De-Specialization, Dutch Disease and Sectoral Productivity Differences[1]

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Abstract

We use macro cross-country data and micro US county level data to demonstrate that resource rich regions have significantly higher TFP in manufacturing than resource poor regions, but slightly lower TFP in non-manufacturing. We suggest a process of de-specialization to explain these facts. In a standard Dutch disease story, endowments of natural resources induce labor to move from the (traded) manufacturing sector to the (non-traded) non-manufacturing sector. We argue that in resource rich economies, many of those working in the non-manufacturing sector, are those whose comparative advantage is not in non-manufacturing sector work, whilst those left working in the manufacturing sector are the most suited to manufacturing work. Since manufacturing employs relatively less workers, the impact of shifting labor will be more pronounced within that sector. We construct a two sector, general equilibrium, open economy Roy (1951) model of self-selection - in the spirit of Lagakos and Waugh (2009). A calibrated version of the model predicts significantly higher output per worker in manufacturing between resource rich and resource poor countries, and somewhat lower output per worker in non-manufacturing - even though countries and sectors have the same aggregate efficiency terms.

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1 Introduction

Productivity differences between resource rich and resource poor countries are large in manufacturing and much smaller in (non-resource) non-manufacturing. In particular, resource rich countries have significantly higher productivity in manufacturing than resource poor countries but (slightly) lower productivity in non-manufacturing. Yet, typical resource rich countries devote a smaller proportion of their labor force to the manufacturing sector and a larger proportion of their labor force to the non-manufacturing sector than resource poor countries, in a process of de-industrialization known as "Dutch disease". A growth accounting exercise shows that sectoral productivity differences can be important in accounting for aggregate productivity differences between resource rich and resource poor countries. For example, if the share of labor in the manufacturing sector in resource rich Saudi Arabia were hypothetically raised to that of resource poor Germany, 63% of aggregate productivity differences between Germany and Saudi Arabia would be eliminated. This suggests, that understanding differences in sectoral productivity is important to understanding why resource rich countries are "cursed" with lower (non-oil) income than resource poor countries.[2]

In a standard Dutch disease story, resource rich countries can meet a part of their higher demand for traded goods by purchasing them on a world market in exchange for natural resources. To meet higher demand for (non-traded) non-manufacturing goods however, labor that would otherwise have been employed in the (traded) manufacturing sector, shifts into the (non-traded) non-manufacturing sector. Although standard models of Dutch disease can account for this sectoral labor re-allocation, they do not account for changes in sectoral productivity that are associated with it.

The mechanism suggested by this paper is a process of de-specialization that accompanies the movement of labor. Many of the new workers in the non-manufacturing sector in resource rich countries are those whose comparative advantage is not in non-manufacturing sector work, but rather lie in manufacturing sector work. In countries with no endowments of natural resources on the other hand, those that work in the non-manufacturing sector are those who are the most efficient at that sector's work. This suggests that non-manufacturing productivity in resource rich countries will be lower than in resource poor countries. At the same time, workers that choose to remain in the manufacturing sector in resource rich countries are those who are most skilled at manufacturing sector work. This suggests that the productivity of manufacturing in resource rich countries will be higher than that in resource poor countries.

Finally, since the manufacturing sector is typically smaller than the non-manufacturing sector, the movement of a fixed number of workers from manufacturing to the non-manufacturing

[2] For a review of the literature on the resource curse, see Stevens (2003).

sector affects sectoral productivity asymmetrically - output per worker changes more in manufacturing (where the outflow of workers is large relative to the original level) and less in non-manufacturing (where inflow of workers is relatively small).

A similar problem exists within the growth and development literature: poorer countries have a larger portion of their labor force employed in agriculture, due to subsistence requirements. Improvements in aggregate productivity shift labor out of agriculture into non-agriculture. This results in increased specialization in agriculture and decreased specialization in non-agriculture. This mechanism (based on a classic model by Roy (1951)) has been formalized and quantitatively analyzed by Lagakos and Waugh (2009), who show that a significant portion of sectoral productivity differences in agriculture can be explained by specialization of workers. This paper applies their mechanism to the story of Dutch disease. The key link between the two stories, is the observation that natural resource endowment's act like non-homothetic preferences on labor distributions. Whereas subsistence levels in agriculture, "pull" labor out of industry into agriculture, endowments of natural resources "pull" labor out of the (traded) manufacturing sector into the (non-traded) non-manufacturing sector. This paper applies the solution from the growth literature and shows that it can explain all the cross-country productivity differences in non-manufacturing and manufacturing between resource rich and resource poor countries.

Empirically, the contribution of the paper is to document the fact that - controlling for aggregate levels of productivity - resource rich regions are significantly more productive in manufacturing and slightly less productive in (non-resource) non-manufacturing than resource poor regions. We demonstrate this using both cross-country macro data and using US county level data.

The main theoretical exercise of the paper is to construct and calibrate a two sector, general equilibrium, open economy Roy (1951) model of selection - in the spirit of Lagakos and Waugh (2009). We use the model to see whether exogenous variation in endowments of natural resources can result in 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 that the model with heterogenous workers does a remarkably good job in explaining both differences in employment and in sectoral productivity across countries.

Just as Lagakos and Waugh's paper has implications for the way economists think about aggregate productivity in the developing world, our paper has implications for how economists think about aggregate productivity between resource rich and resource poor economies. In particular, the analysis suggests that lower aggregate productivity in resource rich countries in not *caused* by a shift of labor away from the high productivity manufacturing sector. Rather, it is de-industrialization that causes productivity of manufacturing to rise and productivity of non-manufacturing to fall. The policy implications of the two views are quite different. Whereas, accounting exercises might suggest an industrial policy encouraging the movement of labor from low productivity services to high productivity manufacturing, the implication of the model is that such policies would be self defeating. Increasing employment in manufacturing would simply lower productivity of that sector as more unskilled workers flowed in. Instead, the theory predicts that improvements in education and training may be important in eliminating sectoral productivity differences and increasing living standards in resource rich economies.

In section 2 we introduces the macro data used in this study. Section, 3 then establishes the facts for productivity and employment in resource rich and resource poor countries. Section 4, demonstrates how standard models are able generate de-industrialization but are unable to match observed facts in productivity. Section 5 then presents our model, calibration and results. The following two sections then extend the model to more complicated skill processes and to include migration. Finally, in sections 8 and 9 we present micro evidence for the observed facts and direct evidence in support of our mechanism.

2 Basic Data

The empirical part of this paper concerns itself with establishing the differences in sectoral employment and productivity between resource rich and resource poor countries. This section outlines the construction of the macro data necessary to examine the relationship between productivity, employment and resource wealth.

In order to perform our analysis, we need to construct sector level data for: value added, physical capital, human capital and employment. We also need to construct a measure of resource wealth for an entire economy. In general, the lowest level of aggregation at which all the data is available is the one sector ISIC classification.[3] We then define non-resource non-manufacturing as the sum of agriculture, construction and services (A+C+S) and we take the non-resource economy to consist of agriculture, construction, services and manufacturing (A+C+S+M).

In the main body of the paper, we consider a panel of the 120 richest countries for the 1980-2006 period.[4] We proceed to keep all country-date points for which we have all necessary data. In an attempt to ensure data quality, we drop all country-date points where sectoral value added

[3] In particular throughout this paper we define the following sectors: A: Agriculture, hunting and forestry (ISIC A), MU: Mining and quarrying (ISIC C) and Electricity, gas and water (ISIC E), M: Manufacturing (ISIC D), C: Construction (ISIC F), S: Wholesale and retail trade (ISIC G), Hotels and restaurants (ISIC H), Transport, storage and communication (ISIC I) and Other service activities (ISIC J-P).

[4] These are ranked according to the average Real GDP per capita (RGDPL) from the Penn World Tables for 1980-2006. We consider only richer countries for two reasons: First, since we are examining more disaggregate data than is standard, poor data quality is a serious concern - especially in the sectoral value added and sectoral employment data. Second, we feel that the mechanism of specialization and de-specialization described later will probably play more of a prominent role in richer countries.

and sectoral employment data show a large discrepancy (more than half a standard deviation) between ILO/UN and WDI sources (see Appendix 11.2). This leaves a total of 46 countries in our sample. On average there are 18 observations for each country and 29 observations for each year, for a total of 806 data points. For summary statistics of all resulting variables see Appendix 11.1. Although we have restricted our sample through the process outlined above, it is important to note that all empirical results hold for the entire sample. In Appendix 11.11, we reproduce all our results with all available data.

2.1 Productivity Measures

In what follows, we build three measures of productivity, each derived as a residual from one of three particular production functions:

$$Y_s = A_s L_s \tag{1}$$

$$Y_s = B_s (K_s)^{\alpha_s} (L_s)^{1-\alpha_s} \tag{2}$$

$$Y_s = D_s (K_s)^{\alpha_s} (h_s L_s)^{1-\alpha_s}, \tag{3}$$

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. The three residual measures of productivity are: A_s, B_s and D_s. In principle each subsequent measure of total factor productivity is better than the last, since it controls for a greater variety of factor inputs. Each measure however, requires additional data that is often hard to come by and as such has to be estimated. Given these data constraints, considering all three measures gives a better overall picture of productivity.

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. Due to a lack of comprehensive sectoral cross-country data, we make use of OECD data and 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 then assume that these labor shares are common to all countries and constant over time. From this exercise we find labor share in manufacturing is 0.57 whilst in (non-resource) non-manufacturing it is 0.53. For details, see Appendix 11.7.

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 of the US) is given by:

$$P_s^i/P_s^{PPP} = E_s^i/E_s^{PPP}. \tag{4}$$

For more details see Appendix 11.3.[5]

Sectoral Value Added Next, we construct sector specific value added measured in international dollars for the period 1980-2006. To do this, we divide constant (2005) price sectoral value added data from the UN by the relative price levels, P_s^i/P_s^{PPP}, from expression 4. 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. For details see Appendix 11.4.

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 to construct employment in agriculture, manufacturing, mining and utilities, construction and services.[6] Notice also, that we do not consider employment data based entirely on urban surveys - as these significantly underestimate employment in agriculture and overestimate employment in other sectors.

Aggregate Capital We follow Caselli (2005) and use the investment series from the Penn World Tables to construct estimates of aggregate capital stock, K, using the perpetual inventory method. See Appendix 11.5 for details.

[5] The ICP study is especially constructed to control for quality differences in goods across countries (for example, through very well defined product specification) and hence to provide accurate cross-country measures of price differences. Nonetheless, there are some well known limitations of the ICP data. 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. From our perspective, this may be an issue if taxes or subsidies vary systematically with resource wealth. We recognize this fact, but our hands are tied for lack of better data. Furthermore, in what follows, we show that unrealistically large subsidies would be necessary to account for observed productivity differences.

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

Sectoral Capital We also follow Caselli (2005) in estimating sectoral capital, K_s. This is done by assuming sectoral production functions of the form in equations 2 or 3 and assuming that rates of return on capital are equalized across sectors (an arbitrage condition). These assumptions can then be used to assign aggregate capital (calculated above), between sectors. For details see Appendix 11.6.

Aggregate Human Capital We follow Caselli (2005) and Hall and Jones (1999) in constructing a measure of aggregate human capital, h, based on schooling achievement data from Barro and Lee (2010). This is computed using a formula linking years of education to human capital through Mincerian returns. For construction details see Appendix 11.8.

Sectoral Human Capital 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. 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 sector in the United States in 2008.[7] 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. This then allows us to infer sectoral education levels in all countries. Sectoral measures of schooling are then linked to sectoral human capital through the 'standard' Mincerian returns formula. For details see Appendix 11.10.

Natural Resource "Wealth" We follow Sachs and Warner (2001) in defining natural resource "wealth" as the ratio of exports of natural resources to gross domestic product, both measured in current period prices. Countries that have high exports of natural resources relative to gross domestic product are resource rich, whilst those that have low exports of natural resources relative to gross domestic product are resource poor. Natural resources are taken to be fuels, ores and metals and both sets of data come from the WDI.[8] Unlike Sachs and Warner (2001), we use PPP GDP in the denominator of our measure. We do this for two reasons. First, unlike Sachs and Warner (2001) who used cross-sectional data, we use panel data. Second,

[7] For construction details see Appendix 11.9.

[8] The series used are: Fuel exports (% of merchandise exports) (TX.VAL.FUEL.ZS.UN), Ores and metals exports (% of merchandise exports) (TX.VAL.MMTL.ZS.UN), Merchandise exports (current US$) (TX.VAL.MRCH.CD.WT), Fuel imports (% of merchandise imports) (TM.VAL.FUEL.ZS.UN), Ores and metals imports (% of merchandise imports) (TM.VAL.MMTL.ZS.UN), Merchandise imports (current US$) (TM.VAL.MRCH.CD.WT), GDP (current US$) (NY.GDP.MKTP.CD).

