure 10 summarizes the main findings. Here we report the observed and counterfactual change of each factor income share between 2000 and 2010, the period of the boom. The counterfactual is calculated as the predicted change of the factor share if the natural resource share was fixed at the level of 2000. The red bar is the difference between observed and counterfactual change, our measure of the impact of the boom. There are three takeaways: *i*. the natural resource boom negatively affected the total labor (-0.67pp), human capital (-0.87pp), and physical capital (-0.94pp) shares, *ii*. the natural resource boom left the raw labor share unaffected, and *iii*. the natural resource boom redistributed the total labor share in favor of raw labor compensation.

5.3 Robustness Exercises

We perform several robustness checks aimed to understand the sensitivity of our estimates. Besides testing multiple fixed effects specifications for both OLS and IV estimates in Tables 1-6, we also study if our results hold with alternative measures of our variables of interest. In particular, we estimate our preferred specification using different measures for *i*. the human capital and raw labor shares, *ii*. the physical capital and natural resources shares, and *iii*. the shift-share instrument. In Tables A.3-A.5 we present the effect of the natural resource boom on each factor share using these different measures.[21] In general, we find similar results both qualitatively and quantitatively.

First, Table A.3 shows the estimates when we use the human capital and raw labor shares of Sturgill (2012). Sturgill (2012) isolates the value of the human capital and raw labor shares using returns on education estimated by Psacharopoulos and Patrinos (2004), combined with data on the share of a country's population in seven education categories taken from Barro and Lee (2013).[22] Thus, these estimates do not use microdata nor need

[21] In each robustness check we change the relevant variables by one group of measures at a time, to assure comparability with the main results.

[22] The seven education categories from Barro and Lee (2013) are: no schooling, incomplete primary, complete primary, incomplete secondary, complete secondary, incomplete higher education, and complete higher education.

any imputation or prediction method, in contrast to our measures proposed in Section 3. We find virtually identical results to our baseline estimates both in magnitude and statistical significance, for all the 6 factor shares dependent variables.

Second, one shortcoming of our methodology to separate natural resource and physical capital factor shares is that we rely on the assumption of equalized rents between types of capital. In Table A.4 we report our results using the physical capital and natural resource shares of Zuleta and Sturgill (2015) based on Weil and Wilde (2009). This alternative measures use crops and pasture land rents and mining and quarrying value added to compute the natural resource share without needing any assumption about capital rents. The results are qualitatively similar, but the magnitude is slightly larger for the labor related factor shares, while the effect on the physical capital share is lower. Although our estimated coefficients for total labor and physical capital are only marginally significant, the direction of the effects is the same.

Finally, in the estimates of Table A.5 we change the China shock used to construct the shift-share instrument. We now define the demand shock as the cumulative growth of the value imported by China of each selected product relative to 1992 (as in Figure 6 panel (a)). We also substract the value of imports by China from each country to get a cleaner measure of the exogenous component of the shock.[23] Besides some differences in the magnitude of the estimates, the first stage relevance of this alternative instrument is much lower, with an F-statistic on the excluded instrument between 6.58 and 7.65. However, even though the estimates for total labor and physical capital are again only marginally significant, the qualitative results for all factor shares are equivalent.

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 deferentially affects factor shares depending on their 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 the natural resource share 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

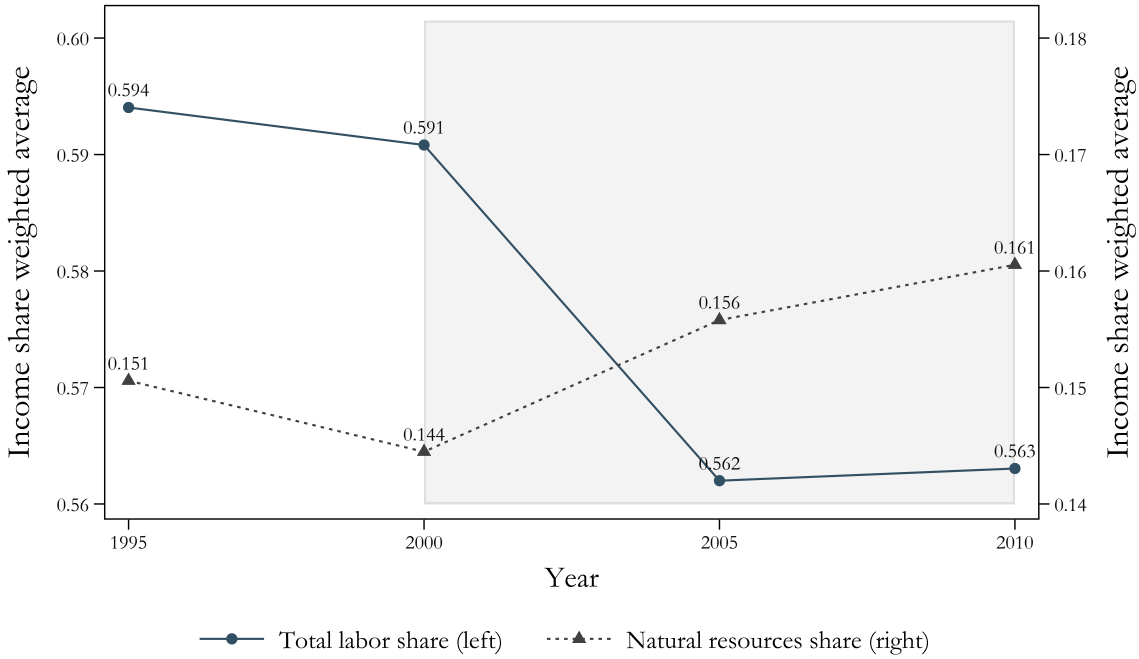
[23] In particular, we define the shock as $g_{j,t}^{-c} = \frac{(M_{j,t}-M_{j,t}^{c})-(M_{j,1992}-M_{j,1992}^{c})}{M_{j,1992}-M_{j,1992}^{c}}$, and build a leave-one-out shift-share instrument.

