Windfalls, Structural Transformation and Specialization[1]

Karlygash Kuralbayeva
Grantham Research Institute (LSE) and OxCarre

Radoslaw (Radek) Stefanski
Laval University and OxCarre

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Abstract

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

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1 Introduction

This paper investigates the impact of structural transformation in open economies on sectoral productivity through a process of specialization. Structural transformation is a reallocation of labor across sectors. Whilst there are potentially many sources of structural transformation,[2] we focus on labor reallocation induced by a windfall of revenue. Furthermore, we concentrate only on windfall revenue arising from the export of natural resources (fuels, ores and metals), although our entire analysis is applicable to other types of windfalls such as - for example - foreign aid, remittances, EU structural funds or war reparations.

In the paper we do two things. First, we use a panel of macro cross-country data and a cross-section of micro US county-level data to show that resource-rich regions tend to have a) *small* but *relatively productive* manufacturing sectors and b) *large* but *relatively unproductive* non-manufacturing sectors. Whilst the difference in sectoral size is well known and in line with theoretical predictions,[3] the productivity facts are novel and we show that standard models are ill-equipped to replicate them. Second, we construct and calibrate a small, open economy model with two sectors in which observed differences in sectoral productivity emerge endogenously as a consequence of windfall-induced labor reallocation and subsequent worker specialization.

In the model, we assume manufacturing goods are traded whilst non-manufacturing goods are non-traded and that agents have heterogeneous skills at performing different tasks in each sector. A region with higher windfall revenues will demand more of both types of goods than a region without windfalls. Whilst the region's higher demand for manufacturing goods can be satiated by imports from abroad, more workers need to be employed in non-manufacturing to meet the higher demand for locally produced non-manufacturing goods. This generates a reallocation of labor from manufacturing to non-manufacturing and results in a process of self-selection. Workers who choose to remain in manufacturing despite a windfall are those who are most skilled at manufacturing sector tasks, which leads to a more specialized and hence a more productive manufacturing sector. Workers who re-allocate to non-manufacturing do so only in response to the higher demand generated by the windfall and will be less skilled at non-manufacturing sector tasks than workers already employed in that sector. This leads to a more de-specialized and hence less productive non-manufacturing sector. Windfalls thus induce labor reallocation which in turn generates asymmetric changes in sectoral productivity.

We calibrate the model and show that the exogenous variation in endowments of natural resources does remarkably well in explaining the differences in sectoral employment structure and the large, asymmetric differences in sectoral productivity observed across countries. The

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

[3] See for instance, Corden and Neary (1982), Matsuyama (1992) or Michaels (2011) for theoretical and empirical treatments of this so-called Dutch Disease.

model also does well in explaining differences in non-manufacturing prices in the data. Finally, we take advantage of the fact that there exist systematic and exogenous differences in brawn endowments between men and women to provide micro-level evidence of our mechanism.

Our model has important implications for understanding the role of economic structure as a driver of aggregate productivity differences between resource-rich and resource-poor regions. We perform a hypothetical growth-accounting exercise and show that if the biggest resource exporters had manufacturing employment shares as large as those of the typical resource-poor country but kept their own high levels of manufacturing productivity, the aggregate productivity of the resource-rich countries could rise by as much as 20%. In contrast to this naive growth-accounting exercise, the model suggests that low aggregate productivity found in many resource-rich economies is *not* driven by a windfall-induced decline of a relatively productive manufacturing sector - but rather that the higher manufacturing productivity in those countries is a direct consequence of the smaller size of their manufacturing sector.

This observation provides guidance to economists trying to explain low aggregate productivity found in some resource-rich economies. In our model there is no first-order effect of windfall-induced sectoral labor reallocation on aggregate productivity since sectoral productivity is endogenous and depends on sectoral size. Our theory thus supports the arguments of Robinson et al. (2006), van der Ploeg (2010) and others who argue that explanations of the so-called "resource curse" should be sought outside economic structure, perhaps - as they suggest - in areas such as political economy, weak institutions and property rights or volatile resource prices. The model also suggests that policy makers in resource-rich countries hoping to increase aggregate productivity by encouraging workers to move towards more productive manufacturing sectors will not be successful. Through the lens of our model such policies would be self-defeating. New manufacturing sector workers will be less talented at manufacturing sector work than those who are already employed in that sector, causing manufacturing productivity to fall whilst leaving aggregate productivity unchanged. Economists and policy makers should note however, that other sectoral factors that are beyond the scope of our model (such as sector-specific learning-by-doing externalities) could still influence aggregate productivity. Our argument should thus be seen as providing supporting evidence - rather than conclusive proof - against a structural explanation of the resource curse.