	E Res./ GDP	GDP/ cap.	Emp. Share NM	Emp. Share M	Lab. Prod. $\frac{NM}{N+NM}$	Lab. Prod. $\frac{M}{N+NM}$	TFP (k) $\frac{NM}{N+NM}$	TFP (k) $\frac{M}{N+NM}$	TFP (k,h) $\frac{NM}{N+NM}$	TFP (k,h) $\frac{M}{N+NM}$
10^{th}%-ile	0.19	25169	0.84	0.14	1.01	1.04	0.94	1.44	0.94	1.42
90^{th}%-ile	0.00	21123	0.78	0.21	1.08	0.72	0.99	1.10	0.99	1.07
$10^{th}/90^{th}$			1.08	0.65	0.93	1.43	0.95	1.31	0.95	1.32

Table 1: Summary statistics for top and bottom 10% percentiles of natural resource exporters. Natural resource export share, GDP per capita, sectoral employment as well as three measures of sectoral productivity (relative to aggregate non-resource productivity).Data for a panel of 44 countries, for for the period 1980-2006. (Source: UN, ILO, ICP)

endowments of resources can potentially impact prices of non-resource goods. Suppose, higher resource endowments lead to higher service goods prices (and leave all other prices unchanged), then an increase in real oil endowments would increase the numerator but also increases the denominator through higher service prices. Using the Sachs and Warner (2001) measure would underestimate the increase in resource wealth.[9]

3 Facts

This section establishes two facts using the above data: (1) Resource rich countries tend to employ a lower share of workers in the manufacturing sector and a higher share of workers in the non-manufacturing sector than resource poor countries and (2) Resource rich countries are (slightly) less productive in non-manufacturing but (much) more productive in manufacturing than resource poor countries. A summary of the results is shown in Table 1. This table compares the largest 10 percent with the lowest 10 percent of natural resource exporters. From the table, we see that resource rich countries employ 8% more workers in (non-resource) non-manufacturing and 35% less workers in manufacturing than resource poor countries. At the same time, productivity in non-manufacturing relative to manufacturing in resource rich countries is between 65% ($\approx 0.93/1.43$) and 73% ($\approx 0.95/1.31$) that of resource poor countries. Breaking this relationship into sectoral components, resource rich economies are between 5-7% less productive in the non-manufacturing goods sector but 31-43% *more* productive in the manufacturing goods sector (controlling for aggregate productivity). In what follows, we examine these relationships more carefully, to check for robustness.

[9] 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). The results that follow however, are unaffected by the choice of natural resource wealth measure.

COEFF.	(1) NM. Emp. Sh.	(2) NM. Emp. Sh.	(3) NM. Emp. Sh. (TD)
nrExpSh.	0.265***	0.205***	0.213***
	(0.026)	(0.025)	(0.024)
logGDP	-	-0.718***	-0.645***
		(0.060)	(0.057)
sqlogGDP	-	0.038***	0.034***
		(0.003)	(0.003)
Obser.	806	806	806
R^2	0.116	0.251	0.363
COEFFICIENT	M. Emp. Sh.	M. Emp. Sh.	M. Emp. Sh. (TD)
nrExpSh.	-0.312***	-0.262***	-0.272***
	(0.025)	(0.024)	(0.023)
logGDP	-	0.663***	0.591***
		(0.058)	(0.055)
sqlogGDP	-	-0.035***	-0.030***
		(0.003)	(0.003)
Obser.	806	806	806
R^2	0.164	0.282	0.397

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

Table 2: Changes in sectoral employment and resource wealth. Standard errors in parentheses.

Employment and Resource Wealth Table 2 tests the relationship between employment in manufacturing (top) and non-manufacturing (bottom) and resource wealth. Column (1) shows the regression of the share of employment in non-manufacturing and manufacturing versus the natural resource export share of GDP. Resource rich countries employ more workers in the non-manufacturing sector and less workers in the manufacturing sector. These results are statistically significant at the one percent level.[10]

Finally, a well known fact from the development literature is that employment in in manufacturing follows an inverted-U with per capita income. We thus check whether our results are robust to changes in income. Column (2) of Table 2, controls for changes in income (and income squared) and shows that the results remain unchanged. Finally, column (3) adds time dummies to the regressions of column (2). The results also remain unchanged.[11]

[10] In Appendix 11.12 we disaggregate the non-manufacturing sector and show that movement to workers to the Service sector is key in causing employment in non-manufacturing to rise.

[11] Notice that 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

(a) Changes in relative non-manufacturing to manufacturing sector labor productivity and resource wealth

COEFF.	(1) Log NM/M Prod.	(2) Log NM/M Prod.	(3) Log NM/M Prod. (TD)
nrExpSh.	-2.119***	-2.148***	-2.118***
	(0.215)	(0.210)	(0.214)
logLProd	-	-0.153***	-0.129***
		(0.023)	(0.024)
Obser.	806	806	806
R^2	0.107	0.153	0.193

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

(b) Changes in relative non-manufacturing to manufacturing sectoral TFP (K) and resource wealth

COEFF.	(1) Log NM/M Prod.	(2) Log NM/M Prod.	(3) Log NM/M Prod. (TD)
nrExpSh.	-1.452***	-1.307***	-1.318***
	(0.186)	(0.167)	(0.171)
logKProd	-	-0.507***	-0.471***
		(0.036)	(0.037)
Obser.	806	806	806
R^2	0.070	0.252	0.276

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

(c) Changes in relative non-manufacturing to manufacturing sectoral TFP (K,H) and resource wealth

COEFF.	(1) Log NM/M Prod.	(2) Log NM/M Prod.	(3) Log NM/M Prod. (TD)
nrExpSh.	-1.471***	-1.294***	-1.303***
	(0.187)	(0.173)	(0.176)
logKHProd	-	-0.516***	-0.481***
		(0.044)	(0.044)
Obser.	806	806	806
R^2	0.072	0.209	0.244

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

Table 3: The impact of resource wealth on productivity.

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

COEFF.	NM. Prod	NM. Prod TD	M. Prod	M. Prod TD
nrExpSh.	-14,989.75***	-14,299.23***	69,748.64***	66,536.54***
	(1556.75)	(1510.33)	(6667.48)	(6665.86)
LProd	1.00***	1.01***	1.00***	0.96***
	(0.00)	(0.00)	(0.02)	(0.02)
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.

COEFF.	NM. Prod	NM. Prod TD	M. Prod	M. Prod TD
nrExpSh.	-37.85***	-38.20***	308.00***	306.63***
	(4.46)	(4.41)	(32.06)	(32.46)
KProd	0.87***	0.89***	1.75***	1.68***
	(0.01)	(0.01)	(0.04)	(0.04)
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.

COEFF.	NM. Prod	NM. Prod TD	M. Prod	M. Prod TD
nrExpSh.	-21.64***	-21.79***	186.58***	185.64***
	(2.70)	(2.64)	(19.27)	(19.33)
KHProd	0.89***	0.90***	1.65***	1.59***
	(0.01)	(0.01)	(0.05)	(0.05)
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 4: The impact of resource wealth on productivity.

Sectoral Productivity Next, we establish that resource rich countries are relatively less productive in non-manufacturing than in manufacturing. We then decompose this relationship and show that in absolute terms resource rich countries are (slightly) less productive in non-manufacturing but (much) more productive in manufacturing than resource poor countries.

Table 3 tests the assertion about relative productivity by showing three regressions for each of our productivity measures: (1) (the log of) the ratio of non-manufacturing to manufacturing productivity versus resource wealth; (2) same as the first regression but controlling for aggregate (non-resource) productivity; (3) same as the second regression but adding time-dummies.[12] From the regressions, we see that resource richer countries tend to be relatively less productive in non-manufacturing than in manufacturing sectors.

Table 4, decomposes these relationship into its sectoral components. It shows how sector specific productivity changes with resource wealth and aggregate TFP (with and without time dummy variables). We see that - controlling for aggregate productivity - resource rich countries are less productive in non-manufacturing goods but more productive in manufacturing goods. What's more, changes in sectoral productivity are highly asymmetric - the increase in manufacturing productivity is 5-9 times larger than the decrease in non-manufacturing productivity.[13]

4 Resources and De-industrialization

In this section, we show how a standard, multi-sector model with trade can generate a Dutch Disease story that is consistent with the sectoral employment data but is unable to generate changes in sectoral labor productivity. We also use the model to show how endowments of natural resources act like non-homothetic preferences. We then use this observation and the parallels it evokes to the growth literature, to motivate our suggested model.

Households Suppose there is a measure one of identical agents. Furthermore, assume each agent's preferences are given by:

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

where c_s is consumption of non-manufacturing (mostly service) goods and c_m is consumption of manufacturing goods, ν determines the relative taste for traded goods, whilst σ is the elasticity

natural resource export share. Thus country dummies, seem to pick up a country's resource wealth, ultimately serving the same purpose as our export share measure of resource wealth.

[12] As before, we do no consider country-dummy variables since they are highly correlated with our measure of resource wealth.

[13] In Appendix 11.12 we disaggregate the non-manufacturing sector and show that changes in Service sector productivity are key in falling productivity in non-manufacturing.

of substitution in consumption between manufacturing and non-manufacturing goods.

The representative agent is endowed with a unit of labor, which he supplies inelastically on the labor market. The agent is also endowed with a resource tree that provides a stream of O units of natural resources each period. These resources are not directly used by the agent but are sold on the market. The budget constraint of the agent is given by:

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

where, p_s is the relative price of non-manufacturing goods and p_o is the relative price of the natural resource. The traded good is taken as numeraire.

Production There is a competitive market in each of the two sectors. The technologies in each sector are given by:

$$Y_s = A_s L_s \text{ and } Y_m = A_m L_m \tag{7}$$

Output in each sector, Y_s (Y_m), is produced using labor, L_s (L_m) and each sector is characterized by a sector-specific productivity, A_s (A_m). In what follows, for simplicity and without loss of generality, we assume that $A_s = A_m$.

Trade It is assumed that manufacturing goods are traded whilst non-manufacturing goods are non-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 manufacturing goods (recall that the traded sector is numeraire). Notice that p_o is the world market price for oil (relative to manufacturing goods). Also notice, that the above specification dictates, that all resources are exported in exchange for manufacturing goods. Furthermore, no resources are used in home country production and no resources are imported from abroad.

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

$$c_m = Y_m + m \tag{9}$$

$$c_s = Y_s \tag{10}$$

$$L_m + L_s = 1. \tag{11}$$

Competitive Equilibrium For each price of oil, p_o, an equilibrium in the above economy consists of a relative price of non-manufacturing goods, p_s, a wage rate, w and allocations for agents and firms so that labor and output markets clear and trade remains balanced.

Optimization Agents take prices as given and choose the optimal quantities of manufacturing and non-manufacturing goods to consume. The problem for an agent is to maximize (5) subject to (6). The optimal demands are:

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

Firms then set prices to maximize profits:

$$p_s = \frac{A_m}{A_s} = 1 \text{ and } w = A_m \tag{13}$$

and choose to hire the following quantities of labor:

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

Implications of the Model Notice that the model predicts that economies with higher endowments of natural resources (or those facing higher oil prices), will devote a larger share of their labor force to the non-manufacturing sector than identical countries without natural resources. Thus, higher endowments of natural resources act in the same way as non-homothetic preferences by causing labor to shift from one sector to another. [14] The model however, fails on a fundamental dimension: it predicts a constant labor productivity of manufacturing and non-manufacturing in resource rich and poor countries. In particular, in the model, sectoral productivity is given by: $\frac{Y_s}{L_s} = \frac{\bar{p}_s A_s L_s}{L_s} = \bar{p}_s A_s = A_m$ in the non-manufacturing sector and by: $\frac{Y_m}{L_m} = \frac{A_m L_m}{L_m} = A_m$ in the manufacturing sector.[15] The failure of the model simply stems from the assumption that sector specific productivities are exogenously given within the model - labor reallocation across sectors does not effect sectoral productivity.

Physical Capital and Labor Productivity Our measures of TFP in the data are based on various assumptions on physical and human capital formation and returns to capital across sectors. The cleanest measure of productivity (in terms of number of assumptions made on the

[14] 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 $L_s = \frac{1}{1+\nu^\sigma}\left(1 + \frac{p_o O + \bar{m}}{A_m}\right)$. Thus, in terms of employment, endowments of natural resources act exactly like non-homothetic preferences in manufacturing goods.

[15] We measure productivity at constant prices, $\bar{p}_s$. However, since changing endowments of oil does not affect the price, we can substitute for $\bar{p}_s$ from equation (13).

data) is labor productivity. In the above model, TFP and labor productivity are the same, but in more complicated models (for instance those with capital), the two measures of productivity are distinct. If the reader is unwilling to believe the measures of TFP that we have constructed, then a relevant question would be whether more complicated models could go some way in explaining the observed asymmetric sectoral *labor* productivity differences.

As a first step, suppose we added capital accumulation to the above model. In Appendix 11.13, 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.

A second possibility, would be to force the above model to match sectoral labor productivity by introducing subsidies to the rental rate of capital inputs in the manufacturing sector 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. 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 improbably high.[16] Whilst some resource rich countries may have high subsidies, we observe asymmetric productivity differences in countries like Australia, Norway and Canada were capital subsidies are not any higher than in resource poor OECD countries.

The third possibility to generate asymmetric labor productivity differences from labor reallocation, would be the specific factors model. If we assume that each sector uses a sector specific type of capital, for instance, then labor moving from one sector to another will encounter diminishing returns. Each additional worker to a sector will have a lower marginal productivity than the last, resulting in declining sectoral 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 interpretation of the fixed factor. There are generally two accepted explanations in the literature. First, specific 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 of countries. Cross-sectional data however, captures the long run adjustments that time series data does not.

[16] Subsidies of nearly 90% of the rental rate of capital are needed. Results available on request.

This suggests that differences in productivity across sectors are persistent over time and do not disappear as the specific factor view would predict.

Our data showed that there exist asymmetric differences in TFP between resource rich and resource poor countries. Models with exogenous TFP, cannot account for assymetric 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. Thus, a different approach is needed. In what follows, we suggest an alternative channel through which labor reallocation could generate asymmetric productivity changes: specialization and de-specialization of particular sectors that is associated with labor reallocation.