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 tradable sectors are relatively more intensive in labor, human capital, and physical capital than the natural resources sectors, 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 -4.0 percentage points. These estimates suggest that the natural resource boom explains nearly 25.7 percent of the global decline of 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 the total labor income share.

Figures and Tables

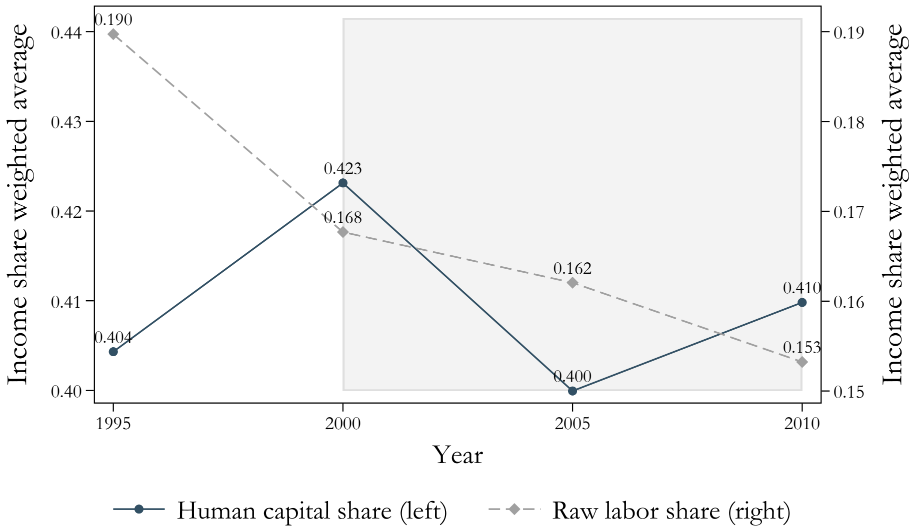
Figure 1: Declining Total Labor Share and the Rise of Natural Resources



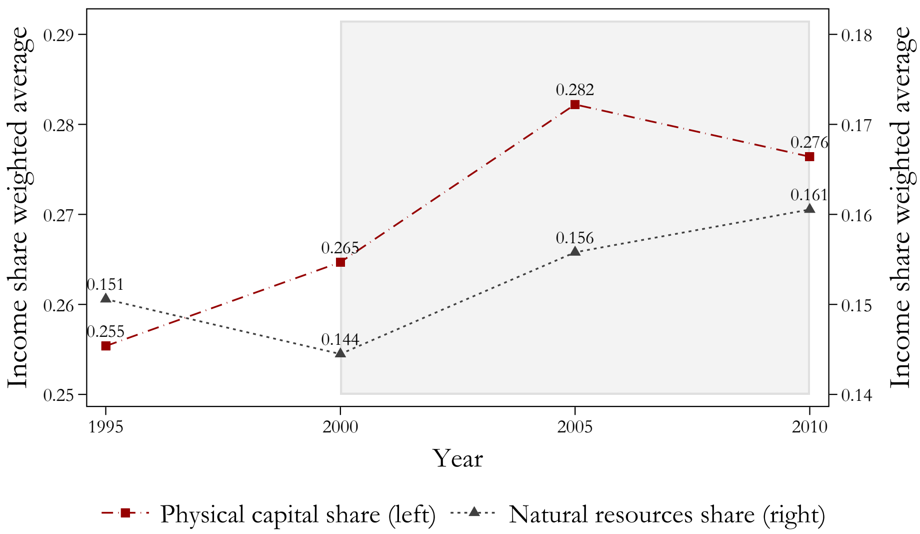
Note: The figure shows the (population-weighted) average total labor ($\alpha_{Zc,t}$) and natural resources ($\alpha_{Ec,t}$) factor income shares. Each series corresponds to the fixed effects from a regression of the factor share on country and year fixed effects. Regressions are weighted by population 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: Evolution of Factor Income Shares

