Windfalls, Structural Transformation and Specialization[1]

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Abstract

Macro cross-country data and micro US county data indicate that resource rich regions have *small and productive manufacturing* sectors and *large and unproductive non-manufacturing* sectors. We suggest a process of specialization to explain these facts. Windfall revenue induces labor to move from the (traded) manufacturing sector to the (non-traded) non-manufacturing sector. A self selection of workers takes place. Only those most skilled in manufacturing sector work remain in manufacturing. Workers that move to non-manufacturing however, will be less skilled at non-manufacturing sector work than those who were already employed there. Resource induced structural transformation thus results in higher productivity in manufacturing and lower productivity in non-manufacturing. We construct and calibrate a two sector, open economy model of self-selection and show that exogenous cross-country variation in natural resource endowments is large enough to explain the direction and magnitude of sectoral employment and productivity differences between resource rich and resource poor regions. The model implies that low aggregate productivity found in some resource rich countries is *not caused* by a resource induced decline of a relatively productive manufacturing sector. Rather, the higher manufacturing productivity in those countries is a *consequence* of manufacturing's smaller size.

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1 Introduction

Growth accounting exercises suggest that differences in sectoral employment and productivity may be important in explaining differences in aggregate productivity between resource rich and resource poor countries. Table 1 shows a stylized example of resource rich Saudi Arabia and resource poor Germany. It depicts employment shares and three measures of (relative) sectoral productivity in manufacturing and non-manufacturing.[2] Although Germany has higher *levels* of labor productivity in both sectors, relative to aggregate productivity, Saudi Arabia is 154% more productive in (non-resource) manufacturing than Germany. Despite this, Saudi Arabia employs proportionally 69% less workers in manufacturing and instead employs 20% *more* workers in non-manufacturing, where its productivity is 12% lower then Germany's. Saudi Arabia thus has a comparatively *small and productive* manufacturing sector and a *large and unproductive* non-manufacturing sector. If the share of labor in manufacturing in Saudi Arabia were hypothetically raised to that of Germany, 26% of aggregate labor productivity differences between Germany and Saudi Arabia would be eliminated. This suggests that understanding differences in sectoral productivity may, in principal, be important to explaining why some resource rich countries are "cursed" with lower income.[3]

	Output/	Emp. Share		Lab. Prod.		TFP (k)		TFP (k,h)	
	worker	NM	M	NM	M	NM	M	NM	M
Saudi Arabia	36,785	93%	7%	0.90	2.38	0.88	2.36	0.88	2.35
Germany	68,634	78%	22%	1.02	0.94	0.93	1.46	0.93	1.43
Ratio	0.66	1.20	0.31	0.88	2.54	0.94	1.62	0.95	1.64

Table 1: Output per worker, sectoral employment and three measures of sectoral productivity (relative to each country's aggregate productivity) for Saudi Arabia and Germany, 2006. (Source: see Section 2)

We investigate the impact of structural transformation in open economies on sectoral and aggregate productivity through a process of specialization. Structural transformation is a reallocation of labor across sectors. Whilst there are potentially many sources of structural transformation,[4] we focus on labor reallocation in countries facing a windfall of revenue. Furthermore, we concentrate only on windfall revenue arising from the export of natural resources (fuels, ores and metals), although - in principle - our entire analysis is applicable to other types of windfalls.[5]

[2] These are: labor productivity, TFP that controls for physical capital and TFP that controls for physical and human capital. Sectoral productivity is shown *relative* to aggregate productivity. Manufacturing excludes mining and utilities. Construction details are given later.

[3] For a review of the literature on the resource curse, see Stevens (2003) and van der Ploeg (2010).

[4] Gollin et al. (2002), Duarte and Restuccia (2010), Rogerson (2008), Dekle and Vandenbroucke (2011) and Yi and Zhang (2010), for instance, focus on labor reallocation induced by non-homotheticities in agriculture.

[5] These can include foreign aid, migrant remittances, EU structural funds or war reparations.

We begin by showing the robustness of the above facts. Using both macro cross country and micro US county level data we show evidence that resource rich regions: 1) have small manufacturing and large non-manufacturing sectors and are 2) more productive in manufacturing and less productive in non-manufacturing than resource poor regions. The first fact is relatively well known and is in line with theoretical predictions,[6] the second fact is novel and we show that standard models are ill-equipped to replicate it.

Next, we provide a mechanism that explains the above asymmetric productivity differences (Fact 2) as a consequence of windfall induced labor reallocation (Fact 1). We construct a two sector, general equilibrium, open economy model of self selection, in the spirit of Lagakos and Waugh (2010), Roy (1951) and Lucas (1978). The basic assumptions of the model are that manufacturing goods are traded, whilst non-manufacturing goods are non-traded and that agents have endowments of sector specific skills. A windfall of revenue increases demand for both types of goods. Whilst higher demand for manufacturing goods can be satiated by imports, workers need to move to the non-manufacturing sector in order to meet the higher demand for locally produced non-manufacturing goods. This outflow of workers from manufacturing is accompanied by a process of self-selection. Workers that choose to remain in manufacturing are those who are most skilled at manufacturing sector work, which leads to a more specialized and more productive manufacturing sector. Those who move, do so only in response to higher demand generated by the windfall and are hence less skilled than the workers already employed in non-manufacturing, which leads to a de-specialization of that sector and a decline in its productivity. Windfalls thus induce labor reallocation which in turn can generate asymmetric changes in sectoral productivity.

The model is then calibrated to test whether the exogenous variation in endowments of natural resources is large enough to explain the observed shifts in employment across sectors and whether those shifts are significant enough to generate the large, asymmetric differences in sectoral productivity observed in the data. We find the model does remarkably well in explaining differences in both employment and in sectoral productivity across countries. Finally, we take advantage of inherent and exogenous skill differences in manufacturing and non-manufacturing sector tasks between men and women[7] to provide micro level evidence in support of our specialization mechanism.

The model has important implications for understanding the role of economic structure as a driver of aggregate productivity differences between resource rich and resource poor regions. In contrast to growth accounting exercises, it suggests that low aggregate productivity found in many resource rich countries is *not* caused by a resource induced decline of a highly productive

[6] See for instance, Corden and Neary (1982), Matsuyama (1992) or Michaels (2009) for theoretical and empirical treatments of this so-called Dutch Disease.

[7] See for example, Galor and Weil (1996), Galor and Weil (1999) and Fan and Lui (2003).

manufacturing sector. Rather, it is precisely the small size of manufacturing in resource rich countries that is responsible for that sector's above average productivity. Policies aimed at increasing aggregate productivity in resource rich countries by encouraging workers to move towards more productive manufacturing, would largely be self defeating. As the size of the manufacturing sector increases, more unskilled workers flow in and cause sectoral productivity to fall, leaving aggregate productivity unchanged. As such, our theory supports arguments by Robinson et al. (2006), van der Ploeg (2010) and others that explanations of the resource curse should be sought outside economic structure perhaps - as they suggest - in areas such as political economy, weak institutions or property rights.

Section 2 introduces the macro and micro data used in this study and establishes the productivity and employment facts. Section 3 then introduces a general version of our model, whilst sections 4 and 5 consider the role of heterogeneity in our framework. Sections 6 and 7 present our calibration and results, whilst section 8 presents direct evidence in support of our mechanism. In section 9, we present a number of possible alternative mechanism, some extensions and a general discussion. Finally, we conclude in section 10.

2 Data and Facts

In our analysis we divide economies into mining and utilities (MU), manufacturing (M) and non-resource non-manufacturing (NM) sectors:[8]

$$\text{Total Economy} = \overbrace{\underbrace{A + C + S}_{\text{Non Res. Non-Mfg.}} + \underbrace{M}_{\text{Mfg.}}}^{\text{Non-Resource Economy}} + \underbrace{MU}_{\text{Mining and Utilities}}. \tag{1}$$

Furthermore, we focus only on the productivity and employment structure of the non-resource economy.[9] In the following two subsections we construct measures of employment shares and productivity in manufacturing and non-resource non-manufacturing and show how they vary with measures of resource wealth. In particular, we use a panel of cross country macro data as well as a cross section of US county level data to establish that resource rich regions have small and productive manufacturing sectors and large and unproductive non-manufacturing sectors.

[8] The lowest level of aggregation available for all data is the one sector ISIC classification. NM here is defined as the sum of agriculture (A), construction (C) and services (S).

[9] Thus, when we refer to aggregate productivity or sectoral employment share, we always mean aggregate productivity of the *non-resource* economy or sectoral employment relative to *non-resource* employment.

2.1 Macro Data and Facts

Data We construct three residual measures of productivity, A_s, B_s and D_s, from the following production functions:

$$
\begin{aligned}
Y_s &= A_s L_s && (2)\\
Y_s &= B_s (K_s)^{\alpha_s} (L_s)^{1-\alpha_s} && (3)\\
Y_s &= D_s (K_s)^{\alpha_s} (h_s L_s)^{1-\alpha_s} && (4)
\end{aligned}
$$

where Y_s is sector s's value added, L_s is sectoral employment, K_s is sectoral physical capital and h_s is average sectoral human capital, so that $h_s L_s$ is the 'quality adjusted' workforce.[10] Constant price sectoral value added data comes from the UN, and is adjusted to control for cross-country sectoral price level differences using the World Bank's 2005 International Comparison Program (ICP) price data. Employment data comes from the ILO and physical capital is constructed using the perpetual inventory method from the PWT. We follow Caselli (2005) in constructing aggregate human capital from the Barro and Lee (2010) education data set and in constructing sectoral physical capital. Finally, due to lack of data, we assume that the ratio of human capital between any two sectors is constant across countries and time and equal to the corresponding ratio in the US and that labor shares in the last two measures of productivity, $1 - \alpha_s$, are identical across countries, constant over time and equal to OECD averages. For details of construction, see Appendix 11.

In principle, each subsequent measure of TFP is better than the last, since it controls for a greater variety of factor inputs. In practice, each measure requires additional data that is often hard to come by and as such has to be estimated. Considering all three measures gives a better overall picture of sectoral productivity. Lastly, we follow Sachs and Warner (2001) in defining natural resource "wealth" as the ratio of exports of natural resources (fuels, ores and metals) to GDP using WDI data.

In our baseline sample, we consider a panel of the 120 richest countries for the 1980-2006 period.[11] We keep all country-date points for which we have all necessary data and those that do not deviate significantly across different data sources. This leaves us with a total of 46 countries in our sample. On average, there are 18 observations for each country, 29 observations for each year and a total of 806 data points. For countries in the sample and summary statistics, see Appendix 11. In Appendix 12.1, we re-do all our empirical work with a full (and much larger) sample of countries and find that all subsequent results hold.

[10] We also refer to A, B and D as the corresponding measures of aggregate (non-resource) productivity.

[11] We focus on richer countries for three reasons: First, we are examining more disaggregate data than is standard so data quality in poorer countries is a serious concern. Second, we feel that the mechanism of specialization described later may play a more prominent role in richer countries. Finally, focusing on richer countries may avoid the worst of unobserved cross country heterogeneity. Since this procedure may in principle result in unobserved selection bias, in Appendix 12.1 we show that results are independent of this cutoff.

	E Res./ GDP	Output/ worker	Emp. Share NM	M	LP (A_s) NM	M	TFP (B_s) NM	M	TFP (D_s) NM	M
10^{th}%-ile	0.19	41,042	0.86	0.14	1.01	1.04	0.94	1.44	0.94	1.42
90^{th}%-ile	0.00	49,601	0.79	0.21	1.08	0.72	0.99	1.10	0.99	1.07
$10^{th}/90^{th}$			1.09	0.66	0.93	1.43	0.95	1.31	0.95	1.32

Table 2: Resource export share, output per worker, sectoral employment and three measures of sectoral productivity (relative to aggregate productivity) for top and bottom 10% of natural resource exporters.Data for 46 countries, for 1980-2006. (Source: see Section 2)

Facts Table 2 shows summary results for the macro data by comparing the largest 10 percent of natural resource exporters with the smallest 10 percent. From the table we see that resource rich countries: 1) employ proportionally 34% less workers in manufacturing and 9% more workers in (non-resource) non-manufacturing than resource poor countries and 2) that they are 31%-43% more productive in manufacturing and 5-7% less productive in non-manufacturing (relative to aggregate productivity) than resource poor countries. Finally, notice that the change in productivity in manufacturing is far larger than the change in non-manufacturing. In Appendix 12.1, we show the robustness and statistical significance of these results.

Discussion A skeptical reader may ask what statistical or other issues could be driving apparent productivity effects. The first concern is our sectoral prices constructed to control for variation in price levels across countries. Although the ICP study is especially built to provide accurate cross-country measures of price differences, it does have some well known limitations. For our purposes, the main objection is that expenditures are valued at the actual transaction prices paid by purchasers and hence may include delivery charges and any taxes payable (or subsidies received) on purchased products. This may be an issue if taxes/subsidies vary systematically with resource wealth. We recognize this fact, but our hands are tied for lack of better data. Later in the paper, we use a simple version of our model to show that to account for observed productivity differences unrealistically large subsidies would be necessary. Finally, notice that this re-basing is not driving our results and we see similar productivity differences when value added is left in constant US dollars.

Second, since we look at more disaggregated data than is usual there is an issue of data quality across countries. We have tried to deal with this in our baseline sample by only considering data that matches across different sources and restricting our sample to richer countries.

Third, is our potential failure to account for important sources of unobserved cross-country heterogeneity. We try to eliminate some of this heterogeneity by considering only richer countries and controlling for aggregate income and aggregate productivity levels, however there could still be some factors we are not capturing.

Finally, it is difficult to know to what extent our productivity differences are driven by resource abundant economies having capital intensive resource processing sectors. Since we do not have disaggregated manufacturing data at the cross-country level, it seems difficult to address this issue with our macro data.

For all these reasons, in the following section, we repeat our empirical exercise at the micro county level in the US, using exogenous variation in oil endowments across counties to show that the facts found at the macro level are robust and hold at the micro level. Differences in price levels should not be an issue across counties. The data we use will also be of better quality and since neighboring counties are often very similar, we manage to remove much unobserved heterogeneity. Finally, and most importantly, using US data allows us to disaggregate manufacturing and show that our facts are not driven by the resource processing sectors.

2.2 Micro Data and Facts

Data Since we do not have county level data on GDP and natural resource exports, we use an alternate measure of resource wealth proposed by Michaels (2009). We define a county as oil rich if it lies above an oil field which has an ultimate oil recovery exceeding 100 million barrels. Given this classification there are three main groups of oil rich counties in the US located in Alaska, California and the US South. We restrict our analysis entirely to the third region, since Alaska and California are divided in to a few, very large counties with almost all oil located in a single county, making comparisons difficult. Counties in the South however are small, evenly distributed and oil can be found in a large fraction of them. To minimize the chance of unobserved heterogeneity driving our results, we choose control counties that lie within 200 miles of the oil rich counties. The counties in our sample can be seen in Figure 4 in Appendix 11.

We calculate sectoral labor productivity as a county's average sectoral hourly wage, which we determine using 1980 US state census data from IPUMS (Ruggles et al., 2008). We use 1980 data, since it is the latest year to provide detailed geographic identifiers that can be mapped to our oil data. Unfortunately the IPUMS data are more coarsely aggregated than the county level, only identifying which county group (rather than a particular county) each individual resides in. As such, we define a county group as oil rich if it has at least one oil rich county. We then calculate the sectoral employment and labor productivity (measured as the hourly wage) of each county group. Our final sample contains 184 county groups, 75 of which are oil rich. For details of construction see Appendix 11.