A Mechanism from the Growth Literature The mechanism we suggest is closely linked to a similar discussion in development economics. It is a well known fact that poorer countries have a larger portion of their labor force employed in agriculture, due to subsistence requirements. Research by Caselli (2005) and Restuccia et al. (2008) also shows that enormous cross country relative sectoral productivity differences exist between rich and poor countries. In particular, controlling for aggregate income, the agriculture sector is far more productive than non-agriculture in richer countries than in poor countries. Lagakos and Waugh (2009) formalize and test the idea - based on the Roy (1951) model of ability - that specialization of workers with different skills can explain cross-sector productivity differences. Due to non-homothetic preferences in agriculture, poorer countries employ more workers in agriculture. As countries grow richer, workers move towards non-agriculture. This results in labor productivity increasing in the agricultural sector by more than it does in non-agriculture, since only those workers that are most productive in agriculture, remain in that sector. Since resource endowments act like non-homothetic preferences in shifting labor across sectors, we can expect a similar channel to operate in our case. We explore this in the next section.

5 Heterogenous Agents

We expand the model of the previous section to include heterogenous agents (i.e. agents with sector specific skills) to allow for worker specialization and to test whether the mechanism from the growth literature is capable of explaining observed asymmetric productivity differences between resource rich and resource poor countries.[17]

The key link between the two stories, is the observation that natural resource endowments act in a similar fashion to non-homothetic preferences, pulling workers into the agriculture

[17] In Appendix 11.14, we show that the model with heterogenous agents is isomorphic to a location model with heterogenous firms. The parametrization of the model however, makes more sense when considering the model from the perspective of heterogenous agents.

sector and preventing them from specializing in the sector in which they have a comparative advantage. In the same way, endowments of natural resources pull workers into the (non-traded) non-manufacturing sector. Since endowments of natural resources allow countries to purchase their (traded) manufacturing goods from abroad, labor is 'freed' from the manufacturing sector and moves to the non-manufacturing sector. Thus endowments of natural resources induce workers who may have had a comparative advantage in manufacturing, to move into the non-manufacturing sector and effectively de-specialize, lowering overall sectoral productivity in non-manufacturing. At the same time, the workers that stay in manufacturing are those that are exceedingly productive in manufacturing work - this results in higher sectoral productivity in manufacturing.

Whilst algebraically, the model of this section parallels Lagakos and Waugh (2009) quite closely, conceptually the two models are very different. In Lagakos and Waugh (2009), the driver of cross-sectoral productivity differences is the combination of non-homothetic preferences and growing income. Our model however, has homothetic preferences and the driver of cross-sectoral productivity differences is the changing value of resource endowments. Furthermore, unlike Lagakos and Waugh (2009) who have a closed economy model, a prominent and essential feature of our model is trade in manufactured goods. We show that endowments of oil act much like non-homothetic preferences in shifting labor across sectors. Unlike non-homothetic preferences (where the subsistence term in utility is the same across countries), what varies across regions is the (value of) endowment of oil.

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

$$\left((c_s^i)^{\frac{\sigma-1}{\sigma}} + \nu(c_m^i)^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}, \tag{15}$$

Suppose that each agent in the economy has a vector of innate skills, $\{z_s^i, z_m^i\}$, representing the efficiency of one unit of their labor in non-manufacturing (predominantly service) goods (s) and the manufacturing sector (m). 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 $G(z_s, z_m)$.[18]

Agents earn a wage income, w^i. The agent is also endowed with a resource tree that provides a stream of O units of natural resources each period. These resources are not directly used by

[18] Although these types of models are often taken to be short run due to the assumption of exogeneity in skill endowments, we argue that the relatively high volatility of resource prices allows us to interpret our model as a longer run model. Changes in the value of endowments of resources shift labor between sectors. In principle, once agents move, they can acquire human capital to improve their ability in a particular sector's work. However, in the data, resource prices in a wide range of countries over long periods of time, tend to be significantly more volatile than both manufacturing and non-manufacturing prices. Hence, agents will find themselves moving between sectors according to the high volatility of resource prices. If there is some cost in re-training and agents know that they will soon move to another sector due to the higher volatility of the resource price, agents may find it optimal not to retrain and retain their given human capital.

the agent but are also sold on the market. The budget constraint of the agent is given by:

$$p_s c_s^i + c_m^i \leq w^i + p_o O, \tag{16}$$

where, p_s is the relative price of non-manufacturing goods and p_o is the relative price of the natural resource. Traded goods are taken as numeraire.

Production The output of worker-consumer i is given by

$$Y_k^i = A z_k^i, \tag{17}$$

where A is aggregate (potentially sector specific) TFP and z_k^i is the workers idiosyncratic productivity in sector k. Each worker in sector k produces the same good and gets paid his marginal product. As such, there is a competitive market in each of the two sectors, and each has its own sector aggregate production function. Let Ω^k be the set of agents electing to work in sector k. The sector aggregate labor inputs, $\tilde{L}_k$, are defined as:

$$\tilde{L}_k \equiv \int_{i \in \Omega^k} z_k^i di \tag{18}$$

and represent the sum of all talent working in each sector. Aggregate output in sector k is given by:

$$Y_k \equiv \int_{i \in \Omega^k} Y_k^i di. \tag{19}$$

The aggregate technologies in each sector are then given by:

$$Y_k = A\tilde{L}_k, \tag{20}$$

where A captures sector-neutral efficiency, and $\tilde{L}_k$ represents the total number of effective labor units employed in sector $k = s, m$.

Trade Trade is identical to the homogenous agent case. It is assumed that manufacturing goods 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:

$$m - p_o O = 0, \tag{21}$$

where, m is the value of imported traded goods (recall that traded goods are numeraire). Notice that p_o is the world market price for oil (relative to traded goods) and is given exogenously.

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

$$\int_{i\in\Omega} c_m^i dGi = Y_m + m \tag{22}$$

$$\int_{i\in\Omega} c_s^i dGi = Y_s \tag{23}$$

$$\tilde{L}_m + \tilde{L}_s = 1, \tag{24}$$

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

Competitive Equilibrium For each price of resource, 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:

$$w_m^i = Az_m^i \text{ and } w_s^i = p_s A z_s^i \tag{25}$$

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, $w^i = \max\{w_s^i, w_m^i\} = \max\{p_s A z_s^i, A z_m^i\}$. This gives rise to the following simple rule: a worker i will work in non-manufacturing if and only if

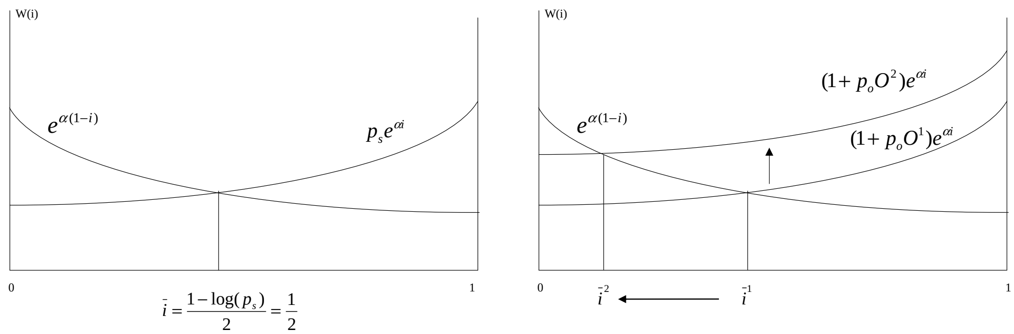
$$p_s > \frac{z_m^i}{z_s^i}. \tag{26}$$

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 (15) subject to (16), which results in the following demands of each agent:

$$c_s^i = \frac{(w^i + p_o O)}{p_s + \nu^\sigma p_s^\sigma} \text{ and } c_m^i = \frac{\nu^\sigma p_s^\sigma (w^i + p_o O)}{p_s + \nu^\sigma p_s^\sigma}. \tag{27}$$

5.1 A simple example

This section, provides a simple example illustrating the mechanism of the model. Suppose the skill distribution G is degenerate and given by $\{z_s^i, z_m^i\} = \{e^i, e^{1-i}\}$ for each worker $i \in [0, 1]$. Furthermore, assume Cobb-Douglas utility ($\sigma = 1$) and equal utility weights ($\nu = 1$).



(a) A workers decision.

(b) A change in the value of oil.

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

Agent i, chooses to work in non-manufacturing if and only if it pays a higher wage: $w_s^i > w_m^i$ or, equivalently, if his skill is above a certain cutoff, $i > \bar{i}(p_s)$ where $\bar{i}(p_s) = \frac{1-\log p_s}{2}$. This is illustrated in Figure $1(a)$. Notice, that the price of non-manufacturing determines the sectoral distribution of workers. It turns out that the value of the resource stream affects this price. A higher value of resource endowment means the income of consumers increases. Given assumptions on utility, consumers spend equal and constant shares of their income on both goods. In order to satiate this higher demand for locally produced non-manufacturing, more workers are needed in the non-manufacturing sector. New workers move into non-manufacturing only if the wage in non-manufacturing rises which can only happen if the non-manufacturing price increases.

More formally, using market clearing and the trade balance, we can show that spending on non-manufacturing must be the same as spending on manufacturing goods: $p_sY_s = Y_m + p_oO$. Given the cutoff $\bar{i}(p_s)$ and the exogenous skill distributions, we obtain expressions for output in each sector as functions of non-manufacturing sector price and then solve the above expression for the equilibrium price of non-manufacturing: $p_s = 1 + p_oO$.[19] Higher value of the resource stream thus, translates into higher non-manufacturing price. This results in an increase in wages which generates a shift in workers from manufacturing to non-manufacturing - a drop in $\bar{i}(p_s)$. 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. As $\bar{i}$ decreases, non-manufacturing productivity $Y_s/(1-\bar{i}) = (e - e^{\bar{i}})/(1-\bar{i})$, falls: new entrants pull down productivity since they are, on average, less skilled than those already employed in non-manufacturing. The above mechanism is illustrated in Figure $1(b)$.

[19] These expressions are given by $Y_s(p_s) = e - e^{\bar{i}(p_s)}$ and $Y_m(p_s) = e - e^{1-\bar{i}(p_s)}$.

5.2 Productivity Differences Larger in Resource Rich Economies

The following section generalizes the above results. We show that countries with higher endowments of natural resources will be less productive in the non-manufacturing sector (relative to the traded sector) than countries with lower endowments of natural resources. These proofs parallel those of Lagakos and Waugh (2009), 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.

Proposition 5.1. *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 respects. 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 11.15. □

The intuition behind this proposition is as follows. Suppose that the price of non-manufacturing goods was 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.

Next, we establish the chief qualitative result of the paper. It is clear that in an economy with homogenous skills, agents are indifferent between sectors for any given value of the price of natural resource (or the endowment of the resource). In an economy with heterogenous skills this does not hold any more. The following proposition shows how changes in the value of natural resources endowments of an economy can affect the sectoral allocation of labor and hence productivity.

Proposition 5.2. *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, 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, and 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:

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

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

□

The first part of the above proposition 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 a greater comparative advantage in manufacturing sector work. Intuitively, 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. The second part of the proposition says that non-manufacturing productivity is higher in the resource poor country if and only if agents with a 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 hold. They 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.[20]

5.3 Solving the Model

Distribution Function To calibrate the model, we must select a distribution function of skill draws, $G(z_s, z_m)$. We have to specify a particular parametric form for the distribution function since the Roy model cannot be identified from cross-sectional wage data alone: 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. In

[20] 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).

what follows, we assume that skills are drawn independently from a Type II extreme value (or Frechet) distribution with CDF:

$$G(z_s) = e^{-\lambda_s z_s^{-\theta}} \text{ and } G(z_m) = e^{-\lambda_m z_m^{-\theta}}, \tag{28}$$

where, $\theta > 1$ and $\lambda_m, \lambda_s > 0$. In this distribution λ_i is the scale parameter, and θ is the shape parameter. To see this, notice that a random talent draw, Z_i, has geometric mean $e^{\gamma/\theta}\lambda_i^{1/\theta}$, where γ is Euler's constant. A larger λ_i thus implies a higher efficiency draw is more likely in sector i. The parameter θ is crucial to our analysis and it governs the amount of variation in skills (and hence the productivity dispersion). It is easy to show that the log of productivity, $\log Z_i$, has standard deviation $\pi/(\theta\sqrt{6})$, where π is the constant. Thus, lower values of θ imply more heterogeneity in ability and higher productivity dispersion. In other words, the lower the value of θ, the slower the probability density's decay as one moves further in the tail and hence fatter tails.[21]

We choose this distribution for several reasons. First, and foremost, the Frechet distribution is one of three extreme value distributions. According to the Fisher - Tippet - Gnedenko theorem from extreme value theory (a sub-field of probability 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 iid random variables converges in distribution to one of three possible distributions: the Gumbel, the Frechet, or the Weibull distribution.[22] 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 (2009) have used it to model talent distribution across sectors. Notice also, that the Frechet distribution is log-concave, hence both restrictions of Proposition 5.2 hold. Lastly, the Frechet distribution also provides very tractable analytic solutions which allow for easy interpretation of results.

Finally, notice that we assume that the dispersion parameter, θ, is the same across 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. Notice however, that in section 7, we extend the model to allow correlated talent draws and different dispersions across sectors and we show that, quantitatively,

[21] Many economic data are described by fat-tailed distributions in contrast to "thin-tailed" ones (e.g., normal distribution). There are examples of application of extreme value analysis mostly in finance (for asymptotic distribution for the extreme changes in stock prices, foreign exchange rates and interest rates, e.g., see Straetmans and Versteeg (2009) and references therein).

[22] 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 **??**.

these channels plays a very limited role. Finally, without loss of generality, we normalize the scale parameters to unity $\lambda_s = \lambda_m = 1$.

Employment Since z_s and z_m are independently drawn from Fréchet 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. The expected employment in non-manufacturing is:[23]

$$L_s = P\left(p_s > \frac{z_m^i}{z_s^i}\right) = \int_0^{\infty}\int_0^{p_s z_s} g(z_s)g(z_m)dz_m dz_s = \frac{p_s^\theta}{1+p_s^\theta} \tag{29}$$

and thus expected employment in manufacturing is:

$$L_m = 1 - L_s = P\left(p_s \leq \frac{z_m^i}{z_s^i}\right) = \int_0^{\infty}\int_0^{z_m/p_s} g(z_s)g(z_m)dz_s dz_m = \frac{1}{1+p_s^\theta} \tag{30}$$

It is clear now that a relative increase in the price of non-manufacturing increases expected employment in non-manufacturing and decreases it in manufacturing.