(a) Labor related factor shares

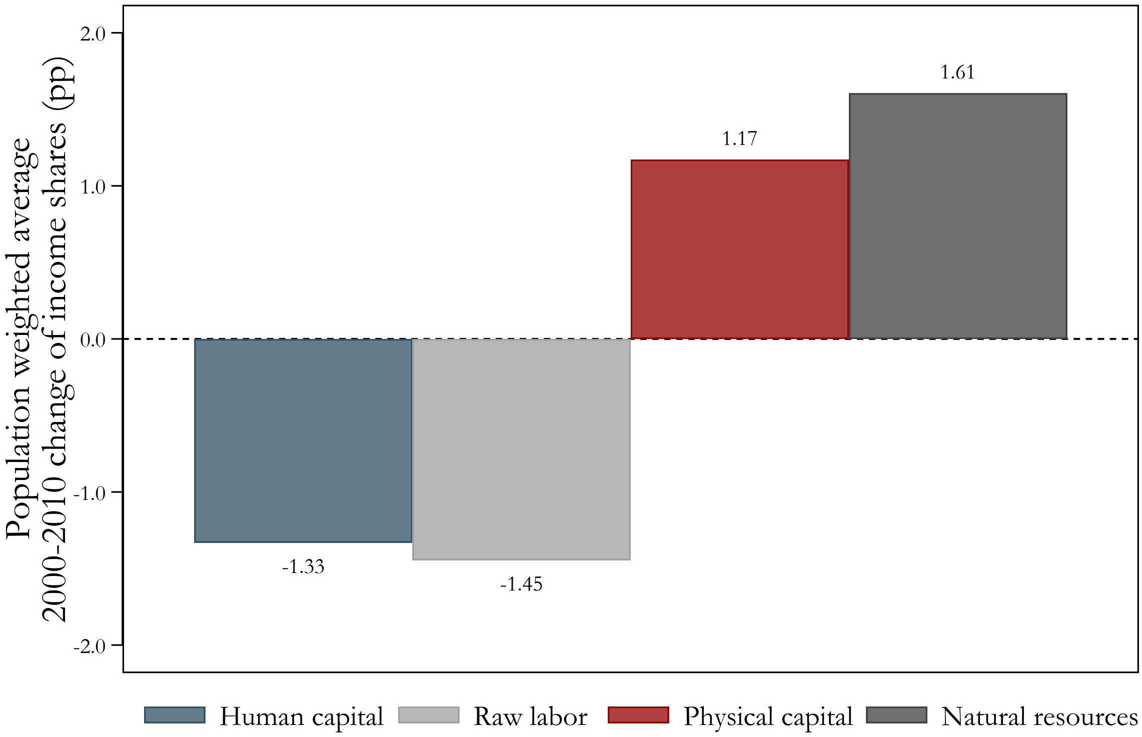


(b) Capital related factor shares



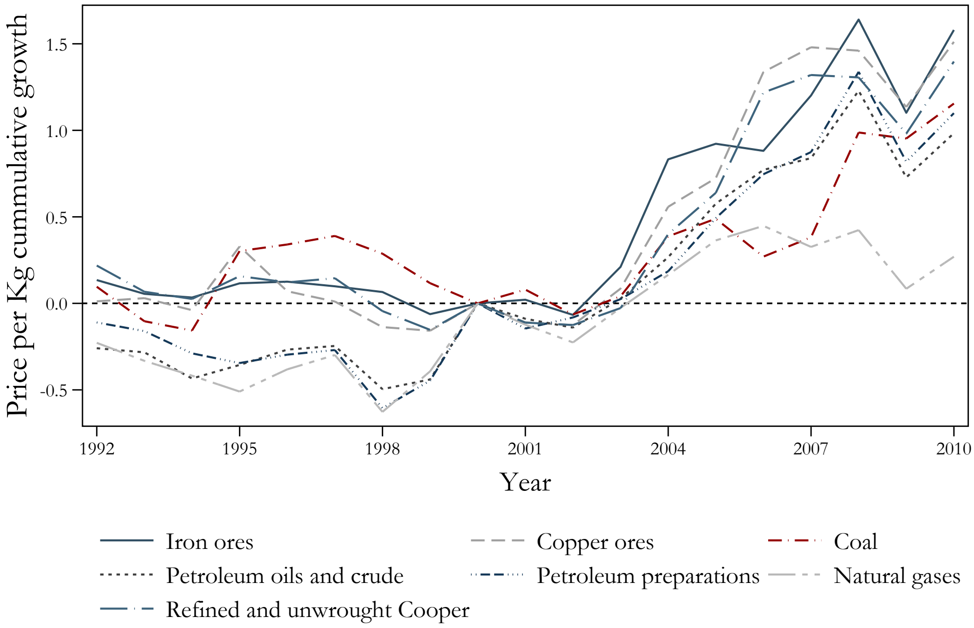
Note: The figure shows the (population-weighted) average factor income share of human capital ($\alpha_{Hc,t}$), raw labor ($\alpha_{Lc,t}$), physical capital ($\alpha_{Kc,t}$), and natural resources ($\alpha_{Ec,t}$). Each series corresponds to the fixed effects from a regression of the factor share on country and year fixed effects. Regressions are weighted by population 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 3: Changes in Factor Shares Between 2000 and 2010



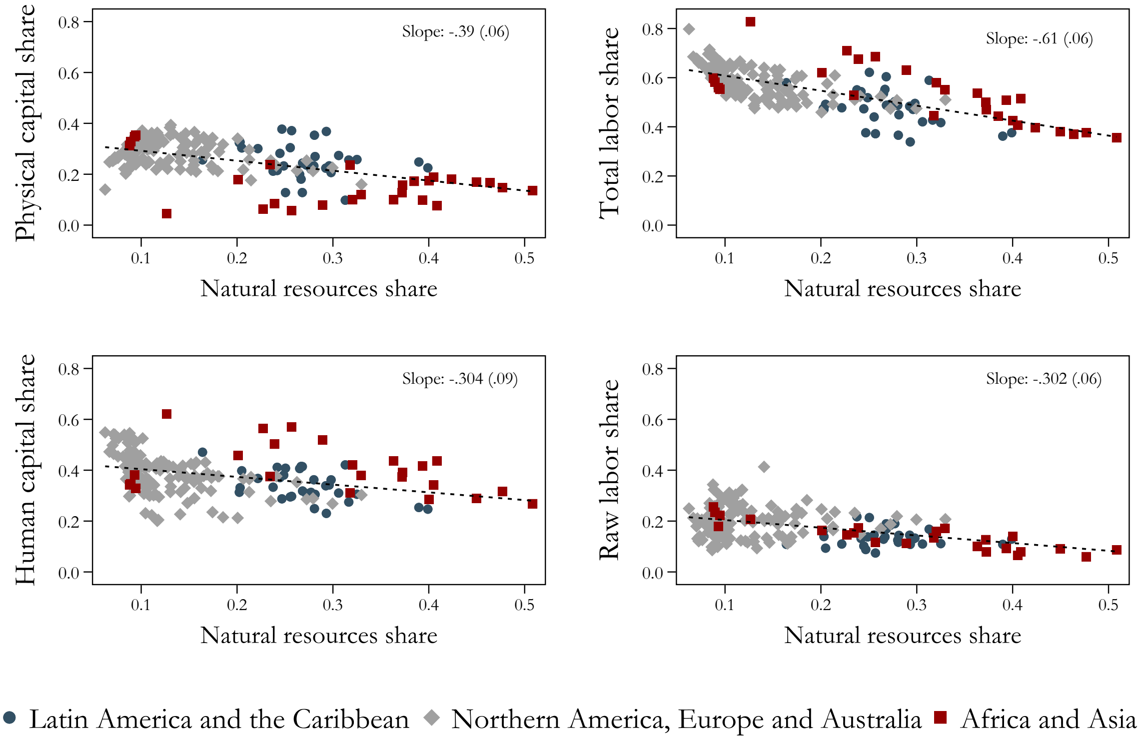
Note: The figure shows the difference in the (population-weighted) average factor income shares between 2000 and 2010. Each bar corresponds to the 2010 year fixed effect from a regression of the factor share on country and year fixed effects. Regressions are weighted by population size.