Our work is in the spirit of Lagakos and Waugh (2012), Roy (1951) and Lucas (1978) and is closely linked to a similar discussion in the development literature. Poorer countries tend to have a larger fraction of their labor force employed in agriculture, due to subsistence requirements. Caselli (2005) and Restuccia et al. (2008) also show that productivity differences in agriculture between rich and poor countries are significantly greater than aggregate productivity differences. Lagakos and Waugh (2012) argue that this fact stems from the specialization that takes place in the smaller agricultural sectors in rich countries. They formalize and test their idea in the framework of a Roy (1951) model of self-selection. Due to subsistence requirements in agriculture (modeled as non-homothetic preferences), poorer countries employ more workers in agriculture. As aggregate productivity increases, subsistence needs can be met with a smaller fraction of the labor force which results in a shift of labor towards non-agriculture. This leads to productivity increasing in the agricultural sector by more than it does at the aggregate level, since only those workers that are most skilled (and hence most productive) in agriculture, self-select to remain in that sector.

Whilst superficially the mechanism of our model closely parallels Lagakos and Waugh (2012), conceptually the two models are quite different. The similarity between the two papers lies in that they both generate a reallocation of workers across sectors which translates to an endogenous change in sectoral productivity. The difference between the two papers concerns the source of this labor reallocation. Lagakos and Waugh (2012) rely on non-homothetic preferences and an exogenous variation in aggregate productivity to generate a shift of workers towards agriculture. Our model has homothetic preferences and instead emphasizes the role of exogenous resource windfalls and the existence of a non-traded sector as the channel driving labor reallocation. Our approach thus avoids what Lagakos and Waugh (2012) call the “key challenge” of their setup which is the requirement of large, exogenous productivity differences to drive workers across sectors.

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

2 Data and Facts

In our analysis we divide economies into mining and utilities (MU), manufacturing (M) and non-resource non-manufacturing (NM) sectors:[4]

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

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

Furthermore, we focus only on the productivity and employment structure of the non-resource economy.[5] In the following two subsections we construct measures of employment shares and productivity in manufacturing and non-resource non-manufacturing and show how they vary with measures of resource wealth. In particular, we use a panel of cross-country macro data as well as a cross-section of US county-level data to establish that resource-rich regions have small and relatively productive manufacturing sectors and large and relatively unproductive non-manufacturing sectors. Using the macro data, we also show how these facts could have important consequences for aggregate productivity of resource-rich countries.

2.1 Macro Data and Facts

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

$$Y_s = A_s L_s \tag{2}$$

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

$$Y_s = D_s (K_s)^{\alpha_s} (h_s L_s)^{1-\alpha_s} \tag{4}$$

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

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

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

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

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

Table 1: Resource export share, output per worker, sectoral employment and three measures of sectoral productivity (relative to aggregate productivity) for top and bottom 10% of natural resource exporters.Data for 46 countries, for 1980-2006. (Source: see Section 2)

natural resource "wealth" as the ratio of exports of natural resources (fuels, ores and metals) to GDP using WDI data.

In our baseline sample, we consider a panel of the 120 richest countries for the 1980-2006 period.[7] We keep all country-date points for which we have all necessary data and those that do not deviate significantly across different data sources. This leaves us with a total of 46 countries in our sample. On average, there are 18 observations for each country, 29 observations for each year and a total of 806 data points. For countries in the sample and summary statistics, see Appendix 11. In Appendix 12.1, we re-do all our empirical work with a full (and much larger) sample of countries and find that all subsequent results hold.

Summary of Facts Table 1 shows summary results for the macro data by comparing the largest 10 percent of natural resource exporters with the smallest 10 percent. The table shows sectoral employment shares as well as sectoral productivity normalized by aggregate productivity of each group. From the table we see that resource-rich countries: 1) employ proportionally 34% less workers in manufacturing and 9% more workers in (non-resource) non-manufacturing than resource-poor countries and 2) that they are 31%-43% more productive in manufacturing and 5-7% less productive in non-manufacturing (relative to aggregate productivity) than resource-poor countries. Notice also, that differences in manufacturing productivity are far larger than in non-manufacturing. We stress that our results refer to *relative* and *not absolute* productivity. So, for example, looking at the column labeled D_m in Table 1, the average productivity of manufacturing in the top 10% of resource exporters is 42% higher than the average aggregate productivity of those same countries, whereas in the bottom 10% of exporters the average manufacturing productivity is only 7% higher than the average aggregate productivity in that group of countries. Countries that have low aggregate (or sector neutral) levels of productivity will have low *absolute*

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

levels of productivity in all sectors irrespective of the size of their resource endowments but may still have high productivity in manufacturing *relative* to aggregate productivity.

Facts: Employment Table 2(a) tests the robustness of the relationship between the employment share of manufacturing and resource windfalls.[8] Column (1) shows the regression of manufacturing employment share on the log of our windfall measure.[9] Resource-rich countries employ less workers in the manufacturing sector and (implicitly) more workers in the non-manufacturing sector. These results are statistically significant at the one percent level. A well-known fact from the development literature is that employment in manufacturing follows an inverted-U with output per worker. Column (2) thus controls for changes in output per worker (and output per worker squared). Column (3) adds time-fixed effects to the regressions in column (2). In both cases, the results remain largely unchanged. Finally, column (4) adds country-fixed effects to the regressions in column (2). The result still holds, although the decline in manufacturing employment is smaller than before.[10] Notice, that this last regression indicates that a smaller manufacturing sector associated with higher resource windfalls is not only a cross-country result, but also holds within countries over time. Since we are predominately interested in cross-country variation, column (3) will be our baseline: a doubling of resource windfalls is associated with a 1.69 percentage point decline in the manufacturing employment share.