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

$$Y_s = \int_0^{\infty}\int_0^{p_s z_s} z_s g(z_s, z_m)dz_m dz_s, \ Y_m = \int_0^{\infty}\int_0^{z_m/p_s} z_m g(z_s, z_m)dz_s dz_m \tag{31}$$

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

$$Y_s = \Gamma(1-\frac{1}{\theta})(1+p_s^{-\theta})^{\frac{1-\theta}{\theta}}, \ Y_m = \Gamma(1-\frac{1}{\theta})(1+p_s^{\theta})^{\frac{1-\theta}{\theta}}, \tag{32}$$

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

Prices Using the market clearing conditions and the demands of each agent from equations (27), we can write:

$$Y_s = \int_0^\infty c_s^i dGi = p_o O \frac{1}{p_s + \nu^\sigma p_s^\sigma} + \frac{1}{p_s + \nu^\sigma p_s^\sigma} \int_0^\infty w^i dGi \tag{33}$$

and

$$Y_m + p_o O = \int_0^\infty c_m^i dGi = p_o O \frac{\nu^\sigma p_s^\sigma}{p_s + \nu^\sigma p_s^\sigma} + \frac{\nu^\sigma p_s^\sigma}{p_s + \nu^\sigma p_s^\sigma} \int_0^\infty w^i dG \tag{34}$$

[23] In deriving (29), we use the result that if x and y are independently drawn from Fréchet 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).

respectively, where G is a joint cumulative distribution function of the vector of skills $\{z_s^i, z_m^i\}$ of the agent i in the economy. Multiplying (33) by $\nu^\sigma p_s^\sigma$ and subtracting it from equation (34), gives:

$$\nu^\sigma p_s^\sigma Y_s = Y_m + p_o O \tag{35}$$

Then, substituting (32) into (35), provides an implicit expression for p_s as a function of the value of resource endowment, $p_o O$:

$$p_o O = \nu^\sigma p_s^\sigma \Gamma(1 - \frac{1}{\theta})(1 + p_s^{-\theta})^{\frac{1-\theta}{\theta}} - \Gamma(1 - \frac{1}{\theta})(1 + p_s^{\theta})^{\frac{1-\theta}{\theta}}. \tag{36}$$

Given this price, we can use equations (29) and (30) to calculate the expected employment in each sector and hence sectoral output and productivity.

Using the implicit function theorem on equation 36, we can confirm Theorem 5.1, $\frac{\partial p_s}{\partial p_o O} > 0$, endowments result in higher non-manufacturing prices. This results in higher non-manufacturing wages and workers moving from manufacturing to non-manufacturing. This can be seen from equations 29 and 30, which (together with the previous result) imply that $\frac{\partial L_s}{\partial p_o O} > 0$ and $\frac{\partial L_m}{\partial p_o O} < 0$. This shift in labor generates increased specialization in one sector (manufacturing) and results in de-specialization in another (non-manufacturing). In particular, it is easy to show that $\frac{\partial Y_s/L_s}{\partial p_o O} < 0$ and $\frac{\partial Y_m/L_m}{\partial p_o O} > 0$ which confirms Theorem 5.2 for the Frechet distribution.

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

Proposition 5.3. *A change in p_s results in a larger change in manufacturing productivity than in non-manufacturing productivity if and only if $L_m < \frac{1}{2}$.*

Proof. To show the above results we must show that $P \equiv \left|\frac{\partial(Y_m/L_m)}{\partial p_s}\right| / \left|\frac{\partial(Y_s/L_s)}{\partial p_s}\right| > 1$ if and only if $L_m < \frac{1}{2}$. From equations 29, 30 and 32, we can show that $P = p_s^{\theta+1} = (L_m^{-1} - 1)^{\frac{\theta+1}{\theta}}$. Since $\theta > 1$, P is greater than one if and only if $L_m < \frac{1}{2}$. □

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 countries 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 non-manufacturing sector's employment, ensuring that the impact on productivity is bigger.

5.4 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. In particular, the distribution of wage offers agents receive in the non-manufacturing sector is given by:

$$G_s^w(w_s) = Pr\{W_s \leq w_s\} = Pr\{p_s A Z_s \leq w_s\} = Pr\{Z_s \leq \frac{w_s}{p_s A}\} = e^{-(p_s A)^\theta w_s^{-\theta}} \tag{37}$$

whilst the corresponding distribution for manufacturing wage offers is given by:

$$G_m^w(w_m) = Pr\{W_m \leq w_m\} = Pr\{A Z_m \leq w_m\} = Pr\{Z_m \leq \frac{w_m}{A}\} = e^{-A^\theta w_m^{-\theta}}. \tag{38}$$

These are both Frechet distributions, with the same dispersion parameter, θ, as in the talent distributions.[24] Since the observed wage of an agent is the maximum of wages an agent could earn in either sector, $w = \max\{w_s, w_m\}$, the distribution of the actual observed wages, $G^w(w)$, is simply the maximum order statistic of wage offers and is given by:

$$G^w(w) = G_s^w(w) G_m^w(w) = e^{-A^\theta (1+p_s^\theta) w^{-\theta}}. \tag{39}$$

The distribution of observed wages is also a Frechet, with the same dispersion parameter but with a different mean. 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. In particular, as mentioned previously, the log of a Frechet variable, has a standard deviation $\pi/(\theta_i\sqrt{6})$. Consequently, 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). Following Lagakos and Waugh (2009) 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 income and business as well as 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. The standard deviation of log wages in this sample are 0.57, which implies a dispersion parameter of $\theta = 2.24$

Finally, additional intuition for θ can be obtained by taking the ratio of equations (29) and (30):

$$\log\left(\frac{L_s}{L_m}\right) = \theta \log(p_s) \tag{40}$$

[24] Notice that these are not distributions of observed wages in either sector, but the distribution of wages agents could earn if they chose to work there. The CDF of observed wages in sector s would be given by: $P(W < w | W_s > W_m) = P(W_s < w | W_s > W_m) = P(W_s < w \bigcap W_s > W_m)/P(W_s > W_m) = \int_0^w \int_0^{w_s} w_s g_s^w(w_s) g_m^w(w_m) dw_m dw_s / L_s$.

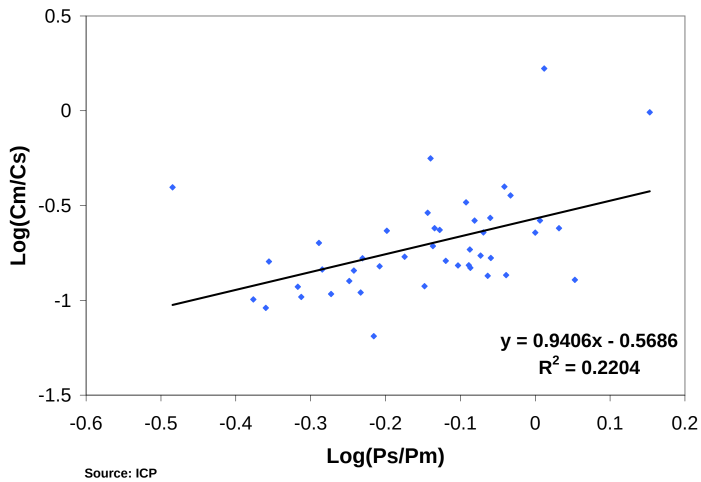


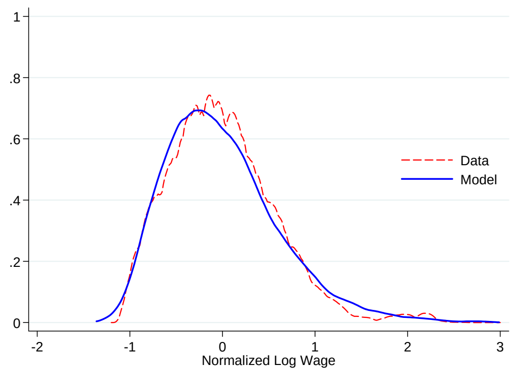
Figure 2: Estimating σ: Relative Prices and Consumption Expenditures, 2005. (Sources: ICP, UN)

From the above we see that the parameter θ can also be interpreted as the elasticity of the relative employment shares between manufacturing and non-manufacturing sectors with respect to the relative price. Given the above parametrization, a one percent increase in price of non-manufacturing will result in a 2.24% increase in relative employment in in non-manufacturing.

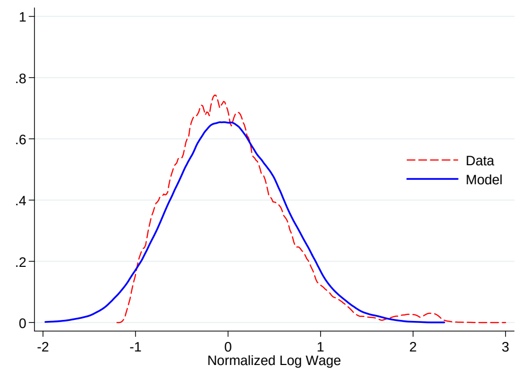
Preference parameters Next, we estimate preference parameters σ and ν. From, the household's problem we derive an equation relating relative consumer expenditure on the relative price: $\frac{c_m}{c_s} = (\nu p_s)^{\sigma}$. Taking logs of this equation, we obtain a relationship that can be estimated. In figure 2 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%).

5.5 Results

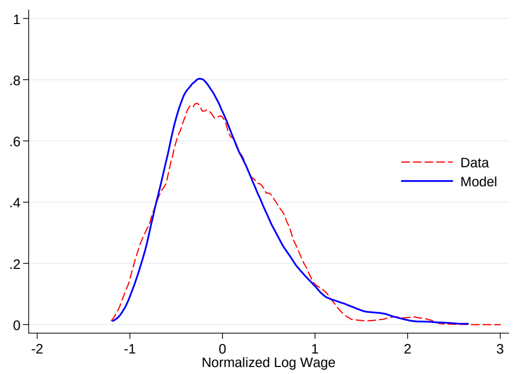
US Wage Distributions The left hand column of Figure 3, shows the theoretical and empirical kernel density of observed wages at the aggregate and sectoral level in the US data and the model using Frechet talent draws. The right hand column, shows a re-calibration of the model to log-normal talent draws. 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.



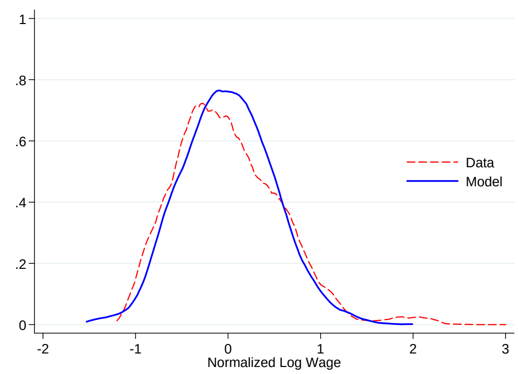
(a) Distribution of Wages, Frechet



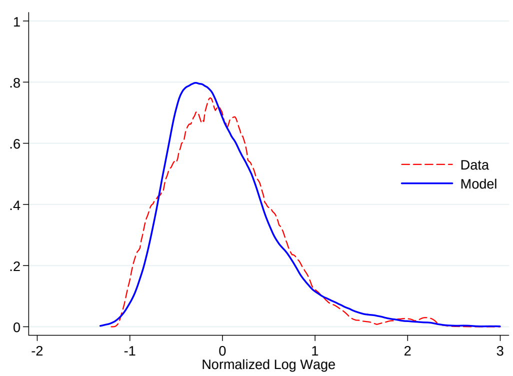
(b) Distribution of Wages, Log-normal



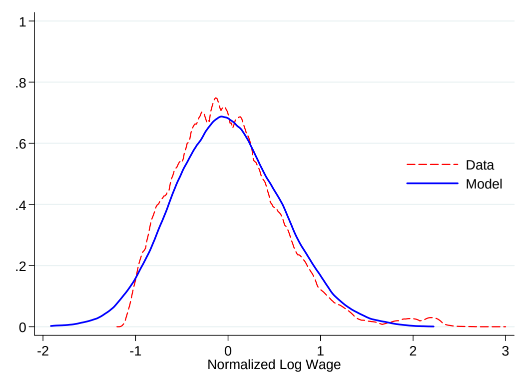
(c) Distribution of Wages in Mfg, Frechet



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

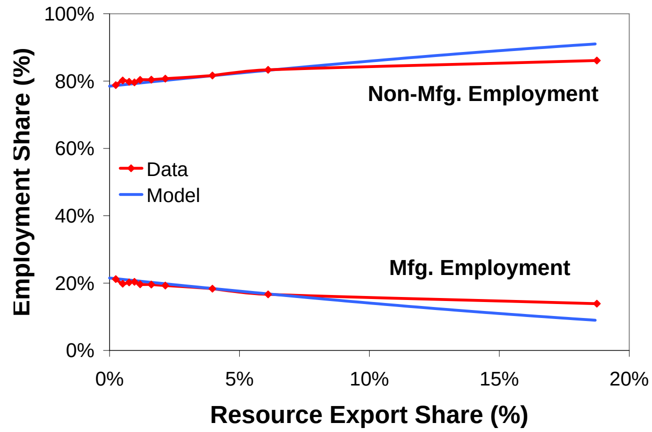


(e) Distribution of Wages in Non-Mfg., Frechet

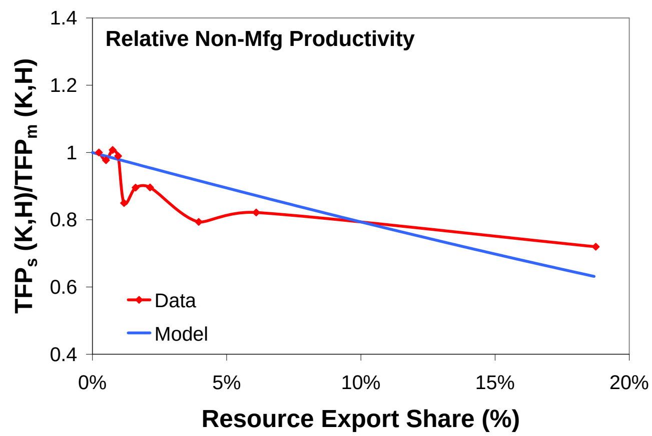


(f) Distribution of Wages in Non-Mfg., Log-normal

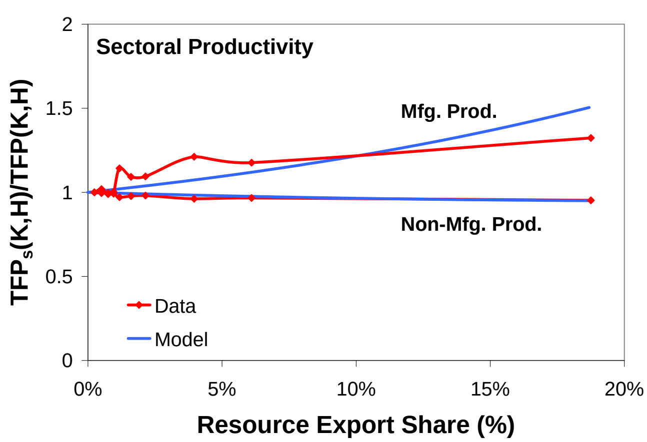
Figure 3: Distribution of wages in model and data, by sector. The first and second columns show outcomes with Frechet and Log-Normal talent draws respectively.