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. Price per Kg is calculated as imports value over imported quantities of China. Petroleum oils and crudes prices are transformed from litres to Kg assuming a gravity coefficient of 0.8, an approximated density of 800 kg/m^3.

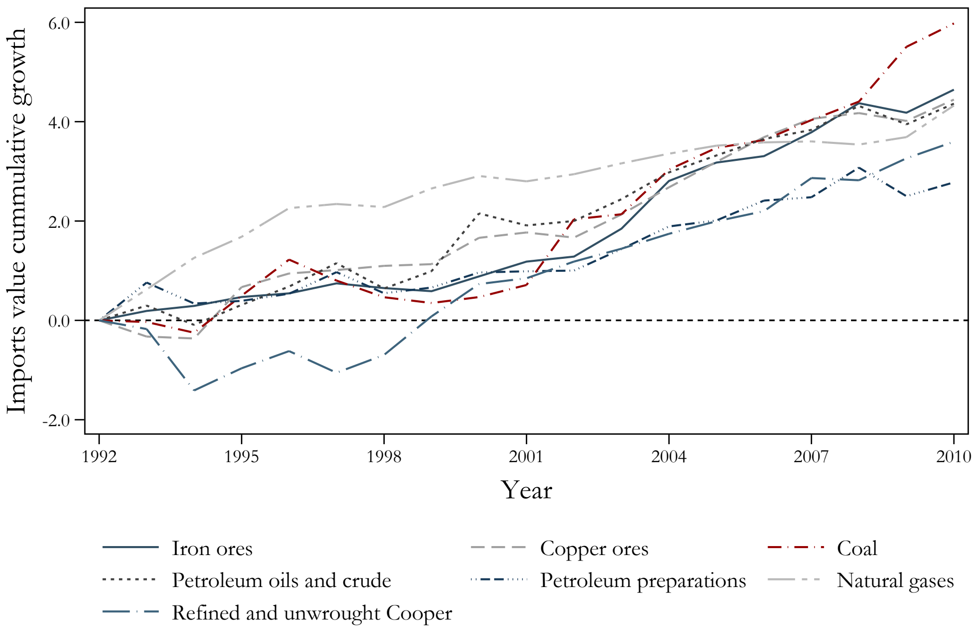
Figure 5: Correlation of the Natural Resource Share with Factor Shares



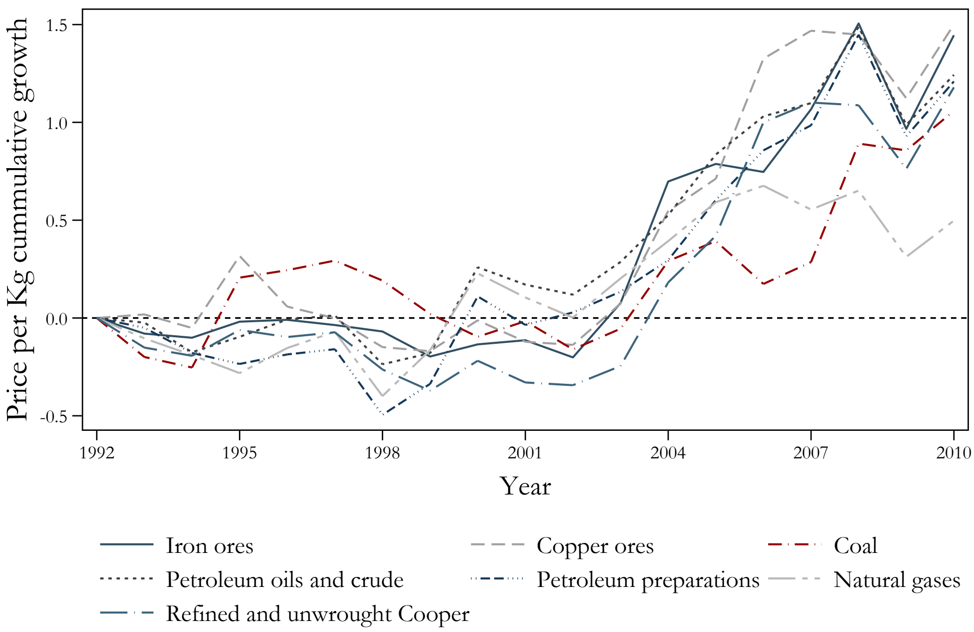
Note: The figure shows the relation between the natural resources share ($\alpha_{Ec,t}$) and the factor income shares of physical capital ($\alpha_{K,c,t}$), total labor ($\alpha_{Z,c,t}$), human capital ($\alpha_{H,c,t}$), and raw labor ($\alpha_{L,c,t}$). Each symbol corresponds to a country-year pair. The dotted line shows the slope of linear regression between the two variables.