	Ave. Wage	Emp. Share NM	M	Lab. Prod. NM	M
Oil rich	7.21	75%	25%	0.98	1.06
Oil poor	7.02	73%	27%	1.00	1.01
OR/OP		1.03	0.93	0.98	1.06

Table 3: Employment shares and labor productivity (relative to aggregate productivity) for manufacturing and non-manufacturing in oil rich/poor counties in the US South in 1980 (Source: IPUMS).

Facts Next, we confirm our macro findings at the micro level. Table 3 shows summary statistics for sectoral employment and productivity (relative to aggregate productivity) in oil rich and oil poor counties in the US South. First, oil rich counties have smaller manufacturing sectors and larger non-manufacturing sectors than oil poor counties (7% smaller and 3% larger respectively). Second, oil rich counties are 6% more productive in manufacturing and 2% less productive in non-manufacturing than oil poor counties.[12] The IPUMS data also allows us to disaggregate manufacturing and show that resource processing industries are not driving higher productivity in manufacturing in resource rich counties. In Appendix 12.2 we show that between 70% and 75% of manufacturing sub-sectors in resource rich counties are smaller and more productive than the same sectors in resource poor counties. Thus, our macro findings seem to hold at the micro level and the micro data indicates that our facts are not driven by resource processing industries. Since counties also tend to be far less heterogenous than countries, the data tends to be of far better quality and we avoid data construction issues by considering a very simple measure of productivity, the micro data gives us greater confidence in our macro results. In the following section we turn to a model that can explain the employment and productivity facts established above. In Appendix 12.2 we show the robustness and statistical significance of these results.

3 Model

In this section we introduce a small, open, multi-sector economy with heterogenous agents that can account for the observed facts in productivity and employment. There are three goods in the economy: manufacturing goods (m), non-manufacturing (predominantly service) goods (s) and a windfall good which, for brevity, we will refer to as oil but could equally well be any other natural resource or alternative source of windfall revenue. We assume that manufacturing

[12] Although quantitatively these differences are smaller than before, it is important to note that the micro data is not directly comparable to the macro data, since we use a different measure of resource wealth. It is also likely that endowments of oil (and hence revenues from oil) in the US are significantly smaller than in the largest international oil exporters.

and oil are traded internationally whilst non-manufacturing is assumed to be non-traded. Oil is assumed to be an endowment good that is not used locally but only exported abroad (and thus serves as a windfall of income), whilst manufacturing and non-manufacturing goods can be produced locally using labor but no oil.

Households Suppose there is a measure one of agents, indexed by i. Preferences are given by:

$$\left((c_s^i)^{\frac{\sigma-1}{\sigma}} + \nu(c_m^i)^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}, \tag{5}$$

Each agent in the economy is assumed to have a vector of innate sector specific skills, $\{z_s^i, z_m^i\}$, representing the efficiency of one unit of their labor in non-manufacturing (s) and the manufacturing (m) sectors. Endowments of skills $\{z_s^i, z_m^i\}$ are exogenous and are assumed to be randomly drawn from a distribution common to the whole population $G(z_s, z_m)$. Since skills are assumed to be perfectly observable, agents earn a wage income, w^i. The agent is also endowed with a resource tree that provides a stream of O units of oil each period. Oil is not directly used by the agent but is exported and provides windfall revenues. The budget constraint of the agent is given by:

$$p_s c_s^i + c_m^i \leq w^i + p_o O, \tag{6}$$

where, p_s is the relative price of non-manufacturing goods and p_o is the relative price of oil determined on international markets. Traded manufacturing goods are taken as numeraire.

Production We assume a competitive market in both sectors so that each worker gets paid his marginal product. The output of worker i in sector k is given by $Y_k^i = Az_k^i$, where A is aggregate (potentially sector specific) efficiency and z_k^i is the worker's sector specific productivity. Aggregate output in sector k is given by:

$$Y_k \equiv \int_{i\in\Omega^k} Y_k^i di = A\tilde{L}_k, \tag{7}$$

where Ω^k as the set of agents electing to work in sector k and $\tilde{L}_k \equiv \int_{i\in\Omega^k} z_k^i di$ represents the total effective labor units employed in sector $k = s, m$

Trade It is assumed that manufacturing goods and oil are traded whilst non-manufacturing goods are not traded. In order to close the model, we assume a period-by-period balanced budget constraint given by:

$$m - p_o O = 0, \tag{8}$$

where, m is the value of imported traded goods (recall that traded goods are numeraire). Thus, in the above setup, all oil endowments are exported in exchange for manufacturing imports. A country with no oil (i.e. $p_o O = 0$) is thus assumed to be closed to trade.

Market Clearing Market clearing conditions for manufacturing, non-manufacturing and labor are given by:

$$\int_{i\in\Omega} c_m^i dGi = Y_m + m \text{ and } \int_{i\in\Omega} c_s^i dGi = Y_s \text{ and } \tilde{L}_m + \tilde{L}_s = 1 \tag{9}$$

where $\Omega = \Omega^m \bigcup \Omega^s$.

Competitive Equilibrium For each price of oil, p_o, and endowment of oil O, an equilibrium in the above economy consists of a relative price of non-manufacturing goods, p_s, agent-specific wages w^i and allocations for all agents and firms so that labor and output markets clear and trade remains balanced, period by period.

Solution Each firm chooses a non-negative quantity of both types of labor to hire and, due to perfect competition, offers the following wage schedule:

$$w_m^i = Az_m^i \text{ and } w_s^i = p_s Az_s^i \tag{10}$$

in manufacturing and non-manufacturing sectors respectively. Each consumer chooses to work in the sector that provides a higher wage. The wage for each consumer is thus given by, $w^i = \max\{w_s^i, w_m^i\} = \max\{p_s Az_s^i, Az_m^i\}$. This gives rise to the following simple cut-off rule: a worker i will work in non-manufacturing if and only if

$$p_s > \frac{z_m^i}{z_s^i}. \tag{11}$$

Agents take as given prices and the wage offers resulting from the firm's problems (and hence the above decision rules). Having picked their specialization, they then proceed to maximize (5) subject to (6), which results in the following demands of each agent:

$$c_s^i = \frac{(w^i + p_o O)}{p_s + \nu^\sigma p_s^\sigma} \text{ and } c_m^i = \frac{\nu^\sigma p_s^\sigma (w^i + p_o O)}{p_s + \nu^\sigma p_s^\sigma}. \tag{12}$$

Using the goods market clearing conditions in equation (9) and the demands of each agent from equations (12), we can show that:

$$\nu^\sigma p_s^\sigma Y_s = Y_m + p_o O \tag{13}$$

Substituting (7) into (13), provides an implicit expression for p_s as a function of the value of oil endowment, $p_o O$.[13]

[13] Notice that we have assumed that windfall income gets distributed evenly across agents. This assumption plays no role in our results since equation (13) (and hence the equilibrium price and cutoff condition) hold regardless of how windfalls are distributed.

4 Homogenous Workers

To demonstrate the impact of windfalls on labor reallocation from manufacturing to non-manufacturing in the above model, we shut down the heterogeneity of agents in this section and assume that the skill distribution G is degenerate and given by $\{z_s^i, z_m^i\} = \{1, 1\}$ for each worker $i \in [0, 1]$. Agents are thus homogenous and have the same skills across both sectors. The production function in each sector $k = s, m$ is then given by: $Y_k = AL_k$, where L_k is sector k employment.[14] We choose to focus on mixed equilibria where the economy produces goods from both sectors. This imposes that wage offers (and hence wages) are equalized across sectors so that $w = w_s^i = w_m^i = A$ and $p_s = 1$.[15] From equation (13), labor allocations that clear markets are then given by:

$$L_s = \frac{1}{1+\nu^\sigma}\left(1 + \frac{p_o O}{A}\right) \text{ and } L_m = \frac{1}{1+\nu^\sigma}\left(\nu^\sigma - \frac{p_o O}{A}\right). \tag{14}$$

Economies with larger windfalls, will devote a larger proportion of their labor force to the (non-traded) non-manufacturing sector than identical countries without windfalls. From equation (12), observe that windfalls generate a higher demand for both traded and non-traded goods. Whilst, (traded) manufacturing goods can be purchased on international markets, higher demand for (non-traded) non-manufacturing goods must be satiated locally. This pulls workers from the manufacturing sector into the non-manufacturing sector. Higher endowments of oil thus act in the same way as non-homothetic preferences by causing labor to shift from one sector to another.[16] With homogeneity however, the reallocation of workers has no impact on sectoral productivity. In particular, in the model, constant price sectoral productivity is given by: $\frac{Y_s}{L_s} = \frac{\bar{p}_s AL_s}{L_s} = \bar{p}_s A = A$ in the non-manufacturing sector and by: $\frac{Y_m}{L_m} = \frac{AL_m}{L_m} = A$ in the manufacturing sector and remains constant as endowments of resources change.

5 Heterogenous Workers

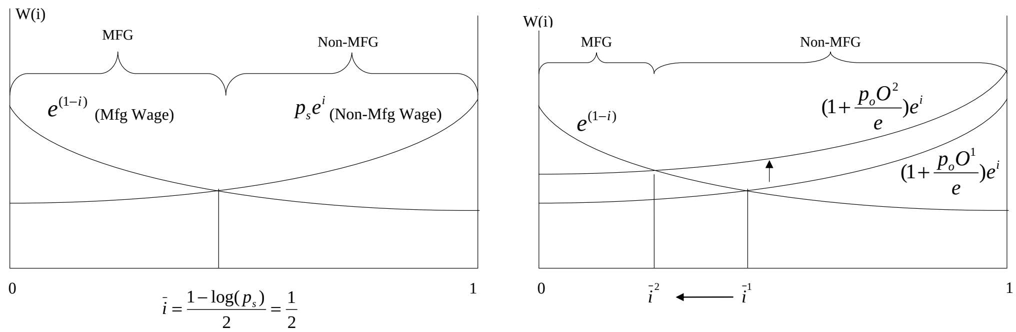
5.1 A Simple Example

To illustrate the impact of worker heterogeneity on sectoral productivity, we begin with a simple example. Suppose the skill distribution G is degenerate and given by $\{z_s^i, z_m^i\} = \{e^i, e^{1-i}\}$

[14] Thus, we know the measure of agents in each sector but not which agent works in which sector.

[15] If one sector had a higher wage, all agents would chose to work there and output would not be mixed.

[16] In particular, if we make utility non-homothetic in manufacturing goods by adding a "home-production" term, $\bar{m}$, $\left(c_s^{\frac{\sigma-1}{\sigma}} + \nu(c_m + \bar{m})^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}$, then the employment share in non-manufacturing goods will be given by $L_s = \frac{1}{1+\nu^\sigma}\left(1 + \frac{p_o O + \bar{m}}{A}\right)$. Thus, in terms of employment, endowments of natural resources act exactly like non-homothetic preferences in manufacturing goods.



(a) A workers decision.

(b) A change in the value of oil.

Figure 1: The mechanics of the model in a simple example.

for each worker $i \in [0,1]$. Furthermore, assume Cobb-Douglas utility ($\sigma = 1$), equal utility weights ($\nu = 1$) and normalize A to unity. Each agent i receives wage offers $w_s^i = p_s z_s^i$ in non-manufacturing and $w_m^i = z_m^i$ in manufacturing and chooses to work in non-manufacturing if and only if it pays a higher wage: $w_s^i > w_m^i$. This gives rise to a cutoff agent, $\bar{i}(p_s) = \frac{1-\log p_s}{2}$, who is indifferent between working in either sector. We illustrate this in Figure $1(a)$ which plots the wage offers in each sector and the cutoff, $\bar{i}(p_s)$. Agents to the left of this cutoff are relatively more skilled in manufacturing sector tasks and hence have higher wage offers and choose to work in manufacturing. Meanwhile, agents to the right of the cutoff are relatively more skilled in non-manufacturing tasks and hence have higher wage offers and choose to work in non-manufacturing.

The cutoff value is dependent on the price of non-manufacturing. Windfalls influence this price and will hence influence the distribution of workers across sectors. A windfall of revenue generates a greater demand for both types of goods. To satiate the higher demand for non-traded non-manufacturing goods, more workers are needed in the non-manufacturing sector. New workers however will choose to work in non-manufacturing only if the wage in non-manufacturing rises which in turn can only happen if the non-manufacturing price increases. More formally, we can write output in each sector as a function of the cutoff (and hence the price): $Y_s(p_s) = e - e^{\bar{i}(p_s)}$ and $Y_m(p_s) = e - e^{1-\bar{i}(p_s)}$. Using this and equation (13), we can then determine the equilibrium price of non-manufacturing: $p_s = 1 + \frac{p_o O}{e}$. A higher windfall translates into a higher non-manufacturing price. This results in an increase in non-manufacturing wage offers, which in turn generates a shift of workers from manufacturing to non-manufacturing - a leftward shift of the cutoff $\bar{i}(p_s)$. As $\bar{i}$ decreases, manufacturing productivity ($Y_m/\bar{i} = (e - e^{1-\bar{i}})/\bar{i}$) rises: those left in the manufacturing sector are most skilled in manufacturing sector work. At the same time non-manufacturing productivity ($Y_s/(1-\bar{i}) = (e - e^{\bar{i}})/(1-\bar{i})$) falls: new entrants in non-manufacturing pull down productivity since they are, on average, less skilled than those already employed in non-manufacturing.

The above mechanism is closely linked to a similar discussion in the development literature. It is a well known fact that poorer countries have a larger fraction of their labor force employed in agriculture, due to subsistence requirements. Research by Caselli (2005) and Restuccia et al. (2008) also shows that productivity differences in agriculture between rich and poor countries are significantly greater than aggregate productivity differences. Lagakos and Waugh (2010) argue that this fact stems from the specialization takes place in the smaller agricultural sectors in rich countries. They formalize and test their idea in the framework of a Roy (1951) model of self selection. Due to subsistence requirements in agriculture (modeled as non-homothetic preferences), poorer countries employ more workers in agriculture. As aggregate productivity increases, subsistence needs can be met with a smaller fraction of the labor force resulting in a shift of labor towards non-agriculture. This leads to productivity increasing in the agricultural sector by more than it does at the aggregate level, since only those workers that are most skilled (and hence most productive) in agriculture, self select to remain in that sector. Since windfalls act like non-homothetic preferences in shifting labor across sectors, we can expect a similar channel to operate in our case.

Whist superficially our model parallels Lagakos and Waugh (2010) quite closely (since both models use the Roy (1951) mechanism of specialization), conceptually the two models are very different. In Lagakos and Waugh (2010) the driver of sectoral labor reallocation that generates specialization, is the combination of non-homothetic preferences and exogenous variation in aggregate productivity between rich and poor countries. Our model has homothetic preferences and emphasizes the role of exogenous resource windfalls and trade (in particular the tradability of manufacturing goods) as a channel that drives labor reallocation and results in specialization.