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



(b) Relative Productivity vs. Resource Export Share



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

Figure 4: Heterogenous Consumers: Data Deciles and Model.

The log-normal distribution is calibrated in a similar fashion.[25] As such, both the Frechet and the Log-normal model do quite well at matching the general dispersion of wages at the aggregate level. Notice however, that the log-normal model fails to match the tails of the data. This finding mirrors that of Lagakos and Waugh (2009) and others. The model also does well in matching the data that we have not calibrated - the observed sectoral wages in the US. Here the Frechet distribution does a better job of matching the data than the normal distribution - both in terms of tails and observed skewness.

Resource Wealth Results Figure 4 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 top panel shows the model predicts rising employment in non-manufacturing and falling employment in manufacturing as resource wealth increases. In general the fit of employment shares is quite good, although the model over predicts the size of the shift towards non-manufacturing. The middle panel shows how relative TFP of non-manufacturing to manufacturing changes with resource wealth. The model does a good job of matching the observed decline although, again, the model predicts a larger decline in relative productivity than is observed in the data. Finally, the bottom panel shows a decomposition of the above graph and demonstrates the change of sectoral productivity with resource wealth.[26] We see that the model is very good at matching the very slight decline in non-manufacturing productivity. We also see that the large decline of relative productivity in the middle graph stems from the fact that the model over predicts the increase in manufacturing productivity.

The message from this calibration exercise is quite surprising. Whilst a priori, the strength of a specialization mechanism may have been questionable, the above calibration proves to be quite powerful and in fact over-predicts observed productivity differences. Of course, other - more complex mechanisms may also be at play in generating the observed data - but given the strength of our mechanism, we feel that it is most probably playing a prominent role.

The Resource Curse One might be interested to know what the effect of re-allocation is on aggregate productivity. In Appendix 11.16, we show that our model exhibits a *very* weak form of a "resource-curse". In particular, non-oil aggregate productivity (measured in resource poor country's prices) will necessarily be lower in countries that have a higher value of resource endowments. This effect however, is very small and is only a consequence of the chosen base-period price and would disappear if chain-weighted prices were used in productivity construction. A similar point is made in Kehoe and Ruhl (2008).

[25] The deviation parameter found to match the data is $\sigma = 0.652$.

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

6 Extension to Migration

In the data, countries that are resource rich tend to have higher proportions of migrants in the population. For example, the population of the lowest decile of resource exporters consists of approximately 7% of migrants, whilst the top tenth percentile has approximately 12%. In this section we consider how adding migration would impact our model's predictions and investigate the impact of including migration on our empirical results.

Theory We extend our model so that now there are two groups of workers in the country: in addition to a measure, L, of local workers there is now an extra (exogenous) quantity of migrants (or foreigners) within a country of measure, L^F so that the total population of the country is of measure $L + L^F$. We assume that these migrants are identical to locals: i.e. they have the same preferences and skill distributions as locals. The rest of the model remains unchanged. The key impact of migrants is to increase the population and make the country relatively more resource scarce and hence weaken the specialization/de-specialization mechanism described above.[27]

Since migrants are identical to locals, the proportion of migrants and locals working in a given sector, will be the same.[28] So employment in each sector, $\bar{L}_s$ and $\bar{L}_m$, will be given by:

$$\bar{L}_s \equiv (L + L^F)L_s \text{ and } \bar{L}_m \equiv (L + L^F)L_m, \tag{41}$$

whilst output in each sector, $\bar{Y}_s$ and $\bar{Y}_m$, will be given by:

$$\bar{Y}_s \equiv (L + L^F)Y_s \text{ and } \bar{Y}_m \equiv (L + L^F)Y_m, \tag{42}$$

where Y_s and Y_m are defined by equation 31 for any distribution of skills g, assumed identical for locals and migrants. Given this, the combined productivity of migrants and locals in each sector is given by:

$$\frac{\bar{Y}_s}{\bar{L}_s} = \frac{(L + L^F)Y_s}{(L + L^F)L_s} = \frac{Y_s}{L_s} \text{ and } \frac{\bar{Y}_m}{\bar{L}_m} = \frac{(1 + L^F)Y_m}{(1 + L^F)L_m} = \frac{Y_m}{L_m}. \tag{43}$$

[27] Notice, that by assuming that migrants are identical to locals, we are assuming that they have the same skill distributions as locals. In reality, migrants often have lower wages which tend to be more dispersed. See for instance Butcher and DiNardo (2002). In what follows we abstract from this additional complication. There are two reasons for doing this. First, our model is not explicit as to why skills should vary between locals and migrants. In our model, skills capture inherent human ability rather than acquired ability. What's more we have tried to control for this in the data through our measures of human capital. Notice however, that it is unclear whether the Barro and Lee education data set (which we use to control for acquired skills) takes into account different education levels of migrants and locals. If it does not, our productivity measures may be biased in countries with large shares of migrants who have different education levels from locals. Another possibility, is that there is a self-selection of migrants that would imply a different skill distribution to the local population. A final possibility is that migrants are selected by governments through a visa process. All the above reasons would justify why skill distributions in the migrant population could be different from those of the local population and would suggest an additional mechanism through which migration would impact prices and hence labor allocations and productivity in resource rich countries. Second, these considerations whilst interesting take us too far afield and for simplicity we leave them for future research.

[28] In particular, it will be given by: $L_s = P\left(p_s \geq \frac{z_m^i}{z_s^i}\right)$ and $L_m = P\left(p_s \geq \frac{z_m^i}{z_s^i}\right)$ for migrants and locals

Sectoral productivity, as before, depends on the equilibrium price of non-manufacturing good which is still determined by equation 35.[29] This equation simplifies to:

$$\nu^{\sigma} p_s^{\sigma} Y_s = Y_m + \frac{p_o O}{L + L^F}. \tag{44}$$

Notice, that migration enters into the above only through its impact on resource wealth per capita - a high migrant stock results in less resources per capita. This gives rise to the following theorem.

Proposition 6.1. *The relative price of services in a resource rich economy after opening the labor market to migration will be lower than before opening the labor market, but - as long as* $\frac{p_o O}{L+L^F} > 0$ *- it will be higher than in a resource poor economy.*

The intuition for this result is simple. As the labor force of the resource rich economy increases, the value of oil endowment per capita, $\frac{p_o O}{L+L^F}$, falls. With lower (per-capita) oil endowments, less (per-capita) traded goods can be imported from abroad, and more (per-capita) traded goods have to be produced locally. In order to induce labor to shift to the traded goods sector to produce these goods, the price of services has to fall. If there are no barriers to migration, oil endowments per capita go to zero and the service price becomes the same as in a resource poor region. If there are barriers to migration, oil endowments per capita remain positive, and the mechanism through which oil "distorts" the economy remains in play. By lowering oil-per-capita endowments, migration reverses the effects of oil on employment and productivity in the economy. If the conditions of Proposition 5.2 hold, and if $\frac{p_o O}{L+L^F} > 0$ then we will still observe an increase in productivity of manufacturing and a drop in productivity of non-manufacturing in a country with migration and resources, relative to a country with no migration and no resources.

It is important to note, that our previous calibration in fact already takes into account the above mechanism since our measures of GDP and labor force already include immigration. More specifically, We choose oil endowments in the model to match export *shares* of resources (exports of resources relative to GDP) observed in the data. Suppose that e_s is the resource export share in the data. We choose $p_o O$ in the model so that the resource share in the model is equal to the resource share in the data:

$$\frac{p_o O}{(L + L^F)(\bar{p}_s Y_s + Y_m) + p_o O} = e_s, \tag{45}$$

where $\bar{p}_s$ is a constant price of non-manufacturing goods. The above can then be solved for $p_o O$,

$$p_o O = \frac{e_s}{1 - e_s}(L + L^F)(\bar{p}_s Y_s + Y_m). \tag{46}$$

[29] Note, that this equation holds regardless of the distribution of oil income between migrants and locals. Also note that this equation is a market clearing condition and it holds irrespective of the ability distribution of agents.

Substituting, this into equation 44, we see that migration terms cancel out. These resource shares in the data include the migrant stock through higher GDP figures in the denominator: higher migrant stock increases (total) GDP levels, and hence decrease resource export share levels. As long as the characteristics of migrants are the same as locals, our previous calibration (and all ensuing results) hold.

Migration in the Data To assess the impact of migration on employment shares and productivity differences between oil rich and oil poor countries, we examine how the presence of oil impacts the employment structure and productivity when controlling for the migration stock in the population. We obtain data for international migrant stock (the number of people born in a country other than that in which they live) as a fraction of population, from the WDI. Since this data is provided every five years and moves quite slowly over time, we linearly interpolate the missing data. The results are reported in Table 5. Notice that the effects on productivity and employment found previously still hold when controlling for migration in the data. To test the implications of the model with migration, we include an interaction term in the regressions between resource wealth and migration. In particular, the theory predicts that the impact of resource wealth will be mitigated by migration. This is confirmed by our empirical findings as determined by the coefficients on the interaction terms.

From column (3) of the top panel of Table 5, we see that employment shares in non-manufacturing are in general higher in resource rich countries. However from the negative interaction coefficient (-0.534), we see that in resource rich countries that also have higher migration, some of the Dutch Disease effects are reversed. Similarly, from column (6) we see that employment share in manufacturing is in general lower in resource rich countries, but in resource rich countries that have higher migration the interaction coefficient is positive (0.456): migration undoes some of the labor reallocation effects.

We see parallel results in sectoral productivity in the bottom panel of the table. In column (3) we see that resource rich countries tend to have lower productivity in non manufacturing, but this de-specialization effect is weakened by higher migration as can be see through the positive interaction effect (70.755). In column (6), we see that resource rich countries tend to have higher productivity in manufacturing, but this specialization effect is weakened by high migration as can be see through the negative interaction effect (-211.69). Thus the above results provide further evidence for our mechanism. High resource endowments induce workers to shift across sectors. This movement of labor generates specialization and de-specialization across different sectors. By lowering the per capita resource wealth, higher migration undoes the shift in the labor force and weakens the specialization/de-specialization mechanism.

(a) Changes in employment, resource wealth and migration

	(1) NM. Emp. (TD)	(2) NM. Emp. (TD)	(3) NM. Emp. (TD)	(4) M. Emp. (TD)	(5) M. Emp. (TD)	(6) M. Emp. (TD)
nrExpSh	0.213***	0.190***	0.265***	-0.272***	-0.246***	-0.310***
	(0.023)	(0.023)	(0.028)	(0.023)	(0.022)	(0.027)
logGDP	-0.645***	-0.611***	-0.619***	0.591***	0.553***	0.559***
	(0.057)	(0.056)	(0.056)	(0.055)	(0.054)	(0.053)
sqlogGDP	0.034***	0.031***	0.032***	-0.030***	-0.028***	-0.028***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Migr		0.094***	0.152***		-0.106***	-0.155***
		(0.017)	(0.021)		(0.016)	(0.020)
Migr×nrExpSh			-0.534***			0.456***
			(0.117)			(0.112)
Observations	806	806	806	806	806	806
R-squared	0.363	0.387	0.403	0.397	0.428	0.440

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(b) Changes in TFP (K, H), resource wealth and migration

	(1) NM Prod (TD)	(2) NM Prod (TD)	(3) NM Prod (TD)	(4) M Prod (TD)	(5) M Prod (TD)	(6) M Prod (TD)
nrExpSh	-21.794***	-16.623***	-26.594***	185.64***	144.14***	173.97***
	(2.636)	(2.564)	(3.089)	(19.33)	(18.59)	(22.77)
KHProd	0.898***	0.926***	0.923***	1.59***	1.36***	1.37***
	(0.007)	(0.007)	(0.007)	(0.05)	(0.05)	(0.05)
Migr		-17.618***	-24.166***		141.39***	160.98***
		(1.901)	(2.206)		(13.78)	(16.26)
Migr×nrExpSh			70.755***			-211.69**
			(12.721)			(93.76)
Observations	806	806	806	806	806	806
R-squared	0.960	0.964	0.965	0.65	0.69	0.69

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5: The Impact of Migration on Sectoral Employment and Productivity, cross country data.