Figure 6: China's Demand Shock

(a) Cumulative Growth of Imports by China

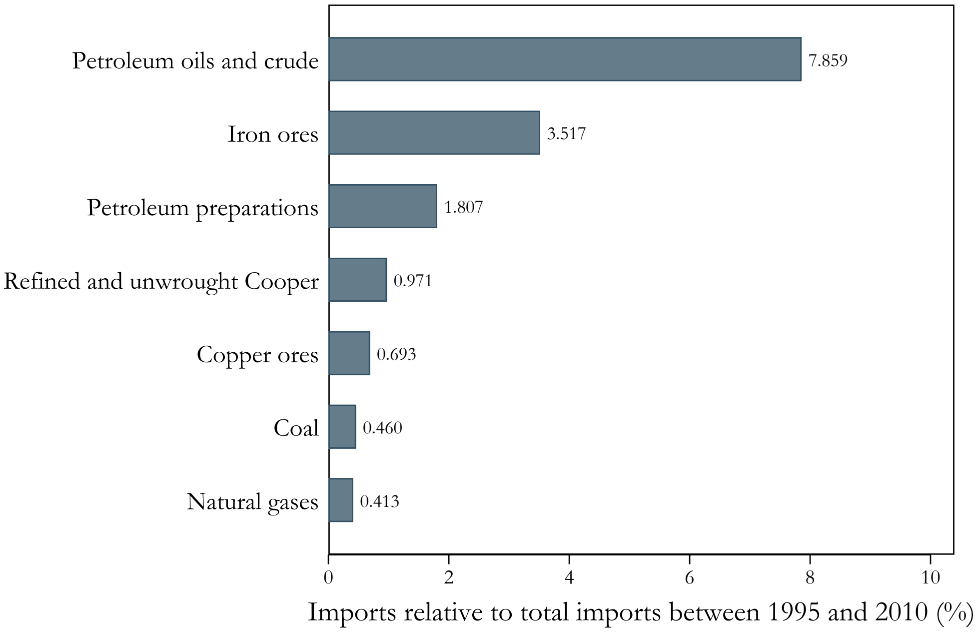


(b) Commodities Prices



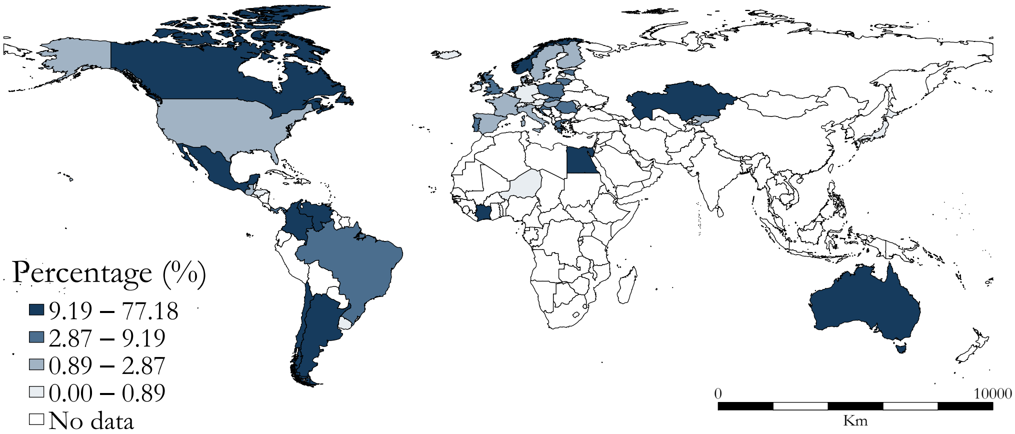
Note: Panel (a) shows the cumulative growth of the value of imports of China between 1992 and 2010 for the seven selected commodities. Panel (b) reports the cumulative growth of the price of each commodity between 1992 and 2010. Price per Kg is calculated as imports value over imported quantities of China. Petroleum oils and crudes prices are transformed from litres to Kg assuming a gravity coefficient of 0.8, an approximated density of 800 kg/m^3.

Figure 7: Share of Selected Commodities on China's Total Imports between 1995 and 2010



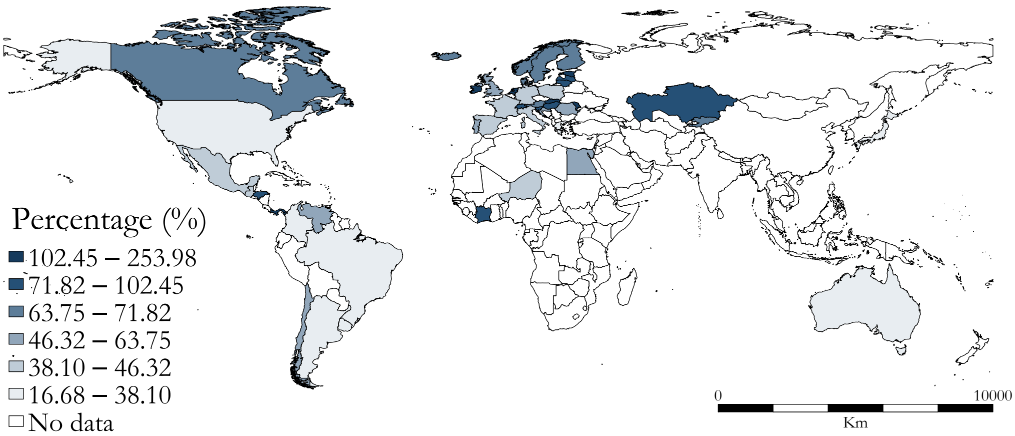
Note: The figure reports the relative importance of each commodity on China's total imports between 1995 and 2010. We measure the relative importance as the specific commodity imports value between 1995 and 2010 over the total imports value. The selected commodities belong to a subset of natural resources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