5.2 Generalization

Next, we generalize the above example and establish conditions on the distribution of talents under which countries with higher endowments of natural resources will be more productive in manufacturing and less productivity in non-manufacturing than their resource poor counterparts. Throughout this section we maintain the assumption that the proportion of workers who are indifferent between sectors is negligible and so that essentially all persons have a strict preference for manufacturing or non-manufacturing.[17] With this assumption we are thus excluding the case of homogenous workers, where the supply of labor to a particular sector was inelastic and all workers were indifferent between sectors. The following proofs parallel those of Lagakos

[17] A sufficient condition for this is that $\{z_s, z_m\}$ are continuously distributed and are non-degenerate random variables.

and Waugh (2010), who show similar results for agriculture and non-agriculture in rich versus poor countries. Versions of these results were also established by Heckman and Honore (1990). We first show that prices of non-manufacturing goods rise with higher values of endowments of natural resources.

Propostion 1. *Consider two countries: a high resource endowment economy ($p_{o,H}O_H > 0$) and a low resource endowment economy ($p_{o,H}O_H > p_{o,L}O_L \geq 0$), that are identical in all other aspects. Then, the relative price of non-manufacturing goods is higher in the high endowment economy than in the low endowment economy: $p_{s,H} > p_{s,L}$.*

Proof. See Appendix 13.2. □

The intuition for the above is as follows. Suppose that the price of non-manufacturing goods were identical in both countries and that markets cleared in the resource poor country. This would imply, by the cut-off condition, that the sectoral labor allocations were also the same in both countries and hence so was total production of both goods. However, demand for non-manufacturing goods is higher in the resource rich country (since it has a higher income than the resource poor country), hence markets do not clear there. The only way for markets to clear in the resource rich country, is for the price of non-manufacturing goods to rise. A direct corollary of the above is that:

Corollary 2. *Employment is lower in manufacturing and higher in non-manufacturing in resource rich countries than in resource poor countries ($L_{s,H} > L_{s,L}$ and $L_{m,H} < L_{m,L}$)*

The proof follows directly from the cutoff condition 11 and the assumption that the proportion of workers who are indifferent between sectors is negligible: a higher price of non-manufacturing goods will translate into higher non-manufacturing wage offers which will induce workers to move to the non-manufacturing sector. Next, we provide two restrictions on talent distribution functions that must be satisfied in order for this reallocation of labor to generate asymmetric productivity changes.

Propostion 3. *Consider two countries: a high resource endowment economy ($p_{o,H}O_H > 0$) and a low resource endowment economy ($p_{o,H}O_H > p_{o,L}O_L \geq 0$), that are identical in all other aspects. Sectoral labor productivity in manufacturing is higher in the resource rich country,*

$$\frac{Y_m^H}{L_m^H} > \frac{Y_m^L}{L_m^L},$$

if and only if $E(z_m|z_m/z_s > a)$ is increasing in a. Sectoral labor productivity in non-manufacturing is lower in the resource rich country,

$$\frac{Y_s^H}{L_s^H} < \frac{Y_s^L}{L_s^L},$$

if and only if $E(z_s|z_s/z_m > a)$ is increasing in a.

Proof. The proof follows from the definition of sectoral productivity. The following hold if and only if the respective restrictions on conditional expectations hold:

$$\frac{Y_m^H}{L_m^H} = E(z_m|z_m/z_s > p_{s,H}) > E(z_m|z_m/z_s > p_{s,L}) = \frac{Y_m^L}{L_m^L}$$

$$\frac{Y_s^H}{L_s^H} = E(z_s|z_s/z_m > 1/p_{s,H}) < E(z_m|z_s/z_m > 1/p_{s,L}) = \frac{Y_s^L}{L_s^L}.$$

□

Intuitively, the theorem states that we obtain asymmetric productivity differences if and only if those with comparative advantage in a sector also have absolute advantage in that sector. Consider, for example, the first part of the proposition which says that manufacturing productivity is higher in resource rich countries than in resource poor countries if and only if expected manufacturing ability is higher for agents with greater comparative advantage in manufacturing sector work. As endowments of resources rise, the price of services increases and only agents with the greatest comparative advantage in manufacturing (i.e. agents with z_m/z_s higher than p_s) remain in that sector. The absolute productivity of manufacturing will increase, if and only if the expected manufacturing sector ability is higher for agents that have the comparative advantage in manufacturing sector work. Similarly, the second part of the proposition says that non-manufacturing productivity is higher in the resource poor country if and only if agents with greater comparative advantage in non-manufacturing have a higher expected ability in that sector.

Heckman and Honore (1990) show that at least one of the above restrictions on conditional expectations must always hold. This implies that our theory will at least be able to account for differences in relative productivity across sectors but, given an appropriate distribution, it can also account for observed differences in both sectors. Heckman and Honore (1990) also demonstrated that for a vector of independent random variables, the log-concavity of individual ability distribution functions is a sufficient condition for both restrictions to hold.[18]

6 Solving the Model

Distribution Function To calibrate and solve the model, we must pick a particular parametric form for the distribution of skills, $G(z_s, z_m)$, since the Roy model cannot be identified

[18] A random vector is log-concavely distributed if the logarithm of its probability density function is concave on its support. This property is equivalent to the ratio of the density function to the c.d.f. being a monotone decreasing function. Log-concave distribution functions include normal, uniform, gamma(r, λ) for $r \geq 1$, beta(a, b) for $a \geq 1$ and $b \geq 1$, generalized Pareto, Gumbel, Frechet, logistic or Laplace - to mention a few. For more details see Bagnoli and Bergstrom (2005).

from cross-sectional wage data alone.[19] In what follows, we assume that skills are drawn independently from a normalized Type II extreme value (or Frechet) distribution with CDF:

$$G(z_s) = e^{-z_s^{-\theta}} \text{ and } G(z_m) = e^{-z_m^{-\theta}}, \tag{15}$$

where, $\theta > 1$. The log of a random talent draw, $\log Z_i$, has standard deviation $\pi/(\theta\sqrt{6})$, where π is the constant. The parameter θ thus governs the amount of variation in skills and hence the observed productivity dispersion: lower values of θ imply more heterogeneity in ability and higher productivity dispersion. It turns out that this parameter is key to our analysis. Notice that we assume that θ is common to both sectors and that talent draws are independent of each other. Whilst both these assumptions may seem restrictive, they allow us to derive simple, analytic solutions which provide insights into the workings of the model. In section 9.3, we extend the model to allow correlated talent draws and different dispersions across sectors and we show that, quantitatively, these channels play only a limited role.

We focus on the Frechet distribution for several reasons. First and foremost, this distribution is one of three extreme value distributions. According to the Fisher - Tippet - Gnedenko theorem from extreme value theory, there are only three types of distributions that are needed to model the maximum or minimum of the collection of random observations from the same distribution. More specifically, the maximum of a sample of i.i.d. random variables converges in distribution to either the Gumbel, the Frechet, or the Weibull distribution.[20] In our case, choosing an extreme value distribution can be thought of as capturing the distribution of agents' "best" talents in each particular sector. Second, of these three distributions we choose the Frechet in keeping with the literature. Eaton and Kortum (2001) have used this distribution to parameterize a Ricardian model of international trade and Lagakos and Waugh (2010) have used it to model talent distribution across sectors. Notice also, that the Frechet distribution is log-concave, hence both restrictions of Proposition 3 hold. Finally, the Frechet distribution also provides very tractable analytic solutions which allow for easy interpretation of results and does a very good job of fitting the data.[21]

Employment Since z_s and z_m are independently drawn from Frechet distribution, the joint density function can be expressed as $g(z_s, z_m) = g(z_s)g(z_m)$. Using this, we can relate sectoral labor supply allocation to the parameter which controls the dispersion of skills across sectors.

[19] This is because we observe only the outcomes of workers choices (in the form of a worker's observed wages) and not the talent draws (and hence the sectoral wage offers) that underpin these outcomes.

[20] Broadly speaking, if one generates N data sets from the same distribution, and then creates a new data set that includes only the maximum values of these N data sets, the resulting data set can only be described by one of the above distributions. For more details see Haan and Ferreira (2006).

[21] In what follows we compare results to a log-normal distribution and show that the Frechet provides a superior match to the data.

The expected employment in non-manufacturing is:[22]

$$L_s = P\left(p_s > \frac{z_m^i}{z_s^i}\right) = \int_0^{\infty}\int_0^{p_s z_s} g(z_s)g(z_m)dz_m dz_s = \frac{p_s^\theta}{1+p_s^\theta} \tag{16}$$

and thus expected employment in manufacturing is:

$$L_m = P\left(p_s \leq \frac{z_m^i}{z_s^i}\right) = \int_0^{\infty}\int_0^{z_m/p_s} g(z_s)g(z_m)dz_s dz_m = \frac{1}{1+p_s^\theta} \tag{17}$$

Output Normalizing $A = 1$, the output of each sector can be expressed as:

$$Y_s = \int_0^{\infty}\int_0^{p_s z_s} z_s g(z_s, z_m)dz_m dz_s,\ Y_m = \int_0^{\infty}\int_0^{z_m/p_s} z_m g(z_s, z_m)dz_s dz_m \tag{18}$$

Using the fact that z_s and z_m are independently drawn from a Frechet distribution, we can simplify the above expressions for output:

$$Y_s = \Gamma(1-\frac{1}{\theta})(1+p_s^{-\theta})^{\frac{1-\theta}{\theta}},\ Y_m = \Gamma(1-\frac{1}{\theta})(1+p_s^{\theta})^{\frac{1-\theta}{\theta}}, \tag{19}$$

where $\Gamma(\cdot)$ is the complete gamma function.

From equation 13, we can confirm Proposition 1: $\frac{\partial p_s}{\partial p_o O} > 0$. It is then easy to show that oil endowments result in a reallocation of labor: $\frac{\partial L_s}{\partial p_o O} > 0$ and $\frac{\partial L_m}{\partial p_o O} < 0$. This shift in labor then generates specialization (in manufacturing) and de-specialization (in non-manufacturing): $\frac{\partial Y_s/L_s}{\partial p_o O} < 0$ and $\frac{\partial Y_m/L_m}{\partial p_o O} > 0$, confirming Proposition 3 for the Frechet distribution.

Magnitudes of Productivity Variation Having specified a distribution for skills, we can also quantify the magnitude of the observed asymmetric productivity changes. The data indicates that there is a sharp increase in sectoral productivity in manufacturing but a smaller decrease in productivity in non-manufacturing in resource rich regions relative to resource poor regions. The model gives us an indication of why this may be the case.

Propostion 4. *A change in L_m results in a larger change in manufacturing productivity than in non-manufacturing productivity if and only if $L_m < \frac{1}{2}$.*

Proof. We show that $P \equiv \left|\frac{\partial(Y_m/L_m)}{\partial L_m}\right| / \left|\frac{\partial(Y_s/L_s)}{\partial L_m}\right| > 1$ iff $L_m < \frac{1}{2}$. From equations 16, 17 and 19, $P = (L_m^{-1} - 1)^{\frac{\theta+1}{\theta}}$. Since $\theta > 1$, P is greater than one if and only if $L_m < \frac{1}{2}$. □

[22] In deriving (16), we use the result that if x and y are independently drawn from Frechet distribution with c.d.f. $G(z) = e^{-z^{-\theta}}$, then x/y has distribution with c.d.f. $F(z) = \frac{z^\theta}{1+z^\theta}$, Nadarajah and Kotz (2006).

Since the non-manufacturing sector tends to employ a large share of the labor force, the new workers that enter non-manufacturing sector in resource rich regions form a relatively small share of the existing non-manufacturing employment - ensuring that the decrease in aggregate sectoral productivity caused by new workers is not that large. Since the manufacturing goods sector employs a small share of the labor force, the workers that leave the sector represent a large share of the manufacturing sector's employment, ensuring that the impact on productivity is bigger.

7 Calibrating the Model

Estimating Skill Dispersion The parameter θ governs the dispersion of (unobserved) underlying skills. To match this parameter to observed variables, we make use of the properties of the Frechet distribution. The distribution of wage offers agents receive in each sector is given by:

$$G_s^w(w_s) = Pr\{W_s \leq w_s\} = Pr\{p_s A Z_s \leq w_s\} = Pr\{Z_s \leq \frac{w_s}{p_s A}\} = e^{-(p_s A)^\theta w_s^{-\theta}} \tag{20}$$

$$G_m^w(w_m) = Pr\{W_m \leq w_m\} = Pr\{A Z_m \leq w_m\} = Pr\{Z_m \leq \frac{w_m}{A}\} = e^{-A^\theta w_m^{-\theta}}. \tag{21}$$

These are both Frechet with the same dispersion parameter, θ, as the talent distributions.[23] The observed wage is simply the maximum an agent could earn in either sector, $w = \max\{w_s, w_m\}$. The distribution of this wage, $G^w(w)$, is then simply the maximum order statistic of wage offers and is given by:

$$G^w(w) = G_s^w(w) G_m^w(w) = e^{-A^\theta (1+p_s^\theta) w^{-\theta}}. \tag{22}$$

The above distribution is also a Frechet with the same dispersion parameter (but with a different mean) as the skill distribution. This is a consequence of the original talent draws taking the form of an extreme value distribution. In order to match the parameter θ, we use a method of moments. Since the log of a Frechet variable has standard deviation $\pi/(\theta_i\sqrt{6})$, we can infer θ from the standard deviation of a sample of log wages. We obtaining cross-sectional wage data from the 2009 US Current Population Survey (CPS) and find that the standard deviation of log wages in this sample is 0.57, which implies a dispersion parameter of $\theta = 2.22$.[24]

[23] Notice that these are not distributions of observed wages in a given sector, but the distribution of (unobserved) wages agents could earn if they chose to work in a particular sector.

[24] Following Lagakos and Waugh (2010) and Heathcote et al. (2009) we include individuals between ages 25 to 60 who have non-missing data on income and hours worked. Wages are before tax, and are taken to be the sum of wage, business and farm income. The sample is further restricted to include workers who average more than 35 hours a week of work and earn at least the Federal minimum wage.

	$\log(D_m)$	$\log(D_m)$	$\log(D_m)$	$\log(D_s)$	$\log(D_s)$	$\log(D_s)$
$\log(L_m)$	-0.37***	-0.33***	-0.53***			
	(0.03)	(0.04)	(0.03)			
$\log(L_s)$				-0.54***	-0.51***	-0.67***
				(0.02)	(0.03)	(0.02)
Time FE	no	yes	no	no	yes	no
Country FE	no	no	yes	no	no	yes
Obser.	806	806	806	806	806	806
R^2	0.13	0.15	0.87	0.38	0.39	0.90

*** p<0.01, ** p<0.05, * p<0.1

Table 4: Changes in sectoral TFP versus sectoral employment share. Productivity measure controls for physical and human capital and is relative to aggregate TFP.