7 Extension to Dependent Ability Draws

In the baseline model we assumed skill draws were independent and hence we ignored the possibility that individuals with higher ability in one sector may have higher ability in the other. In this section, we introduce the possibility of correlated skill draws and show that introducing dependence does little to quantitatively change our results. We follow Lagakos and Waugh (2009) by introducing dependance between skill distribution in the form of a copula function. In particular, we set the joint distribution of abilities to be:

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

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

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

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 Fréchet, with common dispersion parameter, θ. The dependence parameter ρ may assume any real value. Values of ρ below and above one generate negative and positive correlations between z_s and z_m respectively. With $\rho = 0$, the variables are independent and we are back to the baseline case.[30]

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 maintain the assumption that $\theta = 2.22$ and $\sigma = 0.94$ (since these were obtained from cross-country data) and 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%. In table 6, we show the predicted percentage change in sectoral employment and productivity between the top 10th percentile of resource exporters (with 19% resource export share) and the bottom 90th percentile of resource exporters (with 0% resource export share) in each scenario. Since ρ is itself difficult to interpret, we also report an implied linear correlation coefficient from a simulation of 10000 draws of the random variables for each choice of ρ. From the table, we see that increasing the correlation between talent draws from 0 to nearly 0.6, has almost no effect on sectoral productivity and employment between resource rich and resource poor countries.

The reason for this is the assumption that the variance of each talent draw is governed by the same parameter θ, which implies the same variance across talent draws. If we allowed θ

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

ρ	ν	Imp. Corr.	L_s	L_m	Y_s/L_s	Y_m/L_m	$(Y_s/L_s)/(Y_m/L_m)$
0	0.27	0.00	1.14	0.52	0.94	1.41	0.67
1	0.29	0.14	1.14	0.52	0.94	1.41	0.67
2	0.30	0.27	1.14	0.51	0.94	1.43	0.66
3	0.32	0.39	1.14	0.51	0.95	1.43	0.66
4	0.34	0.49	1.15	0.49	0.95	1.46	0.65
5	0.34	0.58	1.15	0.49	0.95	1.47	0.65

Table 6: The Impact of changing dependence between skill draws (re-adjusting ν). Entries reflect the predicted ratio between to 10th and bottom 90th percentile resource exporters.

to vary with sector (and hence generate an unequal variance across sectors) correlations would play a larger role. How realistic is this assumption? It turns out that in our data the variance of log-wages in manufacturing relative to the variance of log wages in non-manufacturing is near one. Hence, the variance of wages seem to be very similar across regions and the assumption of identical θ across sectors is a good one. Given this fact, and the observation that the correlation coefficient makes little difference to the results, we maintain the simpler baseline model is a better way to capture the mechanism than the more complex correlated- skill model.

Different Dispersions TO BE COMPLETED

8 Micro Evidence

This section provides micro-level evidence on sectoral employment and productivity differences by comparing oil rich and oil poor counties of the US South. In particular we show that: (1) Oil rich counties employ a lower share of their (non-resource) workers in the manufacturing sector and higher share in the non-manufacturing sector; and that (2) Oil rich counties are slightly less productive in non-manufacturing sectors but significantly more productive in manufacturing than oil poor counties.

8.1 Data

Natural Resource "Wealth" We do not have county level data on exports or GDP, thus we cannot construct the same measure of oil wealth used in the cross-country analysis. Instead, 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 then 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, which are divided into counties in less regular way then state discussed above. To have a plausible sample of control counties, we restrict our analysis to counties located within 200 miles of the oil rich counties of Texas, Oklahoma and Louisiana. This leaves us with the sample of 789 counties, 169 of which are oil rich. (see Figure 5 in Appendix 11.17).

Sectoral Labor Productivity Next, we use 1980 US state census data from the Integrated Public Use Microdata Series or IPUMS (Ruggles et al., 2008) to determine sectoral labor productivity within counties.[31] 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 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[32] and use hourly wage as a measure of labor productivity of each person.[33]

Matching Resource and Productivity Data Finally, we need to match resource wealth and labor productivity data. IPUMS 1980 census data however, only identifies county groups (rather than particular counties) in which each individual resides. 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.

[31] 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 groups as geographical identifier.

[32] Our sectoral categories are consistent with the International Standard Industrial Classification of all economic activities (ISIC). Non-manufacturing includes agriculture, services and construction and excludes utilities. The mining sector includes mining, crude petroleum and natural gas extraction and quarrying of stone, sand and clay. We also perform robustness checks with narrower definitions of non-manufacturing sector (e.g., excluding agriculture or considering services).

[33] 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.

	Emp. Share		Lab. Prod.		Lab. Prod.
	NM/(M+NM)	M/(M+NM)	NM/(M+NM)	M/(M+NM)	NM/M
Oil rich	75%	25%	0.96	1.05	0.91
Oil poor	73%	27%	0.98	0.96	1.02
OR/OP	1.03	0.93	0.98	1.09	0.90

Table 7: Employment shares and labor productivity (measured as hourly wage) in manufacturing and non-manufacturing sectors in oil rich and oil poor counties in the US south in 1980 (Source: IPUMS).

8.2 Facts

Table 7, provides evidence on sectoral employment and productivity differences between oil rich and oil poor counties in the US South. Oil rich counties employ 3% more of their non-resource workers in non-manufacturing and 7% less of their non-resource workers in manufacturing. Furthermore, oil rich counties are slightly less productive in non-manufacturing (2% less) and significantly more productive in manufacturing (9% more) than oil rich counties, controlling for average wages across county groups. Thus oil rich counties are only 90% as productive in non-manufacturing relative to manufacturing as oil poor countries.

In the appendix we check the robustness of these relationships by running the following regressions: (1) relative labor productivity versus an oil abundance dummy; (2) relative labor productivity versus an oil abundance dummy and average income per capita (3) non-manufacturing labor productivity versus an oil abundance dummy and average income per capita (4) manufacturing labor productivity versus an oil abundance dummy and average income per capita. Results of these regressions are summarized in Table 18. We also run Mincer wage regressions for manufacturing and non-manufacturing (as well as service) sectors (see Table 19 for details). In all of these regression, the above results are confirmed.

9 Comparative advantage: males versus females

In this section, we provide direct evidence of our mechanism using micro level data. Although in general it is difficult to observe differences in ability, one way of doing so is along the dimension of sex where there is some evidence of ability differences in manufacturing and non-manufacturing tasks. Within the development literature, many economists (eg. Galor and Weil (1996), Galor and Weil (1999), Fan and Lui (2003)) have argued that men may have a comparative advantage in manufacturing relative to services due to their greater physical strength. This section uses previous section's micro data to provide direct evidence in support of our mechanism of de-specialization, by looking at ability differences in manufacturing and non-manufacturing work

	Productivity		Employment Shares	
	NM	M	NM	M
Female	5.03	4.89	78%	20%
Male	7.79	7.94	65%	26%

Table 8: Productivity and employment by sector and sex. (Source: IPUMS)

along the gender dimension. In particular we show that: (1) Women have a comparative advantage in non-manufacturing work relative to men; (3) The decline in manufacturing employment in oil rich countries is higher for females than males; and (3) The decline in manufacturing employment in oil rich counties is higher within female intensive industries.

Gender and Sectoral labor productivity First, we show that females have a comparative advantage in non-manufacturing, whilst males have a comparative advantage in non-manufacturing - despite non-manufacturing employing a higher share of female workers. The first two columns of Table 8 show the sectoral productivity of male and female workers. Overall female productivity is lower in both non-manufacturing and manufacturing. 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. In the Appendix 11.19 we examine further robustness of these relationships by estimating Mincer wage regressions by controlling for individual's heterogeneity. The regression results provide support for the implications of Table 8.

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 worker in resource rich regions then men. As evidence of that, Table 9 shows the differences in the structure of non-resource 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 non-resource 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 the non-manufacturing sector than men.

Third, as a final piece of evidence in support of our hypothesis, we show that there is a

	Female Employment		Male Employment	
	NM/(NM+M)	M/(NM+M)	NM/(NM+M)	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 9: Sectoral employment share (disaggregated by gender): oil rich vs. oil poor counties

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

Table 10: Change in female employment in a female intensive industry: oil rich vs. oil poor counties

larger change in employment structure between resource rich and resource poor regions female intensive industries. As an example we pick the textile industry which, according to Kusera and Milberg (2000), is the most female intensive industry.[34] Table 10 decomposes female (non-oil) manufacturing employment shares into textile manufacturing (MT) and non-textile manufacturing (MNT) employment across oil rich and poor regions.[35] This decomposition shows that the decline in employment in the female intensive, textile manufacturing sector between oil poor and oil rich regions was far lower than in non-textile manufacturing. Specifically, oil rich counties employed 40% less females in the textile manufacturing industry than oil poor counties, but only 18% less in (relatively female un-intensive) non-textile industries. Another way of seeing this, is to note that textiles accounted for 29% of female employment in manufacturing in oil poor counties, but only 21% of female employment in oil rich counties.

10 Conclusion

In this paper we: 1) Show that in the data, resource rich regions have significantly higher labor productivity in (traded) manufacturing than resource poor regions, but only slightly lower labor productivity in (non-traded) non-manufacturing, that 2) Standard models of Dutch disease,

[34] 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.

[35] 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.

are unable to account for this fact and 3) We propose a model, derived from the growth and development literature, that explains sectoral productivity differences between resource rich and poor countries, as a consequence of de-specialization. Since endowments of natural resources, shift labor to non-manufacturing (the standard Dutch Disease story), in resource rich economies many of those working in the service sector, are those whose comparative advantage is not service sector work. Since employment in non-manufacturing tends to be higher than the traded goods sector, productivity differences between resource rich and resource poor countries are relatively larger in non-manufacturing and relatively smaller in manufacturing. We find that this model can account for all of the cross-country productivity differences in traded and non-traded sectors found between resource rich and resource poor countries.

11 Appendix

11.1 Summary Statistics

In table 11, we present summary statistics for the main macro economic variables used throughout the paper: 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 11: Summary statistics for macro data.

11.2 Data consistency

To ensure accurate estimates of productivity, we compare sectoral value added data and employment data from WDI and UN sources and drop the country-date data points that differ by more than one half a standard deviation between the two sources. It is important to note that our results do not depend on this procedure, and go through using unfiltered data.

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 how many standard deviations a particular observation is from this average: $e_{i,t} = |r_{i,t} - ave|/sdev$
6. Drop observation if $e_{i,t} > 0.5$

We apply the following procedure to current price sectoral value added data and employment data for 1980-2008 that are available in both WDI and UN databases. As such, we apply the procedure for agriculture, manufacturing and services sectoral value added data and agriculture, services and total employment data.

11.3 Price Categories

The publicly available ICP expenditure data disaggregates expenditure into 19 sectors. These however, do not map very well into ISIC sectors. It is however possible to gain access to proprietary ICP data that is further disaggregated into approximately 129 sectors. We make use this disaggregated data to construct expenditure data at market exchange rates and at PPP for five sectors: agriculture, manufacturing, mining and utilities, construction and services (defined in Appendix 11.3). We then use equation 4 to calculate sector specific prices in each country (relative to the US) for each of the five sectors.

This section describes which ICP categories were assigned to which sector in the construction of sectoral price indices.

Agriculture We define Agriculture as: 1101111 Rice, 1101112 Other cereals and flour, 1101113 Bread, 1101114 Other bakery products, 1101115 Pasta products, 1101121 Beef and veal, 1101122 Pork, 1101123 Lamb, mutton and goat, 1101124 Poultry, 1101125 Other meats and preparations, 1101131 Fresh or frozen fish and seafood, 1101132 Preserved fish and seafood, 1101141 Fresh milk, 1101142 Preserved milk and milk products, 1101143 Cheese, 1101144 Eggs and egg-based products, 1101151 Butter and margarine, 1101153 Other edible oils and fats, 1101161 Fresh or chilled fruit, 1101162 Frozen, preserved or processed fruits, 1101171 Fresh or chilled vegetables, 1101172 Fresh or chilled potatoes, 1101173 Frozen or preserved vegetables, 1101181 Sugar, 1101182 Jams, marmalades and honey, 1101183 Confectionery, chocolate and ice cream, 110119 Food products n.e.c., 110121 Coffee, tea and cocoa, 110122 Mineral waters, soft drinks, fruit and vegetable juices, 1102111 Spirits, 1102121 Wine, 1102131 Beer and 110220 Tobacco.

Manufacturing We define Manufacturing as: 1103111 Clothing materials and accessories, 1103121 Garments, 1103211 Footwear, 110511 Furniture and furnishings, 110512 Carpets and other floor coverings, 110520 Household textiles, 110531 Major household appliances whether electric or not, 110532 Small electric household appliances, 110540 Glassware, tableware and household utensils, 110551 Major tools and equipment, 110552 Small tools and miscellaneous accessories, 110561 Non-durable household goods, 110611 Pharmaceutical products, 110612 Other medical products, 110613 Therapeutical appliances and equipment, 110711 Motor cars, 110712 Motor cycles, 110713 Bicycles, 110820 Telephone and telefax equipment, 110911 Audio-visual, photographic and information processing equipment, 110914 Recording media, 110921 Major durables for outdoor and indoor recreation, 110931 Other recreational items and equipment, 111212 Appliances, articles and products for personal care, 111231 Jewellery, clocks and watches, 111232 Other personal effects, 150110 Metal products and equipment, 150120 Transport equipment and 150300 Other products.