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



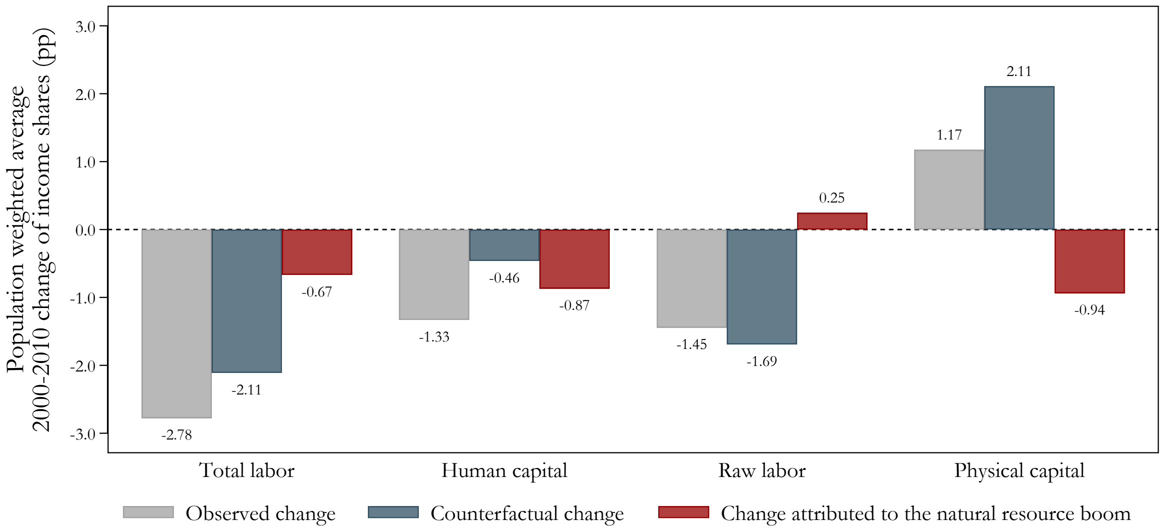
Note: The map shows the share of exports of the seven selected commodities on total exports value in 1995. We measure the exports value share as the sum of the commodities exports value in 1995 over the total exports value across products in the same year. The ranges correspond to quartiles of the export-share distribution across countries.

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 quartiles of the trade-to-GDP ratio distribution across countries.

Figure 10: Changes in Factor Shares Between 2000 and 2010: Observed and Counterfactual



Note: The figure shows the observed and counterfactual change in the (population-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 population size. The counterfactual is calculated as the predicted change of the factor share if the natural resource share was fixed at the level of 2000. We compute this change using the estimated parameters of our preferred specification (column VI of tables 1, 2, 3 and 5). The red bar is the difference between observed and counterfactual change, our measure of the impact of the boom.

Table 1: Estimates for the Impact of the Natural Resources Boom on the Total Labor Share

	Total Labor Share $\alpha_{Zc,t}$					
	OLS	IV	OLS	IV	OLS	IV
	I	II	III	IV	V	VI
Natural resources share $\alpha_{Ec,t}$	-1.124***	-0.468***	-1.235***	-0.413*	-1.099***	-0.415**
	(0.125)	(0.097)	(0.154)	(0.241)	(0.159)	(0.173)
F of excluded instruments		37.950		19.892		43.251
Observations	173	171	169	167	169	167
Countries	47	46	46	45	46	45
Country fixed effects	✓	✓	✓	✓	✓	✓
Year fixed effects	✓	✓				
Region specific time trend			✓	✓		
Income group specific time trend					✓	✓
Controls	✓	✓	✓	✓	✓	✓
Total labor share $\alpha_{Zc,t}$ mean	0.56	0.56	0.56	0.56	0.56	0.56
Total labor share $\alpha_{Zc,t}$ sd	0.09	0.09	0.09	0.09	0.09	0.09
Natural resources share $\alpha_{Ec,t}$ mean	0.18	0.17	0.18	0.17	0.17	0.17
Natural resources share $\alpha_{Ec,t}$ sd	0.10	0.10	0.10	0.10	0.10	0.09
Standardized coefficient	-0.11	-0.04	-0.12	-0.04	-0.11	-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 for the weight of China exports in total imports and baseline manufacturing value added multiplied by year fixed effects. We cluster the standard errors at the country level. Clustered standard errors in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 2: Estimates for the Impact of the Natural Resources Boom on the Human Capital Share

	Human Capital Share $\alpha_{Hc,t}$					
	OLS	IV	OLS	IV	OLS	IV
	I	II	III	IV	V	VI
Natural resources share $\alpha_{Ec,t}$	-0.864***	-0.657***	-0.871***	-0.867***	-0.782***	-0.541***
	(0.100)	(0.134)	(0.146)	(0.224)	(0.119)	(0.191)
F of excluded instruments		36.058		20.747		39.640
Observations	170	168	166	164	166	164
Countries	46	45	45	44	45	44
Country fixed effects	✓	✓	✓	✓	✓	✓
Year fixed effects	✓	✓				
Region specific time trend			✓	✓		
Income group specific time trend					✓	✓
Controls	✓	✓	✓	✓	✓	✓
Human capital share $\alpha_{Hc,t}$ mean	0.38	0.38	0.38	0.38	0.38	0.38
Human capital share $\alpha_{Hc,t}$ sd	0.08	0.08	0.08	0.08	0.08	0.08
Natural resources share $\alpha_{Ec,t}$ mean	0.17	0.17	0.17	0.17	0.17	0.16
Natural resources share $\alpha_{Ec,t}$ sd	0.09	0.09	0.09	0.09	0.09	0.09
Standardized coefficient	-0.08	-0.06	-0.08	-0.08	-0.07	-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 for the weight of China exports in total imports and baseline manufacturing value added multiplied by year fixed effects. We cluster the standard errors at the country level. Clustered standard errors in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 3: Estimates for the Impact of the Natural Resources Boom on the Raw Labor Share

	Raw Labor Share $\alpha_{Lc,t}$					
	OLS	IV	OLS	IV	OLS	IV
	I	II	III	IV	V	VI
Natural resources share $\alpha_{Ec,t}$	-0.271***	0.195	-0.372***	0.440*	-0.323***	0.153
	(0.091)	(0.165)	(0.136)	(0.264)	(0.089)	(0.165)
F of excluded instruments		36.058		20.747		39.640
Observations	170	168	166	164	166	164
Countries	46	45	45	44	45	44
Country fixed effects	✓	✓	✓	✓	✓	✓
Year fixed effects	✓	✓				
Region specific time trend			✓	✓		
Income group specific time trend					✓	✓
Controls	✓	✓	✓	✓	✓	✓
Raw labor share $\alpha_{Lc,t}$ mean	0.18	0.18	0.18	0.18	0.18	0.19
Raw labor share $\alpha_{Lc,t}$ sd	0.06	0.06	0.06	0.06	0.06	0.06
Natural resources share $\alpha_{Ec,t}$ mean	0.17	0.17	0.17	0.17	0.17	0.16
Natural resources share $\alpha_{Ec,t}$ sd	0.09	0.09	0.09	0.09	0.09	0.09
Standardized coefficient	-0.03	0.02	-0.04	0.04	-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 for the weight of China exports in total imports and baseline manufacturing value added multiplied by year fixed effects. 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: Estimates for the Impact of the Natural Resources Boom on the Human Capital to Raw Labor Relative Share