Facts: Sectoral Productivity Columns (1) of Table 2(b) and 2(c) show how (the log of) manufacturing and non-manufacturing productivity varies with (the log of) resource windfalls and aggregate productivity. Higher aggregate (or sector neutral) productivity is unsurprisingly associated with higher sectoral productivity. However, controlling for differences in aggregate productivity, resource-rich countries tend to be more productive in manufacturing and less productive in non-manufacturing than resource-poor countries. Notice also that this difference in productivity is much greater in the manufacturing sector. These results are significant at the one percent level and robust to including time- or country-fixed effects in columns (2) and (3). The results are also robust to all three measures of productivity as shown in columns (4)-(9) of

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

[9] We take a log transformation since the data is concentrated near zero. This ensures that the transformed empirical distribution is closer to normal. Importantly this transformation does not drive our results.

[10] Notice, we do not include both time- and country-fixed effects. Variation over time in our windfall measure comes predominately from variation in natural resources prices that are common across countries whilst most of the variation in quantity comes from exogenous and largely time-invariant variation in cross-country natural resource endowments. Keeping both fixed effects thus leaves us with too little variation in the data. A rule of thumb here is to regress the independent variable - $\log(NRE)$ - on country and time fixed effects. If the value of $1/(1-R^2)$ from the resulting regression is less than ten, the rule of thumb suggests that there is enough variation in the data to include both fixed effects. In our case $1/(1-R^2) = 19.27$ thus suggesting there is too little variation to include both types of fixed effects.

(a) Changes in mfg. employment share and resource wealth (restricted sample).

	(1) M. Emp.	(2) M. Emp.	(3) M. Emp.	(4) M. Emp.
log(NRE)	-1.64***	-1.73***	-1.69***	-0.49***
	(0.12)	(0.11)	(0.11)	(0.16)
logLprod		82.19***	72.50***	135.56***
		(7.86)	(7.46)	(6.51)
sqlogLprod		-3.97***	-3.48***	-6.91***
		(0.38)	(0.36)	(0.31)
Time FE	no	no	yes	no
Country FE	no	no	no	yes
Obs.	806	806	806	806
R^2	0.19	0.29	0.40	0.86

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

(b) Changes in non-mfg. productivity and resource wealth (restricted sample).

	(1) $\log(A_s)$	(2) $\log(A_s)$	(3) $\log(A_s)$	(4) $\log(B_s)$	(5) $\log(B_s)$	(6) $\log(B_s)$	(7) $\log(D_s)$	(8) $\log(D_s)$	(9) $\log(D_s)$
$\log(NRE)$	-0.021***	-0.020***	-0.012***	-0.013***	-0.013***	-0.013***	-0.012***	-0.012***	-0.016***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)
$\log(A)$	0.976***	0.982***	0.877***						
	(0.004)	(0.004)	(0.006)						
$\log(B)$				0.906***	0.914***	0.876***			
				(0.005)	(0.005)	(0.010)			
$\log(D)$							0.902***	0.910***	0.905***
							(0.006)	(0.006)	(0.012)
Time FE	no	yes	no	no	yes	no	no	yes	no
Ctry FE	no	no	yes	no	no	yes	no	no	yes
Obs.	806	806	806	806	806	806	806	806	806
R^2	0.989	0.990	0.998	0.973	0.975	0.990	0.961	0.965	0.986

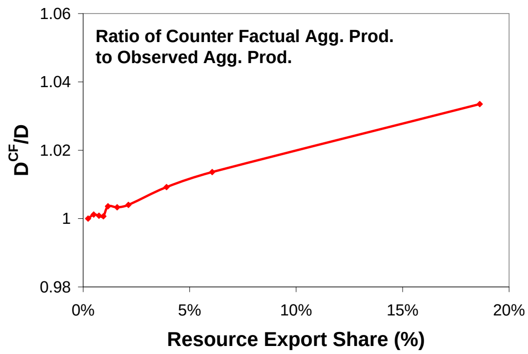
Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(c) Changes in mfg. productivity and resource wealth (restricted sample).

	(1) $\log(A_m)$	(2) $\log(A_m)$	(3) $\log(A_m)$	(4) $\log(B_m)$	(5) $\log(B_m)$	(6) $\log(B_m)$	(7) $\log(D_m)$	(8) $\log(D_m)$	(9) $\log(D_m)$
$\log(NRE)$	0.097***	0.097***	0.060***	0.064***	0.065***	0.066***	0.065***	0.065***	0.081***
	(0.008)	(0.009)	(0.011)	(0.007)	(0.007)	(0.010)	(0.007)	(0.007)	(0.011)
$\log(A)$	1.132***	1.115***	1.465***						
	(0.020)	(0.020)	(0.026)						
$\log(B)$				1.423***	1.399***	1.523***			
				(0.031)	(0.032)	(0.043)			
$\log(D)$							1.434***	1.410***	1.401***
							(0.037)	(0.038)	(0.054)
Time FE	no	yes	no	no	yes	no	no	yes	no
Ctry FE	no	no	yes	no	no	yes	no	no	yes
Obs.	806	806	806	806	806	806	806	806	806
R^2	0.812	0.819	0.972	0.737	0.744	0.946	0.668	0.681	0.928

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

Table 2: The impact of windfalls on sectoral employment and productivity. A, B and D refer to our three measures of sectoral productivity (with subscript) and aggregate productivity (without subscript). NRE refers to the natural resource export share. Results for the restricted sample.