As a check on this calibration, we use the fact that in our model employment shares and productivity are simultaneously determined and can thus be jointly estimated. In particular, combining equations (16), (17) and (19) and taking logs we obtain for each $k = s, m$:

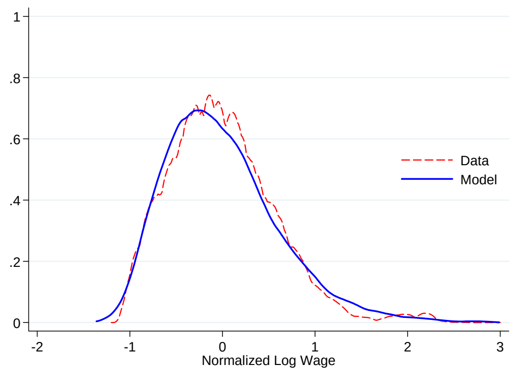
$$\log(\frac{Y_k}{L_k}) = \log(\Gamma(1 - \frac{1}{\theta})) - \frac{1}{\theta}\log(L_k). \tag{23}$$

The model thus predicts that a one percent increase in employment in a sector (for whatever reason) will result in a $1/\theta$ percent decline in productivity in that sector. We use our panel of macro cross-country data to directly estimate θ for manufacturing and non-manufacturing.[25] The regression results relating productivity to sectoral size in each sector are shown in Table 4. The implied θ in manufacturing and non-manufacturing is 1.85 and 2.7 respectively. These values are remarkably close to the value we obtained using our (completely different) micro data and as such provide strong support for our earlier calibration. Since we are more confident in our micro US data, in what follows we stick to the original estimate of $\theta = 2.22$.[26]

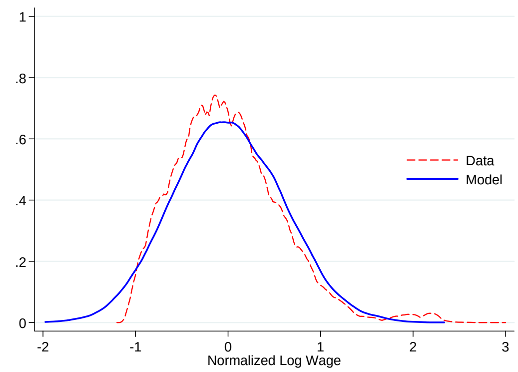
Preference parameters Next, we estimate preference parameters σ and ν. From, the household's problem we derive an equation relating relative consumer expenditure on the relative price: $\frac{c_m}{c_s} = (\nu p_s)^{\sigma}$. Taking logs of this equation, we estimate elasticity of substitution between manufacturing and non-manufacturing goods using ICP data and find that $\sigma = 0.94$. Finally, we choose the preference parameter to be $\nu = 0.27$, to match the employment share in the non-manufacturing sector in resource poor countries in the model to the employment share in non-manufacturing in the lowest decile of exporters (approximately 79%).

[25] Recall, that since we've normalized aggregate TFP in the model to $A = 1$, we normalize sectoral productivity by aggregate TFP in the data.

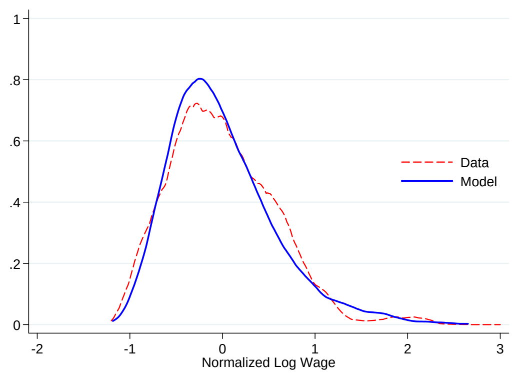
[26] This also places some distance between our calibration and our results.



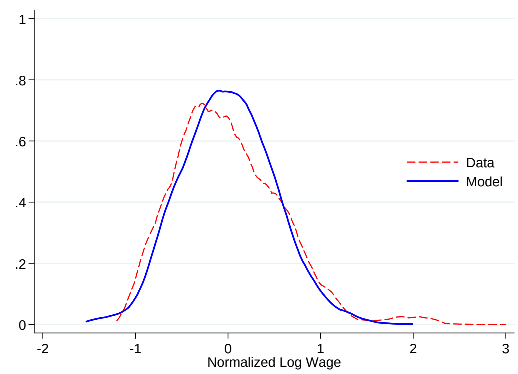
(a) Distribution of Wages, Frechet



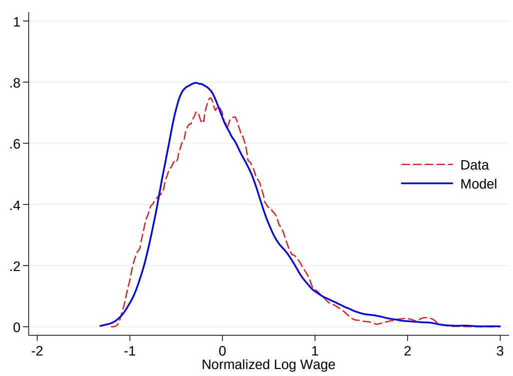
(b) Distribution of Wages, Log-normal



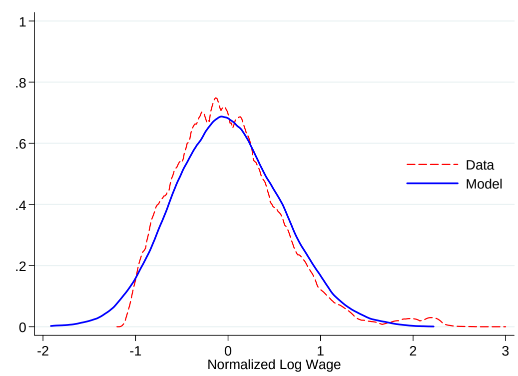
(c) Distribution of Wages in Mfg, Frechet



(d) Distribution of Wages in Mfg., Log-normal

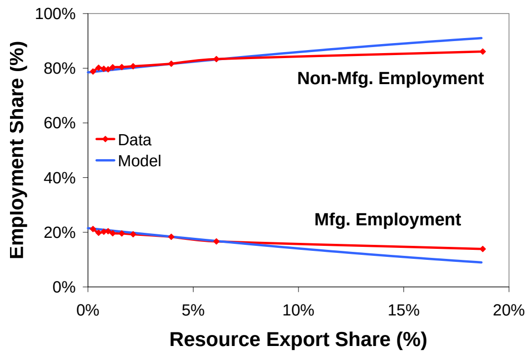


(e) Distribution of Wages in Non-Mfg., Frechet

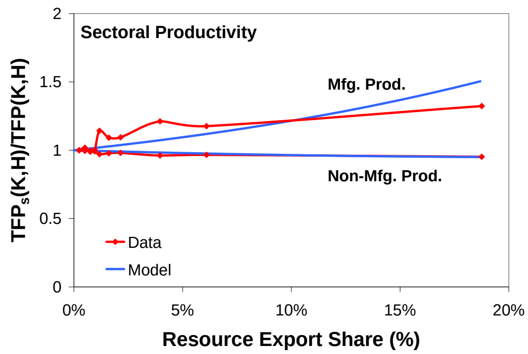


(f) Distribution of Wages in Non-Mfg., Log-normal

Figure 2: Distribution of wages in model and data, by sector. The first and second columns show outcomes with Frechet and Log-Normal talent draws respectively.



(a) Sectoral Emp. Shares vs. Resource Export Share



(b) Norm. Sectoral Productivity vs. Resource Export Share

Figure 3: Heterogenous Consumers: Data Deciles and Model.

7.1 Results

US Wage Distributions The left hand column of Figure 2, shows the theoretical and empirical density of observed wages at the aggregate and sectoral level in the US data and the model using Frechet talent draws. The right hand column, shows a re-calibration of the model to log-normal talent draws. Recall that the key parameter choice in the Frechet model is the dispersion parameter, θ, chosen to match the standard deviation of observed log wages. The log-normal distribution is calibrated in a similar fashion.[27] As such, both the Frechet and the Log-normal model do well at matching the general dispersion of wages at the aggregate level. Notice however, that the log-normal model does poorly in matching the tails of the data. This finding mirrors that of Lagakos and Waugh (2010) and Heckman and Sedlacek (1985). The model also does well in matching the data that we have not calibrated - the observed sectoral wages in the US. Here, again, the Frechet distribution does a better job of matching the tails.

Resource Wealth Results Figure 3 shows the results of the model with respect to employment shares and productivity. We have also included the deciles of the macro data presented earlier. The panel on the left shows that the model predicts rising employment in non-manufacturing and falling employment in manufacturing as resource wealth increases.[28] In

[27] The standard deviation found to match the data with the normalized log-normal distribution is 0.652.

[28] In the data, we measure resource wealth as the ratio of current price exports of natural resources to current price GDP measured in international dollars. International dollar are constructed to have the same purchasing power over GDP as the U.S. dollar has in the United States. Since the US is a resource poor country (according to this measure), we can view GDP in international dollars as the GDP of a country measured using a resource poor country's prices. As such, in the model, we construct our resource wealth measure as the value of exports of natural resources divided by GDP, measured with the prices of a resource poor country (i.e. one what has $p_O O = 0$).

general the fit of employment shares is good, although the model over predicts the size of the shift towards non-manufacturing. The panel on the right demonstrates the change of sectoral productivity with resource wealth.[29] We see that the model is very good at matching the slight decline in non-manufacturing productivity and the large increase in manufacturing productivity (although it overestimates this increase) as explained by Proposition 4. Although other channels may also be driving the facts, the message from the calibration is that our specialization mechanism is strong enough to explain all the observed differences in sectoral employment and productivity between resource rich and resource poor countries through an exogenous variation in their resource endowments.

The Resource Curse What is the effect of resource endowments and the subsequent specialization on aggregate productivity? The answer to this depends on the prices used to measure output in the construction of productivity. If output is measured in resource poor country's prices, aggregate productivity in resource rich countries will necessarily be lower than in resource rich countries.[30] This effect however, is *very* small: given our calibration, the model predicts the highest decile of resource exporters will have a non-oil aggregate productivity that is 0.016% smaller than the lowest decile. On the other hand, if we chose to measure aggregate productivity using the resource rich country's prices, we would get exactly the opposite result: the highest decile of exporters will has a non-oil aggregate productivity that is 0.016% *larger* than the lowest decile. Thus, the measured resource curse in our model is negligible and entirely a remnant of the type of pricing scheme adopted and would disappear with an appropriately weighted price index. Kehoe and Ruhl (2008) make a similar point.

8 Evidence: Males versus females

Since most measures of ability are endogenous, in general it is difficult to observe differences in innate ability. One way of potentially doing so is along the dimension of gender. Within the development literature, economists have argued that men may have a comparative advantage in manufacturing relative to services due to their greater upper-body physical strength.[31] Since variation in gender is exogenous, cutting the data along gender lines allows us to test our theory. In particular, we use the previous section's micro data to provide direct evidence in support of our mechanism, by looking at employment and productivity in manufacturing and non-manufacturing for men and women. In what follows we show that: (1) Women have

[29] Note, to match the model to the data, the bottom graph represents sectoral TFP relative to aggregate TFP in both model and the data.

[30] See Appendix 13.3 for details.

[31] See for instance Galor and Weil (1996), Galor and Weil (1999), Fan and Lui (2003).

	Productivity		Employment Shares	
	NM	M	NM	M
Female	5.03	4.89	79%	21%
Male	7.79	7.94	72%	28%

Table 5: Productivity and employment by sector and sex. (Source: IPUMS)

a revealed comparative advantage in non-manufacturing work relative to men; (2) The decline in manufacturing employment in oil rich counties is higher for females than males; and (3) The decline in manufacturing employment in oil rich counties is higher within female intensive manufacturing industries. These three facts are consistent with our theory for agents with greater skills for non-manufacturing work.

Gender and Sectoral labor productivity First, we show that females have a comparative advantage in non-manufacturing even though that sector employs a higher share of female workers. The first two columns of Table 5 show the sectoral productivity of male and female workers. Overall female productivity is lower in both non-manufacturing and manufacturing: the absolute outcomes of men and women may differ for many reasons and this is not the point of the exercise. Females, however, are *relatively* more productive in non-manufacturing whilst males are *relatively* more productive in manufacturing sector work. The last two columns show that this productivity difference occurs despite a higher fraction of females being employed in non-manufacturing.

Gender and Employment Second, since women have a comparative advantage in non-manufacturing sector work, our mechanism suggests that females are more likely to leave the manufacturing sector and enter the non-manufacturing sector in resource rich regions then men. As evidence of that, Table 6 shows the differences in the structure of (non-oil) employment between resource rich and resource poor counties for men and women. In both oil rich and oil poor counties, a larger fraction of the female labor force is employed in non-manufacturing than of the male labor force. However, 6% more women are employed in non-manufacturing in resource rich counties than in resource poor counties, but only 1% more men. In response to higher oil endowments, part of the labor force moves from the manufacturing to the non-manufacturing sector. Given the comparative advantage of women in non-manufacturing relative to men, female workers are more likely to move to non-manufacturing than men.

Third, as a final piece of evidence, we show that there is a larger change in employment structure in female intensive industries than in male intensive industries between resource rich and resource poor regions. As an example we pick the textile industry which is the most female

	Female Employment		Male Employment	
	NM	M	NM	M
Oil rich	83%	17%	72%	28%
Oil poor	78%	22%	71%	29%
OR/OP	1.06	0.77	1.01	0.97

Table 6: Sectoral employment share (disaggregated by gender): oil rich vs. oil poor counties

	Emp. Share	Decomp. of Empl. in M		Emp. Share
	M	MT	MNT	MT
Oil rich	17%	3%	14%	0.21
Oil poor	22%	5%	17%	0.29
OR/OP	0.77	0.60	0.82	

Table 7: Change in female employment in a female intensive industry: oil rich vs. oil poor counties

intensive industry.[32] Table 7 decomposes female (non-oil) manufacturing employment shares into textile manufacturing (MT) and non-textile manufacturing (MNT) employment across oil rich and poor regions.[33] This decomposition shows that the decline in employment in the textile sector between oil poor and oil rich regions was far larger than in non-textile manufacturing. Oil rich counties employed 40% less females in textiles than oil poor counties, but only 18% less in (relatively female un-intensive) non-textile industries. Similarly, textiles accounted for 29% of female employment in manufacturing in oil poor counties, but only 21% of female employment in oil rich counties. In terms of our model, industries that employed more women are those most likely to see those women move to the non-manufacturing sector in resource rich counties.

9 Alternative Mechanisms, Generalizations and Extensions

9.1 Physical Capital and Labor Productivity

In the homogenous worker model of section 4, TFP and labor productivity are the same, but in more complicated homogenous worker models (for instance those with capital), the two measures of productivity are distinct. If the reader is skeptical of some of the assumptions used to construct measures of TFP, then a relevant question would be whether more complicated

[32] Kusera and Milberg (2000) report the female percentage of employment by industry for 10 OECD countries (including the US) for the late 1980's and early 1990's. Their estimates suggest that textiles are the most female intensive industry with female employment of an average 63% across 10 countries.

[33] Textiles are defined as: knitting mills; dyeing and finishing textiles, except knitting mills; carpets, rugs, and other floor covering; yarn, thread, and fabric; misc textile mill products; apparel and accessories; misc fabricated textile products.

homogenous worker models could go some way in explaining the observed asymmetric sectoral *labor* productivity differences.

Capital As a first step, suppose we added capital accumulation to a homogenous worker model. In Appendix 13.1, we show that in a model with capital and unequal sectoral capital intensities, relative sectoral labor productivities can vary across countries, but that labor productivity in both sectors always moves in the same direction. Adding capital to the model may account for changes in *relative* sectoral labor productivity, but it is unable to account for the observed asymmetric changes. Furthermore, within this framework, TFP still remains exogenous and unaffected by labor moving across sectors.