	Human Capital to Raw Labor Relative Share $\alpha_{H-Lc,t}$					
	OLS	IV	OLS	IV	OLS	IV
	I	II	III	IV	V	VI
Natural resources share $\alpha_{Ec,t}$	-0.593***	-0.851***	-0.499**	-1.307***	-0.459***	-0.694**
	(0.140)	(0.283)	(0.233)	(0.425)	(0.135)	(0.307)
F of excluded instruments		36.058		20.747		39.640
Observations	170	168	166	164	166	164
Countries	46	45	45	44	45	44
Country fixed effects	✓	✓	✓	✓	✓	✓
Year fixed effects	✓	✓				
Region specific time trend			✓	✓		
Income group specific time trend					✓	✓
Controls	✓	✓	✓	✓	✓	✓
Relative factor share $\alpha_{H-Lc,t}$ mean	0.20	0.20	0.20	0.20	0.19	0.19
Relative factor share $\alpha_{H-Lc,t}$ sd	0.12	0.12	0.12	0.12	0.12	0.12
Natural resources share $\alpha_{Ec,t}$ mean	0.17	0.17	0.17	0.17	0.17	0.16
Natural resources share $\alpha_{Ec,t}$ sd	0.09	0.09	0.09	0.09	0.09	0.09
Standardized coefficient	-0.06	-0.08	-0.05	-0.12	-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 for the weight of China exports in total imports and baseline manufacturing value added multiplied by year fixed effects. 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: Estimates for the Impact of the Natural Resources Boom on the Physical Capital Share

	Physical Capital Share $\alpha_{Kc,t}$					
	OLS	IV	OLS	IV	OLS	IV
	I	II	III	IV	V	VI
Natural resources share $\alpha_{Ec,t}$	0.124	-0.532***	0.235	-0.587**	0.099	-0.585***
	(0.125)	(0.097)	(0.154)	(0.241)	(0.159)	(0.173)
F of excluded instruments		37.950		19.892		43.251
Observations	173	171	169	167	169	167
Countries	47	46	46	45	46	45
Country fixed effects	✓	✓	✓	✓	✓	✓
Year fixed effects	✓	✓				
Region specific time trend			✓	✓		
Income group specific time trend					✓	✓
Controls	✓	✓	✓	✓	✓	✓
Physical capital share $\alpha_{Kc,t}$ mean	0.26	0.26	0.26	0.26	0.27	0.27
Physical capital share $\alpha_{Kc,t}$ sd	0.07	0.07	0.07	0.07	0.07	0.06
Natural resources share $\alpha_{Ec,t}$ mean	0.18	0.17	0.18	0.17	0.17	0.17
Natural resources share $\alpha_{Ec,t}$ sd	0.10	0.10	0.10	0.10	0.10	0.09
Standardized coefficient	0.01	-0.05	0.02	-0.06	0.01	-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 for the weight of China exports in total imports and baseline manufacturing value added multiplied by year fixed effects. 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: Estimates for the Impact of the Natural Resources Boom on the Total Labor to Physical Capital Relative Share

	Total Labor to Physical Capital Relative Share $\alpha_{Z-Kc,t}$					
	OLS	IV	OLS	IV	OLS	IV
	I	II	III	IV	V	VI
Natural resources share $\alpha_{Ec,t}$	-1.248***	0.064	-1.470***	0.173	-1.198***	0.169
	(0.251)	(0.194)	(0.307)	(0.482)	(0.318)	(0.346)
F of excluded instruments		37.950		19.892		43.251
Observations	173	171	169	167	169	167
Countries	47	46	46	45	46	45
Country fixed effects	✓	✓	✓	✓	✓	✓
Year fixed effects	✓	✓				
Region specific time trend			✓	✓		
Income group specific time trend					✓	✓
Controls	✓	✓	✓	✓	✓	✓
Relative share $\alpha_{Z-Kc,t}$ mean	0.30	0.30	0.30	0.30	0.29	0.29
Relative share $\alpha_{Z-Kc,t}$ sd	0.13	0.13	0.13	0.13	0.12	0.12
Natural resources share $\alpha_{Ec,t}$ mean	0.18	0.17	0.18	0.17	0.17	0.17
Natural resources share $\alpha_{Ec,t}$ sd	0.10	0.10	0.10	0.10	0.10	0.09
Standardized coefficient	-0.12	0.01	-0.15	0.02	-0.12	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 for the weight of China exports in total imports and baseline manufacturing value added multiplied by year fixed effects. 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 Figures and Tables

Table A.1: Changes in The Functional Distribution of Income from 2000 to 2010

	Factor Income Shares											
	Human Capital Share			Raw Labor Share			Physical Capital Share			Natural Resources Share		
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.2: First Stage: Natural Resources Share and Shift-share Instrument

	Natural Resources Share $\alpha_{Ec,t}$		
	I	II	III
Commodity prices shift-share instrument	0.228***	0.179***	0.244***
	(0.033)	(0.040)	(0.035)
F of excluded instruments	37.950	19.892	43.251
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 $\alpha_{Rc,t}$ mean	0.17	0.17	0.17
Natural resources share $\alpha_{Rc,t}$ sd	0.10	0.10	0.09
Commodity prices shift-share instrument mean	0.03	0.03	0.03
Commodity prices shift-share instrument 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 for the weight of China exports in total imports and baseline manufacturing value added multiplied by year fixed effects. We cluster the standard errors at the country level. Clustered standard errors in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.3: Robustness Check: IV Estimates for Sturgill (2012) Alternative Measures of Human Capital and Raw Labor Income Shares