(a) Decile Plot

	D^{CF}/D	D^{CF}/D	D^{CF}/D
$\log(NRE)$	0.007***	0.007***	0.010***
	(0.001)	(0.001)	(0.001)
Time FE	no	yes	no
Ctry FE	no	no	yes
Obs.	806	806	806
R^2	0.069	0.099	0.797

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

(b) Regressions

Figure 1: A growth-accounting exercise. The graph and regressions show how much higher the counterfactual measure of aggregate productivity, D^{CF}, would be relative to observed aggregate productivity, D, in resource-rich economies.

the same tables. Again, since we are primarily interested in cross-country variation, we will take our baseline to be column (8), where a doubling of natural resource windfalls is associated with a 1.2% lower non-manufacturing productivity and a 6.5% higher manufacturing productivity.

Facts: Aggregate Productivity To see how important differences in sectoral size could be in driving low aggregate productivity in resource-rich economies, we carry out a thought experiment similar in spirit to that of Caselli (2005). Using a counterfactual growth-accounting exercise, he showed that the large size and low productivity of the agricultural sector in low-income countries could be responsible for the low aggregate productivity of those countries. We construct a similar counterfactual measure of aggregate productivity, D^{CF}, that a country would have if it's sectoral productivity remained the same, but it's sectoral sizes were those of a typical resource-poor economy: $D^{CF} = L_m^{rp} D_m + L_s^{rp} D_s$. In this expression, D_m and D_s are the observed measures of sectoral productivity in the data, whilst $L_m^{rp} = 0.21$ and $L_s^{rp} = 0.79$ are the employment shares of non-manufacturing and manufacturing in the bottom ten percent of natural resource exporters as seen in Table 1.

Figure 1(a) shows how much higher this counterfactual aggregate productivity measure would be relative to observed aggregate productivity, for each decile of resource windfalls. Table 1(b) shows the corresponding regressions that test statistical significance. The top ten percent of natural resource exporters would have an aggregate productivity approximately 3.5% greater than what they actually have. Whilst this may seem small, it should be interpreted as the *permanent* impact of natural resource abundance on aggregate productivity. This measure is also of course significantly larger for the very top resource exporters like Saudi Arabia, where the counterfactual productivity is nearly 20% higher.[11] This experiment, *if taken at face value*, suggests that a windfall-induced decline of the small but productive manufacturing sector could be causing a relatively low aggregate productivity in resource-rich countries and hence could be one source of the so-called resource curse. It also suggests that resource-rich countries could benefit from policies aimed at promoting larger manufacturing sectors. The point of our model is that this growth-accounting procedure is somewhat simplistic and the above conclusions are not necessarily correct. Sectoral productivity is endogenous and depends on the size of the sector. Our model suggests that lower aggregate productivity found in many resource-rich economies is not *caused* by a windfall induced decline of a relatively productive manufacturing sector - but rather that the higher manufacturing productivity in those countries is a direct *consequence* of the smaller size of their manufacturing sector.

Robustness In Appendix 12.1, we perform a number of robustness exercises that help address potential issues of data quality and unobserved cross-country heterogeneity and provide additional evidence to support the facts presented in Table 2. In particular, we consider different samples and sub-samples of the data across different income groups and resource wealth levels. We also consider different sources of data and include all previously dropped observations in the analysis. In addition, we add controls for: OPEC membership, average work hours, the rate of unionization and energy subsidies in the baseline regressions and we examine evidence from an individual country over time (Norway). Furthermore, we disaggregate the manufacturing sector data, and show that our results are not driven by individual sub-sectors but rather that they seem to be a feature of a large majority of manufacturing sub-sectors. Finally, we disaggregate the non-manufacturing sector and show that the sectoral productivity and size facts are driven predominantly by the service sector. In each of the above exercises we find that the employment and sectoral productivity results go through largely unchanged - both quantitatively and qualitatively. In the next section we use US county-level data to demonstrate that similar productivity and employment facts hold at the micro level.

2.2 Micro Data and Facts

Data Since we do not have county-level data on GDP and natural resource exports, we use an alternate measure of resource wealth proposed by Michaels (2011). We define a county as oil rich if it lies above an oil field which has an ultimate recovery exceeding 100 million barrels. Given this classification there are three main groups of oil rich counties in the US located in Alaska, California and the US South. We restrict our analysis entirely to the third region,

[11] As we show in Appendix 12.1, the same result is found if the exercise is repeated for an individual country (Norway) over time.