Subsidies A second possibility, would be to force a homogenous worker model with capital to match sectoral labor productivity by introducing subsidies to the rental rate of capital inputs in the manufacturing sector (financed by lump sum taxes) that increase exogenously with resource wealth. This would lead to a greater proportion of capital shifting towards the manufacturing sector in resource rich countries making labor more productive in those countries. We have experimented with a simple calibration of such a model and found that the subsidies needed to achieve the observed asymmetric labor productivity differences between the 10-th and 90-th percentile of exporters are implausibly high.[34] Whilst some resource rich countries may have high subsidies, we observe similar patterns in productivity and employment in resource rich members of the OECD like Australia, Norway and Canada and in oil rich US counties where capital subsidies are unlikely to be high.

Fixed Factors The third possibility would be to introduce specific or fixed factors into our homogenous worker model. Then labor moving from one sector to another would encounter diminishing returns. Each additional worker to a sector would have a lower marginal productivity than the last, resulting in declining sectoral labor productivity in a worker's new sector and an increase in labor productivity in the worker's old sector. The problem with this model is the interpretation of the fixed factors. There are generally two accepted explanations in the literature. First, fixed factors may be fundamentally different and very difficult to use across sectors, for example land plays a key role in agriculture. This interpretation makes less sense in our context. What is a fixed factor in manufacturing? The second interpretation, as in Neary (1978), views capital as sector specific in the short run but becoming interchangeable with the passage of time. In our context, this interpretation also runs into trouble. The facts presented above, demonstrate that sectoral labor productivity differences occur across a wide cross-section

[34] Subsidies of 60% and 75% of the rental rate of capital are needed to match higher productivity in manufacturing and lower productivity in non-manufacturing respectively. Results available on request.

of countries. Cross-sectional data however, captures the long run adjustments that time series data does not. This suggests that differences in productivity across sectors are persistent over time and do not disappear as the specific factor view would predict. Finally, in this setup just like in the mobile capital case, TFP also remains exogenous and unaffected by the movement of labor.

Our data showed that there exist asymmetric differences in TFP between resource rich and resource poor countries. Models where TFP is exogenous and unaffected by labor reallocation, cannot account for asymmetric differences. There is however, some reason to approach our TFP measures with caution. The above examples show that standard models run into trouble even when explaining *labor* productivity differences.

9.2 Learning and ability

It could be argued that our model describes the short run due to our assumption of exogenous skill endowments: in the long run agents could potentially acquire skills to eliminate talent differences. There are two reasons to think why this is not the case and our model is a good approximation of the long run. First, our empirical analysis controls for acquired human capital: our facts reflect productivity differences above and beyond those driven by different levels of education. Consequently, we interpret skills in our model as innate abilities such as physical strength or artistic talent that are exogenous and impossible (or at least very costly) to acquire. Second, the volatility of natural resource prices coupled with the cost of retraining can act as a barrier to acquiring sector specific skills. Changes in the value of endowments of resources shift labor between sectors. Whilst agents could retrain, this may be costly or take time. Resource prices however, tend to be very volatile,[35] driving labor back and forth between sectors and making repeated re-training expensive.

9.3 Extension to Dependence and Variable Dispersion

In the baseline model we assumed skill draws were independent. We also assumed that skills were drawn from a distribution with the same dispersion parameter. As such, we ignored the possibility that ability is correlated across sectors and that it is potentially dispersed unevenly across sectors. In this section, we introduce the possibility of correlated skill draws and different skill dispersions across sectors and show that these changes quantitatively add little to our model. If anything, increasing correlation between sectoral draws makes our results stronger. We follow Lagakos and Waugh (2010) by introducing dependance between skill distribution in

[35] For instance, the standard deviation of the oil price from its HP trend between 1980-2008 was 0.16 (BP). The deviation for a metal price index was 0.19 (IMF). The corresponding measures of manufacturing and non-manufacturing price deviations were 0.02 and 0.007 in the US or 0.09 and 0.04 in Saudi Arabia (UN).

ρ	Imp. Corr.	L_s	L_m	Y_s/L_s	Y_m/L_m	$(Y_s/L_s)/(Y_m/L_m)$
-	0.00	1.15	0.39	0.94	1.53	0.61
0	0.00	1.16	0.39	0.93	1.51	0.62
1	0.18	1.17	0.36	0.93	1.52	0.61
2	0.32	1.18	0.34	0.93	1.55	0.60
3	0.45	1.19	0.30	0.93	1.59	0.59
4	0.56	1.19	0.28	0.93	1.64	0.57
5	0.65	1.20	0.23	0.93	1.71	0.54

Table 8: The Impact of changing dependence between skill draws. Entries reflect the predicted ratio between to 10th and bottom 90th percentile resource exporters.

the form of a copula function. In particular, we set the joint distribution of abilities to be:

$$G(z_s, z_m) = C[F(z_s), H(z_m)]$$

$$\text{where } F(z_s) = e^{-z_s^{\theta_s}} \text{ and } H(z_m) = e^{-z_m^{\theta_m}}$$

$$\text{and } C[u,v] = \begin{cases} -\frac{1}{\rho}\log\left(1 + \frac{(e^{-\rho u}-1)(e^{-\rho v}-1)}{e^{-\rho}-1}\right) & \text{if } \rho < 0 \text{ or } \rho > 0 \\ uv & \text{if } \rho = 0 \end{cases}$$

The function $C[F(z_s), H(z_m)]$, is known as a Frank copula, which allows for dependence between draws from the distributions $F(z_s)$ and $H(z_m)$, which themselves, are Frechet, with dispersion parameter, θ_m and θ_s. The dependence parameter ρ may assume any real value. Values of ρ below and above zero generate negative and positive correlations between z_s and z_m respectively. With $\rho = 0$, the variables are independent. If in addition we assume that $\theta_s = \theta_m$, we are back to the baseline case.[36] The Frank copula is popular in empirical applications because unlike some other copulas, it permits negative dependence between the marginals and the dependence is symmetric in both tails (Trivedi and Zimmer, 2005). In what follows, we investigate the impact of varying the correlation parameter between skill draws, ρ, from 0 to 5. Each time we adjust ρ, we re-calibrate ν to maintain employment share in the non-manufacturing sector in resource poor countries at 79%, θ_s and θ_m to maintain observed standard deviations in sector specific wages and endowments of oil to match the resource export share of the top 10th percentile of resource exporters.

In Table 8, we show the predicted percentage change in sectoral employment and productivity between the top 10th and bottom 90th percentile of resource exporters. Since ρ is itself difficult to interpret, we also report the Spearman correlation coefficient from a simulation of 50,000 draws of the random variable for each choice of ρ. In the top of the table we report the results for our baseline calibration. We then keep the assumption that draws are uncorrelated (i.e.

[36] Notice, that $\lim_{\rho\to 0} -\frac{1}{\rho}\log\left(1 + \frac{(e^{-\rho u}-1)(e^{-\rho v}-1)}{e^{-\rho}-1}\right) = uv$.

$\rho = 0$) and re-estimate the model allowing dispersion parameters to vary across sectors. This has almost no impact on the results. The reason for this is that, in the data, the standard deviation of log wages in manufacturing and non manufacturing are almost the same: 0.57 and 0.58 respectively. Next, we increase ρ from 0 to 5 which results in an increase in correlation between talent draws from 0 to 0.65. This results in an even greater decline in employment in manufacturing in resource rich countries and an accompanying larger increase in productivity in manufacturing. Non-manufacturing productivity is almost unaffected by the change.[37] From this exercise we see that, if anything, increasing correlation between sectoral talent draws will result in an even greater role for our mechanism.

9.4 Heterogenous Firms

Finally, our heterogenous worker setup can also easily be related to one with heterogenous firms. We can recast our model as a special case of a two sector Lucas (1978) span of control model. In particular, assume that there exists a unit measure of agents and that each agent can choose to become an entrepreneur (in either manufacturing or non-manufacturing) or they can hire themselves out as workers in either sector. Each agent i is assumed to be endowed with a vector of sector specific managerial talent, $\{z_s^i, z_m^i\}$, drawn from a distribution common to the whole population $G(z_s, z_m)$. If an agent i decides to become an entrepreneur in sector $k = s, m$, he becomes an owner of a firm producing sector k goods with a production function:

$$Y_k^i = A z_k^i (n_k^i)^{\nu}, \tag{24}$$

where n_k^i refers to the quantity of workers hired by agent-firm i, ν is the span of control parameter which governs the returns to scale and influences the size of the firm and A is the economy wide level of TFP.[38] The benefit for agent i of becoming an entrepreneur is given by the profit agent i's firm would earn, $\Pi_e^i = \max\{\max_{n_s^i} p_s Y_s^i - w n_s^i, \max_{n_m^i} Y_m^i - w n_m^i\}$. If an agent i chooses not to become an entrepreneur (since his entrepreneurial ability is low and hence his profits from running a firm would not be high enough), he will choose to become a worker and earn a sector independent wage w. The the final income earned by agent i will thus simply be $w^i = \max\{\Pi_e^i, w\}$. The remainder of the setup is similar to our heterogenous worker model and remains unstated. Next, we argue that we can nest both the homogenous and heterogenous worker cases in the above framework by varying the span of control parameter and without having to assume different skill distributions.

If $\nu \to 0$, we are in the world of our heterogenous agent model. There is complete decreasing returns to scale at the firm level and it is unfeasible for entrepreneurs/firms to hire any workers.

[37] The asymmetric impact on productivities is again explained by the larger size of the non-manufacturing sector relative to the manufacturing sector.

[38] A firm thus consists of an entrepreneur i and the workers he hires, n_k^i.

Everyone is thus a self-employed entrepreneur and the economy consists only of very small firms. This is a world of corner shops and garage industries. If $\nu \to 1$ however, a measure one of agents (almost everybody in the probabilistic sense) are workers hence (almost) everyone is homogenous. Since there are constant returns to scale at the firm level, only the most productive (i.e. the most managerially talented) individual in each sector becomes an entrepreneur and between them they hire all the remaining workers. Thus, each sector simply has an aggregate productivity equal to the product of the economy wide TFP, A, and the productivity of the most talented worker in each sector.

The homogenous and the heterogenous worker models are thus simply two extreme cases of the standard Lucas span of control model. In this paper we choose to focus on the case of $\nu \to 0$, since the $\nu \to 1$ case does not explain our facts and the $\nu \to 0$ case captures the fundamental mechanism of specialization, can explain the data well and is easy to work with.

10 Conclusion

In this paper, we use macro cross-country data and micro US county level data to show that resource rich regions have small and productive manufacturing sectors and large and unproductive non-manufacturing sectors. We propose and test a mechanism, derived from the growth and development literature, that explains these productivity differences through a process of self selection. Windfall revenue induces labor to move from the (traded) manufacturing sector to the (non-traded) non-manufacturing sector. A self selection of workers takes place. Only those most skilled in manufacturing sector work will remain in manufacturing. Workers that move to the non-manufacturing sector however, will be less skilled at non-manufacturing sector work than those who were already employed there. Resource induced structural transformation thus results in higher productivity in manufacturing and lower productivity in non-manufacturing. A calibrated version of the model can account for all the cross-country productivity and employment differences in manufacturing and non-manufacturing sectors found between resource rich and resource poor countries.

In contrast to growth accounting exercises, the model suggests that low aggregate productivity found in many resource rich countries is *not* caused by a resource induced decline of a highly productive manufacturing sector. Rather, it is precisely the small size of manufacturing in resource rich countries that is responsible for that sector's above average productivity. As such, our theory lends support to arguments by Robinson et al. (2006), van der Ploeg (2010) and others that explanations of the resource curse should be sought outside economic structure perhaps - as they suggest - in areas such as political economy, weak institutions or property rights.

11 Data Appendix

11.1 Macro Data

Resource Wealth We follow Sachs and Warner (2001) in defining natural resource "wealth" as the ratio of exports of natural resources (fuels, ores and metals) to GDP using WDI data. Unlike Sachs and Warner (2001), we use PPP GDP (in current prices) in the denominator of our measure. We do this since higher endowments of resources can potentially impact prices of non-resource goods (and hence measured GDP) influencing both the numerator and the denominator of our measure. Using PPP GDP, keeps prices fixed across countries and hence the measure only captures changing resource wealth. We have experimented with both measures or resource wealth, as well as other measures such as the ratio of *net* exports of natural resources to gross domestic product (both observed price and PPP). Our results however, are unaffected.

Labor Shares To calculate the last two measures of productivity we need to find expressions for labor shares, $1 - \alpha_s$, for each sector s. Although these shares can potentially vary across countries, due to a lack of comprehensive cross-country sectoral data, we make use of OECD data to calculate the average annual share of employee compensation for each sector in OECD countries for the longest period of time that data is available. We calculate the labor share as the ratio of total compensation of employees (wages and salaries before taxes, as well as employers social contributions) over sectoral value added.[39] Table 9 presents the results. We find labor share in manufacturing is 0.57 whilst in non-manufacturing it is 0.53. Notice that these are lower bound estimates since national accounts data does not include incomes generated from self-employment under total compensation. One commonly used technique to correct for this is to re-scale the shares by the ratio of total employment to total employees. In effect, the self-employed are then assumed to be paid the same average rate of compensation as employees and the same marginal rate of productivity is assumed for dependent and independent workers. Doing this with the above data results in higher average labor shares of 0.64 in non-manufacturing and 0.62 in manufacturing. Quantitatively and qualitatively however, this adjustment leaves our results almost unchanged. Since we are uncertain of exactly how compensation of self-employed workers varies across countries and sectors, we choose to retain our first estimates of labor shares.