Mining and Utilities We define Mining and Utilities as: 110440 Water supply and miscellaneous services relating to the dwelling, 110451 Electricity, 110452 Gas, 110453 Other fuels and 110722 Fuels and lubricants for personal transport equipment.

Construction We define Construction as: 150210 Residential buildings, 150220 Non-residential buildings and 150230 Civil engineering works

Services We define Services as: 1103141 Cleaning and repair of clothing, 1103221 Repair and hire of footwear, 110410 Actual and imputed rentals for housing, 110430 Maintenance and repair of the dwelling, 110442 Miscellaneous services relating to the dwelling, 110513 Repair of furniture, furnishings and floor coverings, 110533 Repair of household appliances, 1105621 Domestic services, 1105622 Household services, 110621 Medical Services, 110622 Dental services, 110623 Paramedical services, 110630 Hospital services, 110723 Maintenance and repair of personal transport equipment, 110724 Other services in respect of personal transport equipment, 110731 Passenger transport by railway, 110732 Passenger transport by road, 110733 Passenger transport by air, 110734 Passenger transport by sea and inland waterway, 110735 Combined passenger transport, 110736 Other purchased transport services, 110810 Postal services, 110830 Telephone and telefax services, 110915 Repair of audio-visual, photographic and information processing equipment, 110933 Gardens and pets, 110935 Veterinary and other services for pets, 110941 Recreational and sporting services, 110942 Cultural services, 110943 Games of chance, 110950 Newspapers, books and stationery, 110960 Package holidays, 111000 Education, 111110 Catering services, 111120 Accommodation services, 111211 Hairdressing salons and personal grooming establishments, 111220 Prostitution, 111240 Social protection, 111250 Insurance, 111261 FISIM, 111262 Other financial services n.e.c and 111270 Other services n.e.c.

Not Otherwise Classified This leaves the following categories which are not classified and hence excluded from our price indices: 111300 Net purchases abroad, 130221 Compensation of employees, 130222 Intermediate consumption, 130223 Gross operating surplus, 130224 Net taxes on production, 130225 Receipts from sales, 130421 Compensation of employees, 130422 Intermediate consumption, 130423 Gross operating surplus, 130424 Net taxes on production, 130425 Receipts from sales, 140111 Compensation of employees, 140112 Intermediate consumption, 140113 Gross operating surplus, 140114 Net taxes on production, 140115 Receipts from sales, 160000 Change in inventories and valuables as well as 180000 Balance of exports and imports.

11.4 Sectoral Value added in International Dollars

We obtain one digit ISIC v.3 sectoral value added data from the UN.[36] Since UN data is given in constant 1990 prices (Value Added by Economic Activity at constant 1990 prices (US Dollars) series) and current prices (Value Added by Economic Activity at current prices (US Dollars) series), we first need to re-base the 1990 data to 2005 prices. We do this by calculating (for each sector) the ratio between the 2005 current and constant value added. For each sector s, 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. We do this using the sectoral price indices calculated in the main text. In particular, we group the constant 2005 value added data into agriculture (ISIC A), manufacturing (ISIC D), mining and utilities (ISIC C and E), construction (ISIC F) and service (ISIC G, H and I) sectors. Next, we divide each country's constant (2005) sectoral value added by the relative prices, P_s^i/P_s^{PPP}, calculated in expression 4. This converts sectoral value added calculated in constant (2005) country specific prices into sectoral value added calculated at international (2005) prices that are invariant across countries and time.

[36] Our value added data is divided into: Agriculture, hunting and forestry (ISIC A), Mining and quarrying (ISIC C), Manufacturing (ISIC D), Electricity, gas and water (ISIC E), Construction (ISIC F), Wholesale and retail trade (ISIC G), Hotels and restaurants (ISIC H), Transport, storage and communication (ISIC I) and Other service activities (ISIC J-P).

11.5 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:

$$K_{t+1} = (1-\delta)K_t + I_t, \tag{47}$$

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.[37] As is standard, we compute the initial 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.[38] 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 or g.

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.

11.6 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 2 or 3. 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:

$$\alpha_s \frac{P_s^D Y_s}{K_s} = \alpha_{s'} \frac{P_{s'}^D Y_{s'}}{K_{s'}}, \tag{48}$$

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

[37] 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.

[38] 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.

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:

$$\sum_s K_s = K, \tag{49}$$

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:

$$K_s = \left(\frac{\alpha_s P_s^D Y_s}{\sum_i \alpha_i P_i^D Y_i} \right) K. \tag{50}$$

Finally, to calculate the above expression we need to estimate labor shares, $1 - \alpha_s$ for each sector s. Due to a lack of comprehensive sectoral cross-country data, we make use of OECD data for the year 2005, and calculate average labor shares for each sector. We then assume that all countries have the same sectoral labor shares and these remain constant over time. The results are shown in Table 12 in Appendix 11.7. Given these shares, we can use equation 50 for each sector and the aggregate capital stock (calculated previously) to obtain an estimate of sectoral capital.

11.7 Labor Shares

Table 12 presents the shares of labor compensation relative to a sector's value added in agriculture, construction, services, manufacturing, mining and utilities, as well as the combined (non-resource) non-manufacturing sector (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. The data comes from Tables 7 and 8 in the the OECD Annual National Accounts (Volume 2, 1970-2008 (2009 prov)- Detailed aggregates, in millions of national currency) and represents the yearly average over the longest available period of data, as indicated in the table.

11.8 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

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 12: 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)

missing data by linear interpolation. This data is then turned into a measure of human capital, h, through the formula:

$$h = e^{\phi(x)}, \tag{51}$$

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

$$\phi(x) = \begin{cases} 0.134 \cdot s & \text{if } x \leq 4 \\ 0.134 \cdot 4 + 0.101 \cdot (x-4) & \text{if } 4 < x \leq 8 \\ 0.134 \cdot 4 + 0.101 \cdot 4 + 0.068 \cdot (x-8) & \text{if } 8 < x \end{cases} \tag{52}$$

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 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.

11.9 Estimating Education by Sector in the United States

	Education Distribution								
Sector	<HS	HS	<C	C(A)	C(B)	M	D	Ave. Y.	Ave. Years/Mfg
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 13: 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)

In this section we estimate the distribution of education levels within ISIC one digit sectors and the average years in education within each sector in 2008 in the United States. The results are shown in Table 13. From the BLS we obtain a distribution of occupations within each ISIC sector that specifies what fraction of employees within that sector who work in a given occupation.[39] 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.[40] Finally assuming that education levels (1)

[39] Occupations are classified by major - two digit - 2010 Standard Occupational Classification (SOC).
[40] For example, suppose z_A is a vector that contains the distribution of occupations within agriculture and

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.

11.10 Sectoral Human Capital

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 (from Table 13):

$$\eta_s^{US} = x_s^{US}/x_m^{US}. \tag{53}$$

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:

$$x_s^i = \eta_s^{US} x_m^i. \tag{54}$$

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:

$$\sum_s l_s^i x_s^i = x^i, \tag{55}$$

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 equation 52.

11.11 Results with all data

Tables 14-16 reproduce the employment and productivity results in the main body of the paper but include countries that were dropped since they fell below the 120 richest countries or since their was major deviation in the data on sectoral employment and value added between WDI and UN source. Whilst the fit of the data unsurprisingly lower, all established results go through.

11.12 Disaggregation of Non-Manufacturing

This section shows how productivity and employment in sub-sectors of the non-manufacturing sector (Agriculture, Construction and Services) changes with resource wealth. We find that

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.

COEFF.	(1) NM. Emp. Sh.	(2) NM. Emp. Sh.	(3) NM. Emp. Sh. (TD)
nrExpSh.	0.123***	0.138***	0.158***
	(0.027)	(0.022)	(0.021)
logGDP	-	-0.495***	-0.435***
		(0.025)	(0.024)
sqlogGDP	-	0.026***	0.023***
		(0.001)	(0.001)
Obser.	1,106	1,106	1,106
R^2	0.019	0.382	0.464
COEFFICIENT	M. Emp. Sh.	M. Emp. Sh.	M. Emp. Sh. (TD)
nrExpSh.	-0.163***	-0.185***	-0.207***
	(0.027)	(0.022)	(0.021)
logGDP	-	0.445***	0.382***
		(0.025)	(0.024)
sqlogGDP	-	-0.023***	-0.020***
		(0.001)	(0.001)
Obser.	1,106	1,106	1,106
R^2	0.033	0.375	0.465

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

Table 14: Changes in sectoral employment and resource wealth. Standard errors in parentheses. All data.

(a) Changes in relative non-manufacturing to manufacturing sector labor productivity and resource wealth

COEFF.	(1) Log NM/M Prod.	(2) Log NM/M Prod.	(3) Log NM/M Prod. (TD)
nrExpSh.	-1.504***	-1.425***	-1.478***
	(0.228)	(0.225)	(0.230)
logLProd	-	-0.094***	-0.080***
		(0.017)	(0.018)
Obser.	1,106	1,106	1,106
R^2	0.011	0.537	0.585

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

(b) Changes in relative non-manufacturing to manufacturing sectoral TFP (K) and resource wealth

COEFF.	(1) Log NM/M Prod.	(2) Log NM/M Prod.	(3) Log NM/M Prod. (TD)
nrExpSh.	-1.240***	-1.044***	-1.087***
	(0.195)	(0.179)	(0.184)
logKProd	-	-0.444***	-0.423***
		(0.030)	(0.031)
Obser.	1,106	1,106	1,106
R^2	0.038	0.063	0.093

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

(c) Changes in relative non-manufacturing to manufacturing sectoral TFP (K,H) and resource wealth

COEFF.	(1) Log NM/M Prod.	(2) Log NM/M Prod.	(3) Log NM/M Prod. (TD)
nrExpSh.	-1.267***	-1.069***	-1.121***
	(0.196)	(0.187)	(0.190)
logKHProd	-	-0.394***	-0.379***
		(0.035)	(0.036)
Obser.	1,106	1,106	1,106
R^2	0.037	0.133	0.161

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

Table 15: The impact of resource wealth on relative productivity. All data.

(a) Changes in sectoral productivity and resource wealth.

	NM. Prod		M. Prod	
COEFF.		TD		TD
nrExpSh.	-11,387.65***	-10,211.87***	77,358.19***	70,524.78***
	(1,445.23)	(1,371.52)	(7,705.28)	(7,546.93)
LProd	1.01***	1.01***	0.99***	0.98***
	(0.00)	(0.00)	(0.01)	(0.01)
Obser.	1,082	1,082	1,082	1,082
R^2	0.99	0.99	0.85	0.86

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

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

	NM. Prod		M. Prod	
COEFF.		TD		TD
nrExpSh.	-45.51***	-46.92***	413.65***	418.77***
	(4.42)	(4.11)	(36.55)	(34.88)
KProd	0.95***	0.95***	1.37***	1.34***
	(0.00)	(0.00)	(0.03)	(0.02)
Obser.	1,082	1,082	1,082	1,082
R^2	0.99	0.99	0.74	0.78

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

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

	NM. Prod		M. Prod	
COEFF.		TD		TD
nrExpSh.	-30.50***	-31.46***	276.80***	280.28***
	(2.85)	(2.72)	(23.72)	(22.97)
KHProd	0.95***	0.95***	1.33***	1.33***
	(0.00)	(0.00)	(0.03)	(0.02)
Obser.	1,082	1,082	1,082	1,082
R^2	0.99	0.99	0.74	0.77

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

Table 16: The impact of resource wealth on productivity. All data.

the category "Services" drives the relationships found in productivity and employment in the non-manufacturing sector.

The top panel of Table 17 shows how sectoral TFP (controlling for human and physical capital) 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. Hence the aggregate negative result for non-manufacturing is driven primarily by the service sector productivity.

The bottom panel shows changes in employment in each sector. Agriculture has a statistically insignificant coefficient, whilst construction has a statistically positive but quantitatively small coefficient. The aggregate results are again being driven by the service sector, where resource wealth has a significant positive impact on employment.

Almost all the action in the aggregated non-manufacturing data comes from the service sector. 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.

11.13 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:

$$Y_{m,t} = A_{m,t} L_{m,t}^{1-\theta} K_{m,t}^{\theta}, \text{ and } Y_{s,t} = A_{s,t} L_{s,t}^{1-\alpha} K_{s,t}^{\alpha} \tag{56}$$

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:

$$\frac{w_t}{r_t} = \frac{1-\theta}{\theta} \frac{K_{m,t}}{L_{m,t}}, \text{ and } \frac{w_t}{r_t} = \frac{1-\alpha}{\alpha} \frac{K_{s,t}}{L_{s,t}}. \tag{57}$$

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

$$\frac{1-\theta}{\theta} \frac{K_{m,t}}{L_{m,t}} = \frac{1-\alpha}{\alpha} \frac{K_{s,t}}{L_{s,t}}. \tag{58}$$

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

$$\frac{p_{m,0} Y_{m,t}}{L_{m,t}} = p_{m,0} A_{m,t} \left(\frac{K_{m,t}}{L_{m,t}} \right)^{\theta}, \text{ and } \frac{p_{s,0} Y_{s,t}}{L_{s,t}} = p_{s,0} A_{s,t} \left(\frac{K_{s,t}}{L_{s,t}} \right)^{\alpha}, \tag{59}$$

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

COEFF.	(1) A Prod. (TD)	(2) C Prod. (TD)	(3) S Prod. (TD)
nrExpSh.	2.405***	310.007***	-72.379***
	(0.517)	(34.577)	(7.559)
KHProd	0.016***	1.083***	0.828***
	(0.001)	(0.088)	(0.019)
Obser.	806	806	806
R^2	0.315	0.322	0.715

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

(b) Changes in sectoral employment and resource wealth

COEFF.	(1) A. Emp. Sh.(TD)	(2) C. Emp. Sh. (TD)	(3) S. Emp. Sh. (TD)
nrExpSh.	-0.028	0.022**	0.269***
	(0.038)	(0.011)	(0.039)
logGDP	-0.151***	0.009***	0.135***
	(0.004)	(0.001)	(0.004)
Obser.	806	806	806
R^2	0.684	0.135	0.664

Table 17: Disaggregation of non-manufacturing: The impact of resource wealth on TFP (K,H) and employment.