	Ave.	Emp. Share		Lab. Prod.	
	Wage	NM	M	NM	M
Oil rich	7.08	75%	25%	0.97	1.07
Oil poor	6.95	73%	27%	0.99	1.01
OR/OP		1.03	0.93	0.98	1.06

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

since Alaska and California are divided in to a few, very large counties with almost all the oil reserves located in a single county, making comparisons difficult. Counties in the South however are small, evenly distributed and oil can be found in a large fraction of them. To minimize the chance of unobserved heterogeneity driving our results, we choose control counties that lie within 200 miles of the oil rich counties. The counties in our sample can be seen in Figure 5 in Appendix 11.

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

Facts Next, we confirm our macro findings at the micro level. Table 3 shows summary statistics for sectoral employment and productivity (relative to aggregate productivity) in oil-rich and oil-poor counties in the US South. First, oil-rich counties have smaller manufacturing sectors and larger non-manufacturing sectors than oil-poor counties (7% smaller and 3% larger respectively). Second, oil-rich counties are 6% more productive in manufacturing and 2% less productive in non-manufacturing than oil-poor counties.[12] The IPUMS data also allows us to disaggregate manufacturing and show that resource-processing industries are not driving higher productivity

[12] Although quantitatively these differences are smaller than before, it is important to note that the micro data is not directly comparable to the macro data, since we use a different measure of resource wealth. It is also likely that endowments of oil (and hence revenues from oil) in the US are significantly smaller than in the largest international oil exporters. Finally, there is probably more migration across counties than across countries, which lowers the per capita windfall and partially undoes the sectoral size and productivity impact of the windfall. Since - despite the above - we nonetheless observe significant differences in sectoral size and productivity across counties, we take this as additional evidence of the robustness of our mechanism.

in manufacturing in resource-rich counties. In Appendix 12.2, we show that between 70% and 75% of manufacturing sub-sectors in resource-rich counties are smaller and more productive than the same sectors in resource-poor counties. Thus, our macro findings seem to hold at the micro level and the micro data indicates that our facts are not driven by resource-processing industries. Since counties also tend to be far less heterogenous than countries, the data tends to be of far better quality and we avoid data construction issues by considering a very simple measure of productivity. The micro data thus gives us greater confidence in our macro results. In Appendix 12.2, we show the robustness and statistical significance of the above results.

3 Model

In this section we introduce a small, open, multi-sector economy with heterogenous agents that can account for the observed facts in productivity and employment. There are three goods in the economy: manufacturing goods (m), non-manufacturing (predominantly service) goods (s) and a windfall good which, for brevity, we will refer to as oil but could equally well be any other natural resource or alternative source of windfall revenue. We assume that manufacturing and oil are traded internationally, whilst non-manufacturing is assumed to be non-traded. Oil is assumed to be an endowment good that is not used locally but only exported abroad (and thus serves as a windfall of income), whilst manufacturing and non-manufacturing goods can be produced locally using labor but no oil.

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

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

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

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

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

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

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

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

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

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

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

Market Clearing Defining $\Omega = \Omega^m \bigcup \Omega^s$, the market clearing conditions for manufacturing, non-manufacturing and labor are given by:

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

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

Solution Each firm chooses a non-negative quantity of labor to hire. Due to perfect competition, firms offer the following wage schedule to consumer i:

$$w_m^i = Az_m^i \text{ and } w_s^i = p_s A z_s^i, \tag{10}$$

in manufacturing and non-manufacturing sectors respectively. Consumer i then chooses to work in the sector that provides a higher wage given his particular talent vector. 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 cut-off rule: a worker i will work in non-manufacturing if and only if

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

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

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

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

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

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

4 Homogenous Workers

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

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

Economies with larger windfalls, will devote a larger proportion of their labor force to the (non-traded) non-manufacturing sector than identical countries without windfalls. From equation (12), observe that windfalls generate a higher demand for both traded and non-traded goods. Whilst, (traded) manufacturing goods can be purchased on international markets, higher demand for (non-traded) non-manufacturing goods must be satiated locally. This pulls workers from the manufacturing sector into the non-manufacturing sector. Higher endowments of oil thus act in the same way as non-homothetic preferences by causing labor to shift from one

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

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

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

sector to another.[16] With homogeneity however, the reallocation of workers has no impact on sectoral productivity. In particular, in the model, constant price sectoral productivity is given by: $\frac{Y_s}{L_s} = \frac{\bar{p}_s A L_s}{L_s} = \bar{p}_s A = A$ in the non-manufacturing sector and by: $\frac{Y_m}{L_m} = \frac{AL_m}{L_m} = A$ in the manufacturing sector and remains constant as endowments of resources change. Notice that more complicated versions of the homogenous worker model are no more successful in matching the data. In Appendix 13.1 we show that adding physical capital, fixed factors, sector specific education or resource dependent subsidies on physical capital into the framework of a homogenous worker model still cannot satisfactorily account for the large and asymmetric differences in sectoral productivity between resource-rich and resource-poor countries. Instead, in the following section we show how a heterogenous worker model can bring us closer to accounting for the data.