Sectoral Employment We obtain sectoral employment data for 1980-2006 from the ILO KILM online database. To obtain the largest set of employment data, we combine ISIC revision 2 and ISIC revision 3 employment data.[40]

[39] Tables 7 and 8 in the the OECD Annual National Accounts, Volume 2, 1970-2008 (2009 prov)- Detailed aggregates, in millions of national currency

[40] Since these sector classifications are at the one digit level, there are no issues with the correspondence between ISIC Rev.3 and Rev.2. We use the rule that if data is available in both revisions, we use revision

Country	Period	Labor Shares							
		Agr	Cons.	Ser	Mfg	M&U	ACS	ACSM	Total
Australia	1989-2008	0.26	0.49	0.58	0.55	0.29	0.56	0.56	0.54
Austria	1976-2008	0.11	0.62	0.59	0.67	0.43	0.57	0.60	0.59
Belgium	1995-2008	0.17	0.57	0.57	0.65	0.38	0.56	0.58	0.57
Canada	1981-2006	0.31	0.70	0.60	0.61	0.24	0.59	0.60	0.57
Chile	2003-2008	0.40	0.65	0.51	0.30	0.10	0.52	0.48	0.40
Czech.	1995-2008	0.46	0.50	0.47	0.52	0.33	0.47	0.48	0.48
Denmark	1970-2008	0.26	0.79	0.62	0.72	0.21	0.62	0.63	0.62
Finland	1975-2008	0.19	0.69	0.63	0.60	0.34	0.60	0.60	0.59
France	1999-2008	0.22	0.57	0.58	0.66	0.41	0.57	0.58	0.58
Germany	1991-2008	0.43	0.66	0.53	0.72	0.50	0.54	0.58	0.58
Greece	2000-2008	0.12	0.35	0.40	0.49	0.33	0.38	0.39	0.39
Hungary	1995-2008	0.31	0.51	0.54	0.54	0.50	0.52	0.53	0.53
Iceland	1997-2005	0.61	0.57	0.67	0.70	0.29	0.65	0.66	0.64
Ireland	1995-2008	0.18	0.68	0.53	0.30	0.47	0.53	0.46	0.46
Italy	1970-2008	0.30	0.44	0.47	0.59	0.40	0.46	0.49	0.49
Japan	1996-2007	0.24	0.72	0.50	0.53	0.28	0.51	0.52	0.51
Korea	1970-2008	0.11	0.64	0.49	0.50	0.31	0.44	0.46	0.46
Lux.	1995-2008	0.26	0.67	0.50	0.63	0.35	0.51	0.52	0.52
Mexico	2003-2007	0.16	0.39	0.33	0.30	0.11	0.33	0.32	0.30
Nlands	1970-2008	0.21	0.72	0.62	0.64	0.17	0.60	0.61	0.59
New Zeal.	1986-2006	0.22	0.51	0.47	0.53	0.19	0.45	0.46	0.45
Norway	1970-2009	0.22	0.74	0.62	0.73	0.15	0.61	0.63	0.54
Poland	1995-2008	0.20	0.41	0.42	0.56	0.55	0.40	0.43	0.44
Portugal	1995-2006	0.18	0.63	0.59	0.62	0.30	0.57	0.58	0.57
Slovakia	1995-2008	0.43	0.39	0.44	0.47	0.33	0.44	0.44	0.44
Spain	1995-2008	0.19	0.62	0.54	0.61	0.28	0.53	0.54	0.54
Sweden	1993-2008	0.31	0.76	0.64	0.63	0.25	0.64	0.63	0.62
US	1987-2007	0.29	0.67	0.58	0.64	0.27	0.58	0.59	0.58
Average		0.26	0.59	0.54	0.57	0.31	0.53	0.53	0.52

Table 9: Shares of labor compensation relative to sectoral value added in agriculture, construction, services, manufacturing, mining and utilities as well as (non-resources) non-manufacturing (which consists of agriculture, construction and services), the non-resource sector (agriculture, construction, services and manufacturing) as well as total value added (agriculture, construction, services, manufacturing, mining and utilities) in OECD countries for the periods indicated. (Source: OECD, 2007)

Prices Since we want to compare sectoral productivity across countries, it is crucial to control for any price differences that may exist between sectors across countries. We do this by constructing country and sector specific price levels for each sector. In particular, we use the World Bank's 2005 International Comparison Program (ICP) database which provides cross-country data on the value of final household and government expenditures by sector for the year 2005. Expenditure data is given in current US dollars (at market exchange rates), as well as in PPP terms which allows us to extract country specific sectoral price levels (relative to the corresponding price level in the US). Denoting current price and PPP expenditures on sector s goods in country i by E_s^i and E_s^{PPP} respectively, the price level of sector s in country i (relative to that

3 data. Finally, we do not consider employment data based entirely on urban surveys - as these significantly underestimate employment in agriculture and overestimate employment in other sectors.

Agriculture	Manufacturing	Construction	Services	Min. & Util.	Not Otherwise Class.
1101112 Other cereals & flour	1103111 Clothing mat. & access.	150210 Res. buildings	1103141 Clean. & repair of clothing	110440 Water supply & misc. dwelling ser.	111300 Net purchases abroad
1101113 Bread	1103121 Garments	150220 Non-res. buildings	1103221 Repair & hire of footwear	110451 Electricity	130221 Comp. of empl.
1101114 Other bakery products	1103211 Footwear	150230 Civil eng. works	110410 Rentals for housing	110452 Gas	130222 Interm. cons.
1101115 Pasta products	110511 Furniture & furnishings		110430 Maint./repair of the dwelling	110453 Other fuels	130223 Gross oper. surplus
1101121 Beef & veal	110512 Carpets & other floor coverings		110442 Misc. ser. relating to the dwelling	110722 Fuels/lubes for pers. transp. equip.	130224 Net taxes on production
1101122 Pork	110520 Household textiles		110513 Repair of furniture		130225 Receipts from sales
1101123 Lamb, mutton & goat	110531 Major HH apps.		110533 Repair of HH apps.		130421 Comp. of empl.
1101124 Poultry	110532 Small electric HH apps.		1105621 Domestic ser.		130422 Interm. cons.
1101125 Other meats & preparations	110540 Glassware, tableware & HH utensils		1105622 Household ser.		130423 Gross operating surplus
1101131 Fish & seafood	110551 Major tools & equip.		110621 Medical ser.		130424 Net taxes on prod.
1101132 Pres. fish & seafood	110552 Small tools & miscellaneous access.		110622 Dental ser.		130425 Receipts from sales
1101141 Fresh milk	110561 Non-durable HH goods		110623 Paramedical ser.		140111 Comp. of empl.
1101142 Pres. milk & milk products	110611 Pharmaceutical products		110630 Hospital ser.		140112 Interm. cons.
1101143 Cheese	110612 Other medical products		110723 Maint. & repair of pers. trans. equip.		140113 Gross op. surplus
1101144 Eggs & egg-based products	110613 Therap. apps. & equip.		110724 Other ser. in respect of pers. trans. equip.		140114 Net taxes on production
1101151 Butter & margarine	110711 Motor cars		110731 Pass. trans. by rail		140115 Receipts from sales
1101153 Other edible oils & fats	110712 Motor cycles		110732 Pass. trans. by road		160000 Change in inv. & valuables
1101161 Fresh or chilled fruit	110713 Bicycles		110733 Pass. trans. by air		180000 Balance of ex. & im.
1101162 Frozen, pres. or processed fruits	110820 Tel. & telefax equip.		110734 Pass. trans. by sea & inl& waterway		
1101171 Fresh or chilled vegetables	110911 AV, phot.& info. proc. equip.		110735 Comb. passenger trans.		
1101172 Fresh or chilled potatoes	110914 Recording media		110736 Other purch. transp. ser.		
1101173 Frozen or pres. vegetables	110921 Major durables for outdoor & indoor recreation		110810 Postal ser.		
1101181 Sugar	110931 Other recreational items & equip.		110830 Tel. & telefax ser.		
1101182 Jams, marmalades & honey	111212 Apps., articles & products for pers. care		110915 Repair of AV, phot.& info. proc. equip.		
1101183 Confectionery	111231 Jewellery, clocks & watches		110933 Gardens & pets		
1102111 Spirits	111232 Other pers. effects		110935 Vet. ser. for pets		
1102121 Wine	150110 Metal products & equip.		110941 Rec. & sporting		
1102131 Beer	150120 Transport equip.		110942 Cultural ser.		
110119 Food prod. n.e.c.	150300 Other products.		110943 Games of chance		
110121 Coffee, tea & cocoa			110950 News., books & stationery		
110122 Mineral waters, soft drinks, fruit & veg. juices			110960 Package holidays		
110220 Tobacco.			111000 Education		
			111110 Catering ser.		
			111120 Accom. ser.		
			111211 Hairdressing salons & pers. grooming est.		
			111220 Prostitution		
			111240 Social protection		
			111250 Insurance		
			111261 FISIM		
			111262 Other financial ser.		
			111270 Other ser. n.e.c.		

Table 10: ICP Disaggregated Categories

of the US) is given by:

$$P_s^i/P_s^{PPP} = E_s^i/E_s^{PPP}. \tag{25}$$

The publicly available ICP expenditure data disaggregates expenditure into 19 sectors. These however, do not map very well into ISIC sectors. On request however, it is possible to obtain proprietary ICP data that is further disaggregated into approximately 129 sectors. We make use of this disaggregated data to construct expenditure data at market exchange rates and at PPP for five sectors: agriculture, manufacturing, mining & utilities, construction and services. Our mapping of ICP to ISIC data is shown in Table 10. Notice that the last columns refers to categories that are not classified and hence excluded from our price indices. We then use equation 25 to calculate sector specific price levels in each country (relative to the US) for each of the five sectors.

Sectoral Value added in International Dollars We obtain one digit ISIC v.3 sectoral value added data from the UN. UN data is given in constant 1990 USD prices and current prices.[41] First, we re-base the 1990 data to 2005 prices by calculating (for each sector) the ratio between the 2005 current and constant value added. This gives us a relative sectoral price between 2005 and 1990: P_s^{2005}/P_s^{1990}. Multiplying the constant 1990 value added series for each sector by this sector specific price we obtain constant price sectoral value added data in 2005 prices. Next, we need to convert the constant price (2005) sectoral vale added data into one measured in international (or PPP) dollars. To do this, we divide constant (2005) price sectoral value added data by the relative price levels, P_s^i/P_s^{PPP}, from expression 25. This converts sectoral value added calculated in constant (2005) country specific prices into sectoral value added calculated at international (2005) prices that are (in principle) invariant across countries and time. We recognize that these are imperfect price indices, however they are the best available, given data constraints. Finally, it is important to note, that our empirical results do not - in any way - hinge on this procedure.

Aggregate Capital We follow Caselli (2005) and use the Penn World Tables (version 6.3) to construct estimates of aggregate capital stock. This is done using the perpetual inventory equation:

$$K_{t+1} = (1-\delta)K_t + I_t, \tag{26}$$

where I_t is investment and δ is the depreciation rate. Like Caselli (2005), we measure I_t from the PWT 6.3 as real aggregate investment in PPP.[42] As is standard, we compute the initial

[41] Value added by Economic Activity at constant 1990 prices, USD and Value added by Economic Activity at current prices, USD.

[42] So that $I_t \equiv RGDPL \cdot POP \cdot KI$, where $RGDPL$ is real income per capita obtained with the Laspeyres method, POP is the population and KI is the investment share in real income.

capital stock K_0 as $I_0/(g+\delta)$, where I_0 is the value of the above investment series in the first period that it is available, and g is the average geometric growth rate for the investment series in the first twenty years the data is available.[43] As is discussed in the literature - and by Caselli (2005) - the choice for initial capital stock is tenuous and stems from the assumption that an economy is on a balanced growth path of a Solow model (with a trend growth rate of g) in the initial year. Finally, I follow Caselli (2005) and set the depreciation rate, δ, to 0.06. The results prove not to be very sensitive to choices in either δ, g or initial capital stock.

The above process gives us sequences of capital stocks derived from PWT data. Notice however, that since we will be using UN PPP value added data to calculate sectoral total factor productivity (and not PWT data), we want the capital values to be consistent with our UN total value added data. As such, we use the PWT data to calculate (a unitless) capital-output ratio, $k_t \equiv K_t/Y_t$ (where $Y_t = RGDPL \cdot POP$ and K_t are both from the PWT data) and then use this ratio to construct a capital measure in terms of UN data: $K_t = k_t \cdot VA_t$, where VA_t is the UN measure of total value added in 2005 international dollars, calculated previously.

Sectoral Capital We follow Caselli (2005) in estimating sectoral capital. First, assume that economies consist of five sectors: agriculture (A), mining and utilities (MU), manufacturing (M), construction (C) and services (S). Then, assume that the production function of each sector, s, is of the form given in equations 3 or 4. If we also assume that the rates of return on capital are equalized across sectors (an arbitrage condition), then it is easy to show that the above functional forms implies that for any two sectors s and s', the following holds:

$$\alpha_s \frac{P_s^D Y_s}{K_s} = \alpha_{s'} \frac{P_{s'}^D Y_{s'}}{K_{s'}}, \tag{27}$$

where P_s^D is the domestic producer price of sector s goods. As is emphasized by Caselli (2005), this price will generally differ from the PPP price and it is the price that a domestic investor will care about. Finally, $P_s^D Y_s$ is sector s-es value added (in domestic prices), calculated using UN current price data in local currency units. The above expression provides four distinct equations. Hence, combining these with a capital market clearing condition:

$$\sum_s K_s = K, \tag{28}$$

where K_s is sector specific capital and K is aggregate capital stock, we have a system of five equations in five unknowns from which we obtain an expression for sector specific capital stock, K_s, for each of the five sectors:

$$K_s = \left(\frac{\alpha_s P_s^D Y_s}{\sum_i \alpha_i P_i^D Y_i} \right) K. \tag{29}$$

[43] Caselli (2005) uses the growth rate between the first available year and 1970. We prefer our method, which should provide better estimates for countries whose investment data series start closer to 1970.

Finally, to calculate the above expression we take labor shares, $1-\alpha_s$, for each sector s from Table 9. Given these shares, we can use equation 29 for each sector and the aggregate capital stock (calculated previously) to obtain an estimate of sectoral capital.

Aggregate Human Capital We follow Caselli (2005) and Hall and Jones (1999) in constructing a measure of aggregate human capital. From the data set of Barro and Lee (2010) we obtain the average years of schooling, x, in the population over 25 years old. The schooling data is observed every five years, from 1950 up to (and including) 2010. Since x, moves slowly over time, we estimate the missing data by linear interpolation. This data is then turned into a measure of human capital, h, through the formula:

$$h = e^{\phi(x)}, \tag{30}$$

where x is the average years of schooling and the function $\phi(x)$ is piecewise linear and defined as:

$$\phi(x) = \begin{cases} 0.134 \cdot s & \text{if } x \leq 4 \\ 0.134 \cdot 4 + 0.101 \cdot (x-4) & \text{if } 4 < x \leq 8 \\ 0.134 \cdot 4 + 0.101 \cdot 4 + 0.068 \cdot (x-8) & \text{if } 8 < x \end{cases} \tag{31}$$

The rational for this functional form, as explained by Caselli (2005), is as follows:

> Given our production function, perfect competition in factor and good markets implies that the wage of a worker with x years of education is proportional to his human capital. Since the wage-schooling relationship is widely thought to be log-linear, this calls for a log-linear relation between h and x as well, or something like $h = e^{\phi_x x}$, with ϕ_x a constant. However, international data on education-wage profiles from Psacharopoulos (1994) suggests that in Sub-Saharan Africa (which has the lowest levels of education) the return to one extra year of education is about 13.4 percent, the World average is 10.1 percent, and the OECD average is 6.8 percent. Hall and Jones's measure tries to reconcile the log-linearity at the country level with the concavity across countries.

Estimating Education by Sector in the United States Estimates for sectoral human capital, h_s, are very difficult to come by. As with aggregate human capital, these measures are often based on years of schooling in a particular sector - but this data is not readily available for most countries. When comparing agriculture and non-agriculture, Caselli (2005) infers the years of education in non-agriculture by assuming zero years of schooling in agriculture. Since we are interested in manufacturing versus non manufacturing data, we cannot follow this method.

Sector	Education Distribution							Ave. Y.	Ave. Years/Mfg
	<HS	HS	<C	C(A)	C(B)	M	D		
Agr	24.7	31.7	16.5	5.8	14.5	5.4	1.5	12.49	0.97
Constr.	21.4	39.8	20.4	6.3	9.0	2.3	0.6	12.18	0.94
Ser	7.8	24.3	21.3	9.3	23.1	9.7	4.6	14.22	1.10
Mfg	14.9	36.8	21.5	7.8	13.5	4.2	1.3	12.89	1.00
MU	13.0	33.3	22.6	8.8	15.4	5.1	1.7	13.18	1.02
Total	10.0	27.2	21.2	8.8	20.6	8.3	3.8	13.87	

Table 11: This table shows the distribution of education levels of workers in different ISIC sectors. The levels of education are: Less than a high school diploma (<HS); High school diploma or equivalent (HS); Some college, no degree (<C); Associate's degree C(A); Bachelor's degree C(B); Master's degree (M) and Doctoral/professional degree (D). The table also shows the total implied average years of education by sector and relative to manufacturing. (Source: BLS)

Instead, we base our sectoral educational estimates on US schooling data. In particular, using BLS data, we estimate the average years of schooling of those working in each ISIC one digit sector in the United States in 2008. The results are shown in Table 11. We then assume that the relative number of years of education between any two sectors remains constant (and the same as the US) across countries and time which allows us to infer sectoral education levels in all countries. To construct Table 11 from the BLS we obtain a distribution of occupations within each ISIC sector that specifies what fraction of employees within that sector work in a given occupation.[44] We also obtain the economy wide distribution of educational achievement for each occupation which describes what fraction of people in a particular occupation have achieved: (1) Less than a high school diploma; (2) a High school diploma or equivalent; (3) Some college, no degree; (4) an Associate's degree; (5) a Bachelor's degree; (6) a Master's degree and (7) a Doctoral/professional degree. Given these distributions we can then calculate the distribution of educational levels within each ISIC sector.[45] Finally assuming that education levels (1) though (7) take 8, 12, 14, 14, 16, 18 and 21 years respectively to achieve, allows us to calculate the average number of years of education of people working within each ISIC sector.