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 (58), if capital labor ratio rises/falls in one sector, it rises/falls in the other and hence according to equation (59), labor productivity in both sectors rises/falls. A model with capital predicts that sectoral 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.

11.14 Heterogenous Firms

The problem presented in the main text presents a world with heterogenous agents, who differ by their productivity draws in particular tasks. In this section we show that the model is isomorphic to a model with heterogenous firms who differ in their productivity draws.

Production Suppose their is a unit continuum of locations indexed by $i \in [0, 1]$. Each location plays host to one of two types of firms - a manufacturing firm and a non-manufacturing firm. Firms differ by location: a sector $j \in \{s, m\}$ firm at location $i \in [0, 1]$ has an exogenous labor productivity given by z_j^i. Furthermore, firm productivities, $\{z_s^i, z_m^i\}$, are exogenous and are assumed to be randomly drawn from a distribution common to the entire country $G(z_s, z_m)$. Thus, each firm has access to the following production function:

$$Y_j^i = z_j^i L_j^i. \tag{60}$$

Finally, firms are assumed to be perfectly competitive.

Households At each location there is also an agent who is endowed with a unit of labor. Preferences, as before, are given by:

$$\left((c_s^i)^{\frac{\sigma-1}{\sigma}} + \nu (c_m^i)^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}, \tag{61}$$

Agents at location i earn a wage income, w^i. The agent is also endowed with a resource tree that provides a stream of O units of natural resources each period. These resources are not directly used by the agent but are also sold on the market. The budget constraint of the agent is given by:

$$p_s c_s^i + c_m^i \leq w^i + p_o O, \tag{62}$$

where, p_s is the relative price of non-manufacturing goods and p_o is the relative price of the natural resource. Traded goods are taken as numeraire.

Trade Trade is identical to the heterogenous agent case. It is assumed that manufacturing goods 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:

$$m - p_o O = 0, \tag{63}$$

where, m is the value of imported traded goods (recall that traded goods are numeraire). Notice that p_o is the world market price for oil (relative to traded goods) and is given exogenously.

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

$$\int_0^1 c_m^i di = \int_{i\in\Omega_m} Y_m^i dGi + m \tag{64}$$

$$\int_0^1 c_s^i di = \int_{i\in\Omega_s} Y_s^i dGi \tag{65}$$

$$L_s + L_m = 1 \tag{66}$$

where $\Omega = \Omega^m \bigcup \Omega^s$, $L_s \equiv \int_{i\in\Omega^s} di$ and $L_m \equiv \int_{i\in\Omega^m} di$.

Competitive Equilibrium For each price of resource, po, and endowment of oil O, an equilibrium in the above economy consists of a relative price of non-manufacturing goods, p_s, location 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 firms solves the following problem:

$$\max p_s Y_s - w_j^i L_j^i \text{ s.t. } Y_j^i = z_j^i L_j^i. \tag{67}$$

Due to perfect competition, each firm offers the following wage schedule:

$$w_m^i = Az_m^i \text{ and } w_s^i = p_s A z_s^i. \tag{68}$$

The consumer at location i then chooses to work in the sector that provides a higher wage. The wage for each consumer is thus given by, $w^i = \max\{w_s^i, w_m^i\} = \max\{p_s A z_s^i, A z_m^i\}$. This gives rise to the following simple rule: a worker at location i will work in non-manufacturing if and only if

$$p_s > \frac{z_m^i}{z_s^i}. \tag{69}$$

If an agent chooses not to work in a particular industry in a particular location, the firm exits (i.e. choses not to produce). If, due to a change in p_s, the wage offered by the firm makes the worker wish to chose in that sector, the firm enters again. Notice that in either case, the firm earns zero profits.

Agents take as given prices and the wage offers resulting from the firm's problems (and hence the above decision rules). Having picked the sector to work in, they then proceed to maximize (61) subject to (62), which results in the following demands of each agent:

$$c_s^i = \frac{(w^i + p_o O)}{p_s + \nu^\sigma p_s^\sigma} \text{ and } c_m^i = \frac{\nu^\sigma p_s^\sigma (w^i + p_o O)}{p_s + \nu^\sigma p_s^\sigma}. \tag{70}$$

Isomorphism There is a one-to-one and onto mapping from agent i in the heterogenous agent model to the agent in location i in the heterogenous firms problem. Agents described by i in both model choose to work in the same sector, earn the same wage and have the same consumption. By market clearing, total output in each sector will also be the same across models. Finally, since utility is the same in both models, prices of non-manufacturing will also be the same. The two models are thus essentially the same, and all the analysis of the main text also holds in the heterogenous firm model.

11.15 Proof of Proposition 5.1

Proof. Assume, by contradiction, that $p_{s,H} \leq p_{s,L}$. Notice, from (27), that the ratio of manufacturing to non-manufacturing (aggregate) good consumption is given by $\nu p_{s,H}$ in the high endowment economy and $\nu p_{s,L}$ 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, $C_{m,k} = \int_i c_{m,k}^i$ and $C_{s,k} = \int_i c_{s,k}^i$ 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 (69), 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). 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 fact 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, $p_{s,H} > p_{s,L}$. □

11.16 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:

$$Y_{NO} = \bar{p}_s Y_s + Y_m = \nu^{\frac{\sigma}{1-\theta-\sigma}} \Gamma(1 - \frac{1}{\theta}) L_s^{1-\frac{1}{\theta}} + \Gamma(1 - \frac{1}{\theta})(1 - L_s)^{1-\frac{1}{\theta}}. \tag{71}$$

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 intuition of the above is quite simple. Without resources, a social planner would allocate labor across sectors in order to maximize utility. Utility maximization in a world without resources (and hence trade) would be the same as maximizing aggregate output (measured in resource poor country's prices) - everything that is consumed must be produced. So, in order to maximize consumption, the social planner would also maximize production (weighted by the appropriate equilibrium prices). With resources, employment is chosen to maximize utility. Now, however, consumed goods do not have to be produced locally since some can instead be imported. Maximizing utility, is thus no longer the same as maximizing (non-oil) output. Instead, the social planner will choose an allocation of labor across sectors that produces more non-manufacturing than before. Whilst this, results in lower non-oil productivity (since the previous allocation of labor coincided with the one that maximized productivity) - it does result in a welfare improvement. Thus, the reallocation of labor results in a type of resource curse, where aggregate non-oil productivity (measured in resource poor country's prices) is lower, but overall welfare is higher (due to higher income).

Notice also, that the above effect is very small. Given the above calibration, the model predicts that the highest 10% resource exporters (with approximately 16% export share) will have a non-oil aggregate productivity that is only 1.2% lower than countries that do not export resources. Furthermore, this effect is only a consequence of the particular method of constructing real GDP. If we chose to measure aggregate productivity using the resource rich country's prices, instead of resource poor countries 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. In fact, the model would then predict that the highest 10% of resource exporters (with approximately 16% export share) will have a non-oil aggregate productivity that is 1.6% *higher* than non-exporters. Thus, the measured resource curse, is only a consequence of the type of pricing scheme adopted. Kehoe and Ruhl (2008) show in a similar setup that if productivity is measured using chain-weighted real GDP instead of constant price GDP, then changes in values of endowments have no first-order effect on non-oil productivity.

11.17 Micro Data

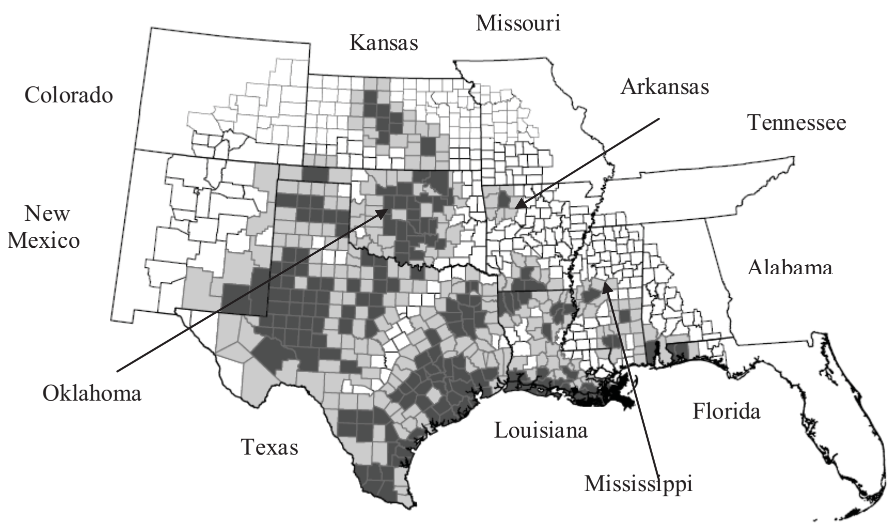


Figure 5: Counties in Micro Sample. Oil rich counties (black), adjacent counties (grey) and other nearby counties (white). (Source: Michaels (2009))

11.18 Mincer Wage regressions and sectoral labor productivity

This section analyzes the robustness of the sectoral productivity result by controlling for individual worker heterogeneity. In particular, we run Mincer wage regressions, relating sectoral productivity and individual characteristics

$$\log(\omega) = \beta_0 + \beta_1 Oil + \beta_2 age + \beta_3 age^2 + \beta_4 school \tag{72}$$

which is estimated for both manufacturing and non-manufacturing (services) sectors. Our model predicts that:

$$\frac{\omega_{NM,oil}}{\omega_{M,oil}} < \frac{\omega_{NM,non-oil}}{\omega_{M,non-oil}}$$

(a) Relative labor productivity in non-manufacturing and oil wealth.

	(1)	(2)
COEFF.	Log NM/M Prod.	Log NM/M Prod.
Oil	-0.076***	-0.061***
	(0.017)	(0.015)
logGDP	-	-0.520***
		(0.057)
Obser.	184	184
R^2	0.090	0.353

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

(b) Absolute labor productivity in non-manufacturing and oil wealth

	(1)	(2)
COEFF.	NM Prod.	M Prod.
Oil	-0.162***	0.246***
	(0.037)	(0.086)
GDP	0.788***	1.381***
	(0.021)	(0.047)
Obser.	184	184
R^2	0.891	0.847

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

Table 18: Relative and absolute labor productivity in non-manufacturing and oil wealth

The regression results are reported in Table 19:

Column (1) of Table 19 shows that labor is more productive in manufacturing in oil rich counties then in oil poor ones. The magnitude is also big, suggesting that manufacturing wages in oil rich counties were about 10 percentage points higher than in control counties. However, as Columns (2) and (3) show, oil abundance seems do not have much difference for labor productivity in non-manufacturing (services) across county groups. Specifically, the parameter of *Oil*, although has a positive sign, is not statistically different from zero. This also implies that differences in labor productivity between oil rich and oil poor counties are mainly driven by differences in labor productivity in manufacturing. Our estimates suggest that relative productivity differences between oil rich and oil poor counties were about 9 percentage points.

11.19 Mincer Wage regressions, Men, Women

In this section we examine the robustness of sectoral productivity differences along the gender dimension, by estimating the following wage equation:

$$log\omega = \beta_0 + \beta_1 sex + \beta_2 age + \beta_3 school + \beta_4 manuf + \beta_5 manuf * sex \tag{73}$$

We argue that:

$$\frac{\omega_{NM,f}}{\omega_{NM,m}} > \frac{\omega_{M,f}}{\omega_{M,m}} \tag{74}$$

Estimates of the wage regression presented in Table 20 confirm that women's productivity is higher in non-manufacturing than in manufacturing not only in absolute terms (i.e., $\beta_4 < 0$), but also relative to men (i.e., $\beta_5 > 0$). Our estimates suggest that the relative productivity

COEFF	(1) Log wage manuf.	(2) Log wage non-manuf.	(3) Log wage services
Oil	0.094***	-0.013	-0.021
	(0.028)	(0.018)	(0.017)
age	0.054***	0.062***	0.064***
	(0.002)	(0.001)	(0.002)
age^2	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)
school	0.083***	-0.008***	-0.003
	(0.020)	(0.007)	(0.007)
Constant	0.584***	0.511***	0.447***
	(0.051)	(0.032)	(0.035)
Obs	29,787	84,440	72,503
R^2	0.068	0.059	0.064

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

Robust standard errors adjusted for clusters in groups

Table 19: Estimates of a Mincer wage regression

of women compared to men is higher in non-manufacturing by about 9 percentage points than in manufacturing. As the lower panel of Table 20 shows, these relationships hold also after controlling for some interaction effects of gender with age and schooling.

Const	age	school	manuf	sex	sex_M	sex_age	sex_sch
1.238***	0.008***	0.033**	-0.031*	0.392***	0.082***		
(0.012)	(0.000)	(0.008)	(0.011)	(0.006)	(0.011)		
1.351***	0.003***	0.095***	-0.034**	0.249***	0.087***	0.006***	-0.111***
(0.011)	(0.000)	(0.011)	(0.011)	(0.023)	(0.011)	(0.000)	(0.007)

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

Obs = 122,683, regression 1: $R^2 = 0.176$, regression 2: $R^2 = 0.181$

manuf=1 if individual works in manufacturing

sex=1 if male; sex_M=sex∗manuf

sex_age=sex∗age;

sex_sch=sex∗school

Robust standard errors adjusted for clusters in groups

Table 20: Sectoral abilities - gender

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