5 Heterogenous Workers

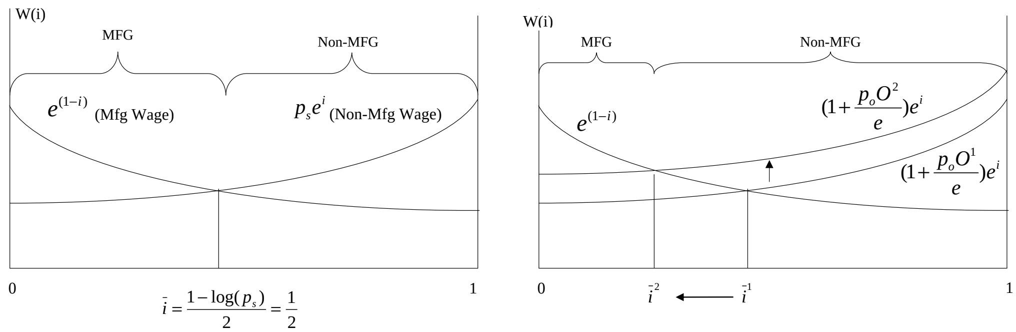
5.1 A Simple Example

To illustrate the impact of worker heterogeneity on sectoral productivity, we begin with a simple example.[17] 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 ($\sigma = 1$), equal utility weights ($\nu = 1$) and normalize A to unity. Each agent i receives wage offers $w_s^i = p_s z_s^i$ in non-manufacturing and $w_m^i = z_m^i$ in manufacturing and chooses to work in non-manufacturing if and only if it pays a higher wage: $w_s^i > w_m^i$. This gives rise to a cutoff agent, $\bar{i}(p_s) = \frac{1-\log p_s}{2}$, who is indifferent between working in either sector. We illustrate this in Figure 2(a) which plots the wage offers in each sector and the cutoff, $\bar{i}(p_s)$. Agents to the left of this cutoff are relatively more skilled in manufacturing sector tasks and hence have higher wage offers and choose to work in manufacturing. Meanwhile, agents to the right of the cutoff are relatively more skilled in non-manufacturing tasks and hence have higher wage offers and choose to work in non-manufacturing.

The cutoff value is dependent on the price of non-manufacturing. Windfalls influence this price and will hence influence the distribution of workers across sectors. A windfall of revenue generates a greater demand for both types of goods. To satiate the higher demand for non-traded

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

[17] Whilst we focus on heterogenous workers, Appendix 13.4 shows that this setup can easily be related to one with heterogenous firms without changing the results.



(a) A workers decision.

(b) A change in the value of oil.

Figure 2: The mechanics of the model in a simple example.

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

5.2 Generalization

Next, we generalize the above example and establish conditions on the distribution of talents under which countries with higher endowments of natural resources will be more productive in manufacturing and less productive in non-manufacturing than their resource-poor counterparts. Throughout this section we maintain the assumption that the proportion of workers who are indifferent between sectors is negligible and so that essentially all persons have a strict preference for manufacturing or non-manufacturing.[18] With this assumption we are thus excluding the case of homogenous workers, in which the supply of labor to a particular sector is inelastic

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

and all workers are indifferent between sectors. The following proofs parallel those of Lagakos and Waugh (2012), who show similar results for agriculture and non-agriculture in rich versus poor countries. Versions of these results were also established by Heckman and Honore (1990). We first show that prices of non-manufacturing goods rise with higher values of endowments of natural resources.

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

Proof. See Appendix 13.5. □

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

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

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

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

$$Y_m^H/L_m^H > Y_m^L/L_m^L,$$

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

$$Y_s^H/L_s^H < Y_s^L/L_s^L,$$

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:

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

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

□

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

Heckman and Honore (1990) show that at least one of the above restrictions on conditional expectations must always hold. This implies that our theory will at least be able to account for differences in relative productivity across sectors but, given an appropriate distribution, it can also account for observed differences in both sectors. Heckman and Honore (1990) also demonstrated that for a vector of independent random variables, the log-concavity of individual ability distribution functions is a sufficient condition for both restrictions to hold.[19]

6 Solving the Model

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

[19] Log-concave distribution functions include normal, uniform, gamma(r, λ) for $r \geq 1$, beta(a, b) for $a \geq 1$ and $b \geq 1$, generalized Pareto, Gumbel, Frechet, logistic or Laplace - to mention a few. For more details see Bagnoli and Bergstrom (2005).

from cross-sectional wage data alone.[20] In what follows, we assume that skills are drawn independently from a normalized Type II extreme value (or Frechet) distribution with CDF:

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

where, $\theta > 1$. The log of a random talent draw, $\log Z_i$, has standard deviation $\pi/(\theta\sqrt{6})$, where π is the constant. The parameter θ thus governs the amount of variation in skills and hence the observed productivity dispersion: lower values of θ imply more heterogeneity in ability and higher productivity dispersion. It turns out that this parameter is key to our analysis. Notice that we assume that θ is common to both sectors and that talent draws are independent of each other. Whilst both these assumptions may seem restrictive, they allow us to derive simple, analytic solutions which provide insights into the workings of the model. In Appendix 13.3, we extend the model to allow correlated talent draws and different dispersions across sectors and we show that, quantitatively, these channels play only a limited role.