Sectoral Human Capital To calculate sectoral human capital we assume that the relative number of years of education between any two sectors remains constant (and the same as the US) across countries and time. More specifically, we define η_s^{US} as the ratio of average years of schooling in sector s relative to the years of schooling in the manufacturing in 2008 in the US

[44] Occupations are classified by major - two digit - 2010 Standard Occupational Classification (SOC).

[45] For example, suppose z_A is a vector that contains the distribution of occupations within agriculture and w^{HS} is the distribution of those workers who have achieved at most a high school degree across all occupations. Then the dot product of the two vectors, $z_A \cdot w^{HS}$, is the fraction of agricultural workers who have achieved at most a high school degree.

(from Table 11):

$$\eta_s^{US} = x_s^{US}/x_m^{US}. \tag{32}$$

We then assume that for country i, the average years of schooling in sector s, x_s^i, is related to the number of years of schooling in manufacturing in that country by:

$$x_s^i = \eta_s^{US} x_m^i. \tag{33}$$

We are thus assuming that the relative number of years of education between any two sectors remains constant (and the same as the US) across countries and time. Finally, education must also satisfy the following aggregation identity for each country:

$$\sum_s l_s^i x_s^i = x^i, \tag{34}$$

where l_s^i is the employment share of sector s in country i (so that $\sum_s l_s^i = 1$) and x^i is the average years of schooling per worker in the entire economy. Given employment shares, the aggregate years of schooling and η_s^{US}, the above expressions yield five equations in five unknowns, which can be solved for years of schooling in each sector and country, x_s^i. For each country, we can then relate the years of schooling in each sector to sectoral human capital through the 'standard' Mincerian returns formula in equation 31.

Data consistency Finally, we restrict our non-missing data to a panel of the 120 richest countries for the 1980-2006 period, ranked by average Real GDP per capita (RGDPL) from the Penn World Tables for 1980-2006. In an attempt to ensure data quality, we also drop all country-date points where sectoral value added and sectoral employment data show a large discrepancy (more than half a standard deviation) between ILO/UN and WDI sources. The procedure for selecting which country-date points to drop is as follows:

1. Choose two sources of the same panel data: $y_{i,t}^{WDI}$ and $y_{i,t}^{UN}$
2. Compute the ratio between each observation: $r_{i,t} = y_{i,t}^{WDI}/y_{i,t}^{UN}$
3. Compute the standard deviation of all the $r_{i,t}$: $sdev$.
4. Compute the average of all these ratios: $ave = \frac{1}{T+C}\sum_{i=1}^{C}\sum_{t}^{T} r_{i,t}$
5. Compute the standard deviations of an observation from average: $e_{i,t} = |r_{i,t} - ave|/sdev$
6. Drop observation if $e_{i,t} > 0.5$

The countries that remain in our baseline sample are: Australia, Austria, Bahrain, Belgium, Botswana, Brazil, Brunei, Bulgaria, Canada, Chile, Cyprus, Denmark, Egypt, Finland, France, Gabon, Germany, Greece, Hungary, Iceland, Ireland, Israel, Italy, Japan, Korea, Kuwait, Luxembourg, Malaysia, Malta, Mauritius, Mexico, New Zealand, Norway, Poland, Portugal, Qatar, Romania, Saudi Arabia, South Africa, Spain, Sweden, Switzerland, Thailand, UK, US and Venezuela. It is important to note that our results do not depend on either procedure and that we re-do our empirical exercise using all the data in Appendix 12.1 which increases our sample size considerably.

Summary Statistics Table 12, presents summary statistics for our main macro economic variables: sectoral employment shares, sectoral labor productivity, sectoral TFP (physical capital only), sectoral TFP (physical and human capital), value added per worker (this is is the sum of all sectoral value added data divided by the total labor force), GDP/capita in international 2005 dollars from the WDI, the natural resource export share and the share of migrants in total population.

Variable	Sector	N	mean	sd	min	max	p10	p90
Emp. Share	A	806	0.11	0.11	0.01	0.71	0.03	0.24
	C	806	0.07	0.02	0.02	0.27	0.06	0.1
	S	806	0.61	0.11	0.19	0.82	0.47	0.73
	M	806	0.19	0.05	0.05	0.35	0.13	0.24
Labor Prod.	A	806	17973	11566	1121	64657	4712	33649
	C	806	42263	16337	8225	122671	19212	62169
	S	806	53182	19388	12433	178698	23380	76341
	M	806	37038	22552	4355	178705	11318	64001
	ACS	806	47724	19533	5340	170554	17623	70507
	ACSM	806	45351	19255	5437	170209	16388	67141
TFP (p.)	A	806	3.14	1.26	0.93	11.6	1.72	4.72
	C	806	404.14	113.5	136.78	968.62	266.58	542.37
	S	806	221.57	40.94	101.11	421.16	167.34	261.5
	M	806	225.6	98.12	43.64	684.6	111.61	335.06
	ACS	806	179.7	39.74	62.21	361.79	126.17	220.31
	ACSM	806	186	44.86	64.3	397.56	127.02	234.58
TFP (p.+h.)	A	806	2.46	1.01	0.71	9.4	1.38	3.7
	C	806	234.69	67.7	77.2	603.18	148.83	310.95
	S	806	127.71	22.83	68.2	234.69	101.94	150.36
	M	806	128.83	52.6	24.26	412.94	71.95	181.89
	ACS	806	105.39	21.22	44.74	210.32	82.88	127.42
	ACSM	806	108.61	23.5	41.73	232.21	82.33	133.61
VA/worker	-	806	48154	22539	5464	245294	17683	69358
gdp/capita	-	806	21321	10193	2123	72783	7771	32729
NR Exp. Sh.	-	806	0.04	0.06	0.00	0.39	0.00	0.08
Migr. Sh.	-	806	0.08	0.09	0.00	0.80	0.01	0.20

Table 12: Summary statistics for macro data.

11.2 Micro Data

Resource Wealth We divide US counties into oil rich and oil poor following the methodology of Michaels (2009). We use the *Oil and Gas Journal Data Book* (2000) to identify major US oil fields - those with ultimate oil recovery exceeding 100 million barrels of oil - and determine in which county/-ies these fields are located using the *Oil and Gas Field Master List* (2001). We define a county as oil rich if it lies above one or more of these oilfields. Most of the oil rich counties are located in three states: Texas (106 counties), Oklahoma (24 counties) and Louisiana (18 counties). We exclude from our analysis the two other oil abundant states, Alaska and California for reasons discussed in the main text. Our control countries are those located within 200 miles of the oil rich.[46] This leaves us with the sample of 775 counties, 168 of which are oil rich and are shown in Figure 4.

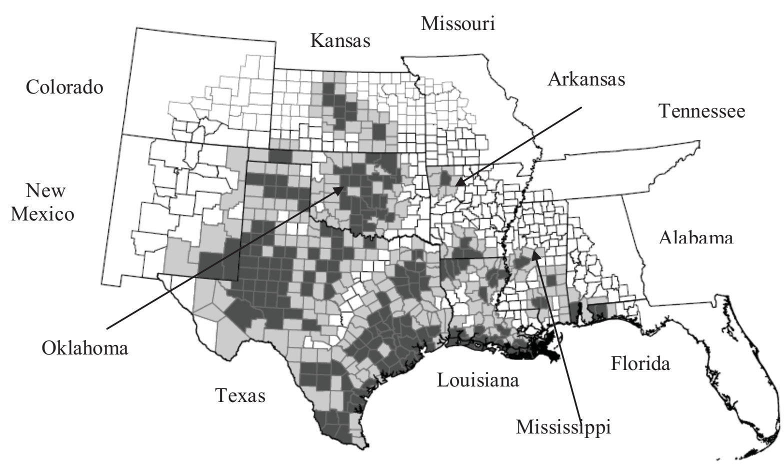


Figure 4: Counties in Micro Sample. Oil rich counties (black), adjacent counties (grey) and other nearby counties (white). (Source: Michaels (2009))

Sectoral Labor Productivity Next, we use 1980 US census data from the Integrated Public Use Microdata Series or IPUMS (Ruggles et al., 2008) to determine sectoral labor productivity within counties.[47] We restrict the sample by including individuals aged 18-65 and who have non-missing data on hours worked, weeks worked and wage income. We consider only individuals who

[46] We do this to focus the analysis on counties that are similar in all but their oil abundance.

[47] Notice that, we use an unweighted "flat" sample that includes 5% of the population. Also, all census data from 1940 onwards does not identify individual's county of residence due to confidentiality requirements. As such, the Census Bureau constructs several other variables to identify residential location. We use the 1980 sample since it is the latest data to use county information as a geographical identifier.

worked at least 1750 hours the previous year, and who earned at least the Federal minimum wage. We classify each individual's employment as belonging to one of three sectors: manufacturing, non-manufacturing or mining[48] and use hourly wage as a measure of labor productivity of each person.[49]

Matching Resource and Productivity Data Finally, we need to match resource wealth and labor productivity data. IPUMS 1980 census data is the latest years with detailed geographic identifiers. Unfortunately the data are more coarsely aggregated than the county level, so they only identify which county group (rather than a particular county) each individual resides in. These may consist of: groups of counties, single counties, single cities or other census-designated places. None of these county groups cross state lines. As such, we define a county group as oil rich if it has at least one oil rich county. We then calculate the average labor productivity of each county group. Finally, we match resource wealth and productivity data across county groups. Our final sample contains 184 county groups, 75 of which are oil rich.

12 Empirical Appendix

12.1 Macro Results

We consider the employment productivity results in the macro data for two samples of data. First we consider a restricted sample which we take to be our baseline. In this sample, we 1) consider only the richest 120 countries, 2) we drop countries that exhibit a deviation in the data on sectoral employment and value added between WDI and UN sources and 3) we keep countries that have data for all our measures of productivity. In the second sample we keep all the data which results in much larger sample sizes for our estimates.[50] Whilst the fit of the data is unsurprisingly not as tight as with the restricted sample, all established results go through.

Employment and Resource Wealth Table 13 tests the relationship between the employment share of manufacturing and resource wealth for both samples of data.[51] Columns (1) regress manufacturing employment share on natural resource export share of GDP. Resource rich countries employ less workers in the manufacturing sector and (implicitly) more workers in the non-manufacturing sector. These results are statistically significant at the one percent

[48] Our sectoral categories are consistent with the ISIC classifications used in the macro data.

[49] We construct this as annual wage income divided by annual hours worked. To compute hours worked, we multiply weeks worked by hours worked per week.

[50] For the employment results with the full sample we have 119 countries. For each of the productivity measures we have 85, 70 and 69 countries respectively.

[51] Since employment share in manufacturing is simply one minus the employment share in non-manufacturing, the regressions for non-manufacturing employment are the same with opposite signs on coefficients.

(a) Restricted Sample

	(1) M. Emp.	(2) M. Emp.	(3) M. Emp.
NRE	-0.310***	-0.258***	-0.267***
	(0.025)	(0.024)	(0.023)
logGDP		0.681***	0.608***
		(0.059)	(0.056)
sqlogGDP		-0.036***	-0.031***
		(0.003)	(0.003)
Time FE	no	no	yes
Obser.	806	806	806
R^2	0.157	0.277	0.391

*** p<0.01, ** p<0.05, * p<0.1

(b) All Data

	(1) M. Emp.	(2) M. Emp.	(3) M. Emp.
NRE	-0.183***	-0.241***	-0.267***
	(0.027)	(0.023)	(0.022)
logGDP		0.353***	0.297***
		(0.027)	(0.025)
sqlogGDP		-0.018***	-0.015***
		(0.001)	(0.001)
Time FE	no	no	yes
Obser.	1,457	1,457	1,457
R^2	0.031	0.322	0.418

*** p<0.01, ** p<0.05, * p<0.1

Table 13: Changes in sectoral employment and resource wealth. M. Emp. refers to manufacturing employment share. NRE refers to the natural resource export share. logGDP refers to log of GDP per capita. sqlogGDP refers to the square of logGDP.

level.[52] A well known fact from the development literature is that employment in manufacturing follows an inverted-U with per capita income. Columns (2) control for changes in income (and income squared) and shows that the results remain unchanged. Finally, columns (3) add time fixed effects to the regressions in column (2). The results also remain unchanged.[53]

Sectoral Productivity Next, we establish that, controlling for aggregate productivity, resource rich countries are more productive in manufacturing and less productive in non-manufacturing than resource poor countries. Tables 14 and 15, show how our sector specific productivity measures change with resource wealth and aggregate TFP in both our samples of data. Controlling for aggregate productivity, resource rich countries are more productive in manufacturing and less productive in non-manufacturing sectors. Notice also that the differences are much greater in manufacturing. These results are significant at the one percent level and robust to including time fixed effects.[54]

[52] Below, we disaggregate the non-manufacturing sector and show that movement of workers to the Service sector is key in driving the increase in non-manufacturing employment. We do not have cross-country data to disaggregate manufacturing to investigate which sub-sectors shrink.

[53] We do not include country dummies as these are highly correlated with our resource wealth measure. In particular, if we re-run all the above regressions but replace our resource wealth measure with a sequence of country dummies, the coefficients of the country dummies are highly correlated with each country's natural resource export share. Thus country dummies are primarily picking up a country's resource wealth, ultimately serving the same purpose as our export share measure of resource wealth.

[54] As before, we do no consider country-dummies since they are highly correlated with our measure of resource wealth. Notice also that in what follows, we disaggregate the non-manufacturing sector and show that changes in service sector productivity are key in falling productivity in non-manufacturing. We do not have cross-country data to disaggregate manufacturing productivity to investigate which sub-sectors become more productive.

(a) Changes in sectoral labor productivity and resource wealth.

	A_s		A_m	
NRE	-14,989.75***	-14,299.23***	69,748.64***	66,536.54***
	(1556.75)	(1510.33)	(6667.48)	(6665.86)
A	1.00***	1.01***	1.00***	0.96***
	(0.00)	(0.00)	(0.02)	(0.02)
Time FE	no	yes	no	yes
Obser.	806	806	806	806
R^2	0.98	0.98	0.75	0.75

*** p<0.01, ** p<0.05, * p<0.1

(b) Changes in sectoral TFP (K) and resource wealth.

	B_s		B_m	
NRE	-37.85***	-38.20***	308.00***	306.63***
	(4.46)	(4.41)	(32.06)	(32.46)
B	0.87***	0.89***	1.75***	1.68***
	(0.01)	(0.01)	(0.04)	(0.04)
Time FE	no	yes	no	yes
Obser.	806	806	806	806
R^2	0.96	0.97	0.70	0.71

*** p<0.01, ** p<0.05, * p<0.1

(c) Changes in sectoral TFP (K, H) and resource wealth.