	Factor Income Shares					
	Sturgill (2012) Human Capital and Raw Labor Shares					
	Total Labor $\alpha_{Zc,t}$	Human Capital $\alpha_{Hc,t}$	Raw Labor $\alpha_{Lc,t}$	Relative $\alpha_{H-Lc,t}$	Physical Capital $\alpha_{Kc,t}$	Relative $\alpha_{Z-Kc,t}$
	I	II	III	IV	V	VI
Natural resources share $\alpha_{Ec,t}$	-0.415**	-0.352***	-0.064	-0.288***	-0.585***	0.169
	(0.173)	(0.121)	(0.067)	(0.090)	(0.173)	(0.346)
F of excluded instruments	43.251	43.251	43.251	43.251	43.251	43.251
Observations	167	167	167	167	167	167
Countries	45	45	45	45	45	45
Country fixed effects	✓	✓	✓	✓	✓	✓
Income level time trend	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
Outcome factor share mean	0.56	0.38	0.19	0.19	0.27	0.29
Outcome factor share sd	0.09	0.07	0.03	0.07	0.06	0.12
Natural resources share $\alpha_{Ec,t}$ mean	0.17	0.17	0.17	0.17	0.17	0.17
Natural resources share $\alpha_{Ec,t}$ sd	0.09	0.09	0.09	0.09	0.09	0.09
Standardized coefficient	-0.04	-0.03	-0.01	-0.03	-0.06	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 for the weight of China exports in total imports and baseline manufacturing value added multiplied by year fixed effects. We cluster the standard errors at the country level. Clustered standard errors in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.4: Robustness Check: IV Estimates for Zuleta and Sturgill (2015) based on Weil and Wilde (2009) Alternative Measures of Natural Resources and Physical Capital Income Shares

	Factor Income Shares					
	Total Labor $\alpha_{Zc,t}$	Human Capital $\alpha_{Hc,t}$	Raw Labor $\alpha_{Lc,t}$	Relative $\alpha_{H-Lc,t}$	Physical Capital $\alpha_{Kc,t}$	Relative $\alpha_{Z-Kc,t}$
	I	II	III	IV	V	VI
Natural resources share $\alpha_{Ec,t}$ Weil and Wilde (2009)	-0.652	-0.817**	0.216	-1.034*	-0.348	-0.303
	(0.417)	(0.398)	(0.276)	(0.538)	(0.417)	(0.833)
F of excluded instruments	3.076	2.800	2.800	2.800	3.076	3.076
Observations	162	159	159	159	162	162
Countries	44	43	43	43	44	44
Country fixed effects	✓	✓	✓	✓	✓	✓
Income level time trend	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
Outcome factor share mean	0.56	0.38	0.19	0.19	0.29	0.28
Outcome factor share sd	0.08	0.08	0.06	0.12	0.06	0.13
Natural resources share $\alpha_{Ec,t}$ mean	0.15	0.15	0.15	0.15	0.15	0.15
Natural resources share $\alpha_{Ec,t}$ sd	0.08	0.07	0.07	0.07	0.08	0.08
Standardized coefficient	-0.05	-0.06	0.02	-0.07	-0.03	-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 for the weight of China exports in total imports and baseline manufacturing value added multiplied by year fixed effects. We cluster the standard errors at the country level. Clustered standard errors in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.5: Robustness Check: IV Estimates for Alternative Shift-share Instrument using China's Trade Value as Shock

	Factor Income Shares					
	Total Labor $\alpha_{Zc,t}$	Human Capital $\alpha_{Hc,t}$	Raw Labor $\alpha_{Lc,t}$	Relative $\alpha_{H-Lc,t}$	Physical Capital $\alpha_{Kc,t}$	Relative $\alpha_{Z-Kc,t}$
	I	II	III	IV	V	VI
Natural resources share $\alpha_{Ec,t}$	-0.550	-0.889**	0.386	-1.275*	-0.450	-0.100
	(0.341)	(0.398)	(0.423)	(0.726)	(0.341)	(0.682)
F of excluded instruments	7.647	6.581	6.581	6.581	7.647	7.647
Observations	167	164	164	164	167	167
Countries	45	44	44	44	45	45
Country fixed effects	✓	✓	✓	✓	✓	✓
Income level time trend	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
Outcome factor share mean	0.56	0.38	0.19	0.19	0.27	0.29
Outcome factor share sd	0.09	0.08	0.06	0.12	0.06	0.12
Natural resources share $\alpha_{Ec,t}$ mean	0.17	0.16	0.16	0.16	0.17	0.17
Natural resources share $\alpha_{Ec,t}$ sd	0.09	0.09	0.09	0.09	0.09	0.09
Standardized coefficient	-0.05	-0.08	0.03	-0.11	-0.04	-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 for the weight of China exports in total imports and baseline manufacturing value added multiplied by year fixed effects. The shift-share instrument shock is calculated as the cumulative growth of the value imported by China of each selected product relative to 1992. We also substract the value of imports by China from each country to get a cleaner measure of the exogenous component of the shock. We cluster the standard errors at the country level. Clustered standard errors in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

B Details on Data and Measurement

This Appendix presents and discusses more details on 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 intuition and empirical applications of the estimation, imputation, and prediction of the raw labor share of wages of section 3.

B.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 its earnings thanks to the returns to skills.

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 comprise 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.[24] 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.

B.2 Imputation: Insufficient Microdata

When estimating the regression of Equation 3.3, we lose every country-year pair in he 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 the estimated values suggest that accrues to raw labor.

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 15.31st 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.

B.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 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 missing raw labor share of wages with a Gradient Boosting Machines (GBM) algorithm

[24]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.

(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.[25]

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.

[25]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.