We focus on the Frechet distribution for several reasons. First and foremost, this distribution is one of three extreme value distributions. According to the Fisher - Tippet - Gnedenko theorem from extreme value theory, there are only three types of distributions that are needed to model the maximum or minimum of the collection of random observations from the same distribution. More specifically, the maximum of a sample of i.i.d. random variables converges in distribution to either the Gumbel, the Frechet, or the Weibull distribution.[21] 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 (2012) have used it to model talent distribution across sectors. Notice also, that the Frechet distribution is log-concave, hence both restrictions of Proposition 3 hold. Finally, the Frechet distribution also provides very tractable analytic solutions which allow for easy interpretation of results and does a very good job of fitting the data.

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

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

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

The expected employment in non-manufacturing and manufacturing is:

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

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

$$Y_s = \int_0^\infty \int_0^{p_s z_s} z_s g(z_s, z_m)dz_m dz_s,\ Y_m = \int_0^\infty \int_0^{z_m/p_s} z_m g(z_s, z_m)dz_s dz_m \tag{17}$$

Using the fact that z_s and z_m are independently drawn from a Frechet distribution, and denoting the complete gamma function by $\Gamma(\cdot)$ we can simplify the above expressions for output:

$$Y_s = \Gamma(1 - \frac{1}{\theta})(1 + p_s^{-\theta})^{\frac{1-\theta}{\theta}},\ Y_m = \Gamma(1 - \frac{1}{\theta})(1 + p_s^{\theta})^{\frac{1-\theta}{\theta}}. \tag{18}$$

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

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

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

Proof. We show that $P \equiv \left|\frac{\partial(Y_m/L_m)}{\partial L_m}\right| / \left|\frac{\partial(Y_s/L_s)}{\partial L_m}\right| > 1$ iff $L_m < \frac{1}{2}$. From equations 16 and 18, $P = (L_m^{-1} - 1)^{\frac{\theta+1}{\theta}}$. Since $\theta > 1$, P is greater than one if and only if $L_m < \frac{1}{2}$. □

Since the non-manufacturing sector tends to employ a large share of the labor force, the new workers that enter non-manufacturing sector in resource-rich regions form a relatively small proportion 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 proportion of the manufacturing sector's employment, ensuring that the impact on productivity is bigger.

7 Calibrating the Model

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

$$G_s^w(w_s) = Pr\{W_s \leq w_s\} = Pr\{p_s A Z_s \leq w_s\} = Pr\{Z_s \leq \frac{w_s}{p_s A}\} = e^{-(p_s A)^\theta w_s^{-\theta}} \tag{19}$$

$$G_m^w(w_m) = Pr\{W_m \leq w_m\} = Pr\{A Z_m \leq w_m\} = Pr\{Z_m \leq \frac{w_m}{A}\} = e^{-A^\theta w_m^{-\theta}}. \tag{20}$$

These are both Frechet density functions with the same dispersion parameter, θ, as the talent distributions.[22] The observed wage is the maximum an agent could earn in either sector, $w = \max\{w_s, w_m\}$. The distribution of this wage, $G^w(w)$, is then the maximum order statistic of wage offers and is given by:

$$G^w(w) = G_s^w(w) G_m^w(w) = e^{-A^\theta (1+p_s^\theta) w^{-\theta}}. \tag{21}$$

The above distribution is also Frechet with the same dispersion parameter (but with a different mean) as the skill distribution. This is a consequence of the assumption that the original talents were drawn form an extreme value distribution. In order to match the parameter θ, we use a method of moments. Since the log of a Frechet variable has standard deviation $\pi/(\theta_i \sqrt{6})$, we can infer θ from the standard deviation of a sample of log wages. We obtain cross-sectional wage data from the 2009 US Current Population Survey (CPS) and find that the standard deviation of log wages in this sample is 0.57, which implies a dispersion parameter of $\theta = 2.22$.[23]

As a check on this calibration, we use the fact that in our model employment shares and productivity are simultaneously determined and can thus be jointly estimated. In particular, combining equations (16) and (18) and taking logs we obtain for each $k = s, m$:

$$\log(Y_k/L_k) = \log(\Gamma(1 - 1/\theta)) - (1/\theta)\log(L_k). \tag{22}$$

The model thus predicts that a one percent increase in employment in a sector (for whatever reason) will result in a $1/\theta$ percent decline in productivity in that sector. We use our panel of macro cross-country data to directly estimate θ for manufacturing and non-manufacturing.[24] The regression results relating productivity to sectoral size in each sector are shown in Table

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

[23] Following Lagakos and Waugh (2012) and Heathcote et al. (2009) we include individuals aged 25 to 60 who have non-missing data on income and hours worked. Wages are before tax, and are taken to be the sum of wage, business and farm income. The sample is further restricted to include workers who average more than 35 hours a week of work and earn at least the Federal minimum wage.