	D_s		D_m	
NRE	-21.64***	-21.79***	186.58***	185.64***
	(2.70)	(2.64)	(19.27)	(19.33)
D	0.89***	0.90***	1.65***	1.59***
	(0.01)	(0.01)	(0.05)	(0.05)
Time FE	no	yes	no	yes
Obser.	806	806	806	806
R^2	0.95	0.96	0.62	0.65

*** p<0.01, ** p<0.05, * p<0.1

Table 14: The impact of resource wealth on productivity. A, B and D refer to our three measures of sectoral productivity (with subscript) and aggregate productivity (without subscript). NRE refers to the natural resource export share. Results for restricted sample.

(a) Changes in sectoral labor productivity and resource wealth.

	A_s		A_m	
NRE	-11,330.98***	-11,495.57***	74,829.03***	76,025.48***
	(1,392)	(1,400)	(7,009)	(7,146)
A	1.03***	1.03***	0.77***	0.77***
	(0.00)	(0.00)	(0.01)	(0.01)
Time FE	no	yes	no	yes
Obser.	1,287	1,287	1,287	1,287
R^2	1.00	1.00	0.83	0.83

*** p<0.01, ** p<0.05, * p<0.1

(b) Changes in sectoral TFP (K) and resource wealth.

	B_s		B_m	
NRE	-32.02***	-33.42***	356.73***	364.74***
	(4.15)	(4.08)	(35.73)	(36.19)
B	0.93***	0.93***	1.33***	1.31***
	(0.00)	(0.00)	(0.03)	(0.03)
Time FE	no	yes	no	yes
Obser.	1,139	1,139	1,139	1,139
R^2	0.99	0.99	0.69	0.70

*** p<0.01, ** p<0.05, * p<0.1

(c) Changes in sectoral TFP (K,H) and resource wealth.

	D_s		D_m	
NRE	-17.85***	-18.72***	183.24***	185.96***
	(2.51)	(2.44)	(19.74)	(19.80)
D	0.94***	0.95***	1.10***	1.09***
	(0.00)	(0.00)	(0.02)	(0.02)
Time FE	no	yes	no	yes
Obser.	1,134	1,134	1,134	1,134
R^2	0.99	0.99	0.67	0.69

*** p<0.01, ** p<0.05, * p<0.1

Table 15: The impact of resource wealth on productivity. A, B and D refer to our three measures of sectoral productivity (with subscript) and aggregate productivity (without subscript). NRE refers to the natural resource export share. Results for all the data.

(a) Sectoral employment and resource wealth

	(1) A. Emp.	(2) C. Emp.	(3) S. Emp.
NRE	-0.03	0.03**	0.31***
	(0.04)	(0.01)	(0.04)
logGDP	-0.154***	0.009***	0.135***
	(0.00)	(0.00)	(0.00)
Time FE	yes	yes	yes
Obser.	806	806	806
R^2	0.685	0.134	0.657

(b) Sectoral TFP (K,H) and resource wealth.

	(1) D_a	(2) D_c	(3) D_s
NRE	2.41***	310.01***	-72.38***
	(0.52)	(34.58)	(7.56)
D	0.02***	1.08***	0.83***
	(0.00)	(0.09)	(0.02)
Time FE	yes	yes	yes
Obser.	806	806	806
R^2	0.32	0.32	0.71

*** p<0.01, ** p<0.05, * p<0.1

Table 16: The impact of resource wealth on sectoral TFP (K,H) and employment in disaggregated non-manufacturing. D and D_s refers to our third measure of sectoral and aggregate productivity respectively. NRE refers to the natural resource export share.

Disaggregation of Non-Manufacturing Next we show how productivity and employment in sub-sectors of the non-manufacturing sector (Agriculture, Construction and Services) changes with resource wealth. We find that the category "Services" drives the relationships found in productivity and employment in the non-manufacturing sector.

The panel on the left of Table 16 shows changes in sectoral employment with resource wealth. Agriculture has a statistically insignificant coefficient, whilst construction has a statistically positive but quantitatively small coefficient. The aggregate results are driven by the service sector, where resource wealth has a significant positive impact on employment. The panel on the right shows how our third measure of sectoral productivity changes with resource wealth. We see that at the sub-sectoral level effects of resource wealth are mixed. A strong positive effect is found in agriculture and construction and a strong negative effect is found in services. The overall negative result for non-manufacturing is thus primarily driven by changes in service sector productivity.[55]

12.2 Micro Data

Table 17 shows how manufacturing employment shares and sectoral labor productivity change with resource wealth across counties. We present results with and without controls for average, sector specific (non-oil) wages.[56] From the tables we see that resource rich counties have

[55] Although it would be interesting to further disaggregate this sector, this proves to be difficult. To construct cross-country comparable data we need comparable price indices which are obtained from expenditure data. At an aggregate level, categories of the expenditure data broadly overlap with ISIC data - making it possible to create price indices that are comparable across countries. At lower levels of disaggregation, the categories of consumer expenditure and producer indices become harder to match.

[56] As with the macro data, we present regressions for manufacturing, since the regressions for non-manufacturing employment are the same with opposite signs on coefficients.

(a) Employment

COEFF.	M. Emp.	M. Emp.
Oil	-0.030**	-0.030**
	(0.015)	(0.015)
W		0.002
		(0.009)
Obser.	184	184
R^2	0.053	0.153

*** p<0.01, ** p<0.05, * p<0.1

(b) Labor productivity

COEFF.	NM Prod.	M Prod.
Oil	-0.121***	0.320***
	(0.034)	(0.085)
W	0.805***	1.397***
	(0.019)	(0.047)
Obser.	184	184
R^2	0.911	0.836

*** p<0.01, ** p<0.05, * p<0.1

Table 17: Employment shares, labor productivity and oil wealth

	Employment			Productivity		
	oil	no oil	ratio	oil	no oil	ratio
Electrical machinery, and equip	1.55%	2.69%	0.58	1.06	0.96	1.105
Petroleum and coal prod	1.66%	0.44%	3.77	1.29	1.18	1.096
Tobacco prod	0.01%	0.03%	0.33	1.16	1.07	1.086
Publishing and Printing	0.93%	1.5%	0.62	1.02	0.95	1.080
Prof., phot. Equi., & watches	0.35%	0.48%	0.73	1.00	0.93	1.074
Chemicals and chemical prod	3.43%	1.71%	2.01	1.23	1.15	1.066
Textiles	0.35%	0.49%	0.71	0.84	0.79	1.054
Apparel, fabricated textile prod	1.00%	1.93%	0.52	0.75	0.72	1.045
Paper and paper prod	0.95%	1.32%	0.72	1.15	1.11	1.044
Food prod and beverages	1.95%	2.47%	0.79	0.91	0.88	1.040
Leather and leather prod	0.08%	0.32%	0.25	0.77	0.74	1.038
Manufacture of basic metals	3.61%	2.95%	1.22	1.08	1.06	1.024
Furniture and fixtures	0.31%	0.83%	0.37	0.90	0.89	1.008
Wood prod except furniture	0.70%	1.00%	0.70	0.86	0.86	1.004
Machinery, except electrical	3.55%	2.66%	1.33	1.03	1.04	0.990
Other transport equip	1.98%	2.3%	0.86	1.00	1.03	0.976
Motor vehicles	0.61%	0.92%	0.66	0.99	1.01	0.972
Mfg. of non-metallic mineral prod	1.12%	0.93%	1.20	0.96	1.00	0.958
N.E.C Mfg	0.78%	1.14%	0.68	0.94	1.01	0.930
Rubber prod	0.33%	0.49%	0.67	1.07	1.20	0.888

Table 18: Employment shares and labor productivity (rel. to agg. prod.) in manufacturing sub-sectors for oil rich/poor counties.

smaller employment shares in manufacturing (and hence implicitly larger employment shares in non-manufacturing.). They are also more productive in manufacturing and less productive in non-manufacturing than resource poor counties. Finally, notice that - like in the macro data - the change in productivity is greater in manufacturing than in non-manufacturing.

Disaggregation of Manufacturing Table 18 shows employment shares and productivity (relative to aggregate productivity) of manufacturing sub-sectors. Fourteen and fifteen out of twenty sub-sectors exhibit lower employment and higher productivity in manufacturing (relative to aggregate productivity) respectively. Lower productivity sectors employ only approximately 30% of manufacturing workers. This provides evidence that higher manufacturing productivity is not driven by higher productivity in resource processing sectors.

13 Theory Appendix

13.1 Adding Physical Capital to the Exogenous TFP Model

Suppose we introduce capital into the exogenous TFP model of section 4, so that the production function of the manufacturing and non-manufacturing sector become:

$$Y_{m,t} = A_{m,t} L_{m,t}^{1-\theta} K_{m,t}^{\theta}, \text{ and } Y_{s,t} = A_{s,t} L_{s,t}^{1-\alpha} K_{s,t}^{\alpha} \tag{35}$$

where α and θ are the capital shares in non-manufacturing and manufacturing respectively. From the manufacturing and non-manufacturing firm's problems, we can show that the ratio of wages (w_t) to capital rental rates (r_t) is given by:

$$\frac{w_t}{r_t} = \frac{1-\theta}{\theta}\frac{K_{m,t}}{L_{m,t}}, \text{ and } \frac{w_t}{r_t} = \frac{1-\alpha}{\alpha}\frac{K_{s,t}}{L_{s,t}}. \tag{36}$$

Combining these equations, we see that the capital-labor ratio in manufacturing is proportional to the capital-labor ratio in non-manufacturing:

$$\frac{1-\theta}{\theta}\frac{K_{m,t}}{L_{m,t}} = \frac{1-\alpha}{\alpha}\frac{K_{s,t}}{L_{s,t}}. \tag{37}$$

Finally, notice that labor productivity in manufacturing and non-manufacturing are given by:

$$\frac{p_{m,0}Y_{m,t}}{L_{m,t}} = p_{m,0}A_{m,t}\left(\frac{K_{m,t}}{L_{m,t}}\right)^{\theta}, \text{ and } \frac{p_{s,0}Y_{s,t}}{L_{s,t}} = p_{s,0}A_{s,t}\left(\frac{K_{s,t}}{L_{s,t}}\right)^{\alpha}, \tag{38}$$

where, $p_{m,0}$ and $p_{s,0}$ are the period zero price of manufacturing and non-manufacturing respectively. Thus, labor productivity in each sector is an increasing function of each sector's capital-labor ratio. But, according to equation (37), if capital labor ratio rises/falls in one sector, it rises/falls in the other and hence according to equation (38), labor productivity in both sectors rises/falls. A model with capital predicts that sectoral labor productivities move in the same direction and hence cannot account for the asymmetric changes in labor productivity observed in the data. Notice however, that the above model can generate a non-constant *relative* productivity, $y \equiv \frac{p_{s,0}Y_{s,t}}{L_{s,t}} / \frac{p_m Y_{m,t}}{L_{m,t}}$, if capital shares vary across sectors. Productivity then changes in in both sectors but it changes *more* in one sector than another.

13.2 Proof of Proposition 1

Proof. Assume, by contradiction, that $p_{s,H} \leq p_{s,L}$. Notice, from (12), that the ratio of manufacturing to non-manufacturing (aggregate) good consumption is given by $\nu^{\sigma} p_{s,H}^{\sigma}$ in the high endowment economy and $\nu^{\sigma} p_{s,L}^{\sigma}$ in the low endowment economy, hence by our assumption:

$$\frac{C_{m,H}}{C_{s,H}} = \nu^{\sigma} p_{s,H}^{\sigma} \leq \nu^{\sigma} p_{s,L}^{\sigma} = \frac{C_{m,L}}{C_{s,L}},$$

where, $C_{m,k} = \int_i c^i_{m,k}$ and $C_{s,k} = \int_i c^i_{s,k}$ is aggregate consumption of manufacturing and non-manufacturing goods respectively, in economy $k = H, L$. By market clearing, this becomes:

$$\frac{Y_{m,H} + p_{o,H}O_H}{Y_{s,H}} = \frac{C_{m,H}}{C_{s,H}} \leq \frac{C_{m,L}}{C_{s,L}} = \frac{Y_{m,L} + p_{o,L}O_L}{Y_{s,L}}.$$

Notice however, that by Equation (11), the higher the price of non-manufacturing goods, the larger the set of consumers working in the non-manufacturing sector (and the smaller the number of people working in manufacturing), and hence the higher the total output of services (and the smaller the total output of non-services).[57] Consequently, (since we've assumed that $p_{s,H} \leq p_{s,L}$), $Y_{s,H} \leq Y_{s,L}$ and $Y_{m,L} \leq Y_{m,H}$. Using this, we can re-write the above inequality as

$$\frac{Y_{m,H} + p_{o,H}O_H}{Y_{s,H}} \leq \frac{Y_{m,L} + p_{o,L}O_L}{Y_{s,L}} \leq \frac{Y_{m,H} + p_{o,L}O_L}{Y_{s,H}}.$$

This then implies that $p_{o,H}O_H \leq p_{o,L}O_L$, which is a contradiction, since $p_{o,H}O_H > p_{o,L}O_L$. Thus, $p_{s,H} > p_{s,L}$. □

13.3 Resource Curse

In an economy without oil, the equilibrium price of non-manufacturing is given by $\bar{p}_s = \nu^{\frac{\sigma}{1-\theta-\sigma}}$. Since there is a unit of workers, non-oil aggregate productivity measured using this price is just equal to non-oil output:

$$Y_{NO} = \bar{p}_s Y_s + Y_m = \nu^{\frac{\sigma}{1-\theta-\sigma}} \Gamma(1 - \frac{1}{\theta}) L_s^{1-\frac{1}{\theta}} + \Gamma(1 - \frac{1}{\theta})(1 - L_s)^{1-\frac{1}{\theta}}. \tag{39}$$

This is a concave function on $0 \leq L_s \leq 1$, which has a unique maximum given by $L_s^{NO} = \frac{\nu^{\frac{\sigma\theta}{1-\theta-\sigma}}}{1+\nu^{\frac{\sigma\theta}{1-\theta-\sigma}}}$. It turns out that the employment that maximizes output, also maximizes utility - i.e. this is the equilibrium employment in the no oil case. Since the utility maximizing employment in a country with resources will necessarily be different to L_s^{NO} (due to a higher demand for non-manufacturing) aggregate non-oil productivity (measured in resource poor country's prices) will necessary be lower. The above effect however, is very small[58] and entirely a consequence of the pricing scheme chosen to measure real GDP. If we chose to measure aggregate productivity using the resource rich country's prices, *we would get exactly the opposite result.* In that case, the employment allocation that would maximize output would be exactly the labor allocation that maximized utility in the oil rich country.[59] Thus, the measured resource curse in our model, is entirely a consequence of the type of pricing scheme adopted. Kehoe and Ruhl (2008) make a similar point.

[57] Notice, that this is also were the assumption that the proportion of workers indifferent between sectors is negligible comes into play.

[58] Given our calibration, the model predicts the highest decile of resource exporters will have a non-oil aggregate productivity that 0.016% smaller than the lowest decile.

[59] The model would then predict that the highest decile of exporters will have a non-oil aggregate productivity that is 0.016% *larger* than the lowest decile.

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