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

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

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

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

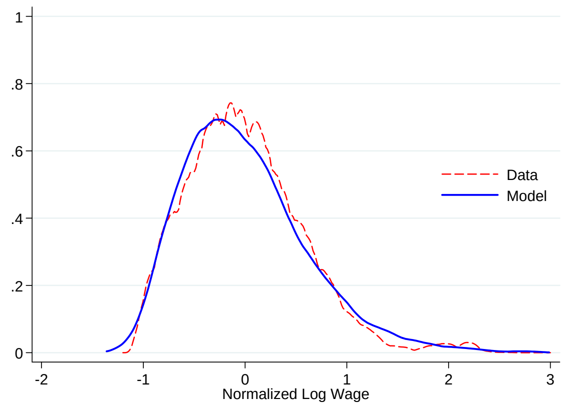
4. The implied θ in manufacturing and non-manufacturing is 1.85 and 2.7 respectively. These values are remarkably close to the value we obtained using our (completely different) micro data and as such provide strong support for our earlier calibration. Since we are more confident in our micro US data, in what follows we stick to the original estimate of $\theta = 2.22$.[25]

Preference parameters Next, we estimate preference parameters σ and ν. From, the household's problem we derive an equation relating relative consumer expenditure on the relative price: $\frac{c_m}{c_s} = (\nu p_s)^{\sigma}$. Taking logs of this equation, we estimate elasticity of substitution between manufacturing and non-manufacturing goods using ICP data and find that $\sigma = 0.94$. Finally, we choose the preference parameter to be $\nu = 0.26$, 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%).

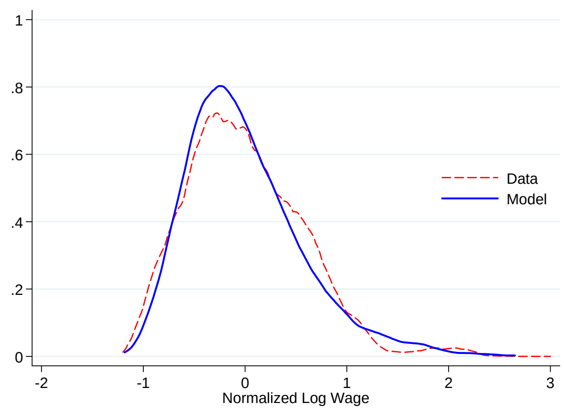
7.1 Results

US Wage Distributions In our calibration, the key parameter choice is the dispersion parameter of the Frechet distribution, θ, chosen to match the standard deviation of observed log wages. Figure 3, shows the theoretical and empirical density of observed wages at the aggregate and sectoral level in the US data and the model. The Frechet distribution does well at matching the general dispersion and the fat tails of wages at the aggregate level.[26] This finding mirrors that of Lagakos and Waugh (2012) and Heckman and Sedlacek (1985). The model with Frechet talent draws also does well in matching the dispersion and the tails of the data that we have not directly calibrated: the observed sectoral wages in the US.

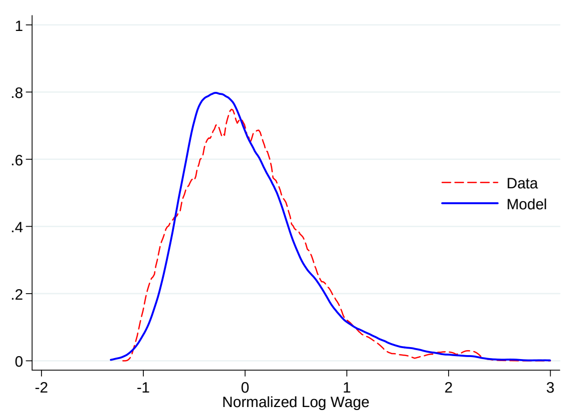
[25] This also places some distance between our calibration and our results.
[26] This is unlike, a log-normal distribution, for instance, which fails to match the fat tails - see Appendix 13.6.



(a) Distribution of Wages, Frechet

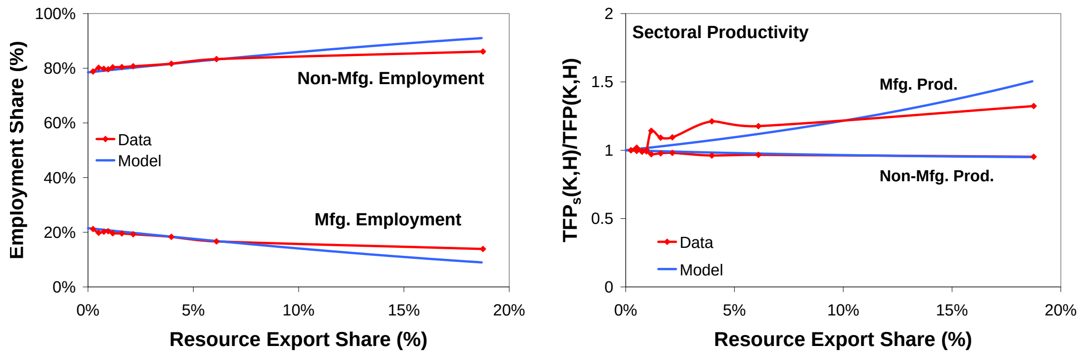


(b) Distribution of Wages in Mfg, Frechet



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

Figure 3: Distribution of wages in baseline model and data, by sector.



(a) Sectoral Emp. Shares vs. Resource Export Share (b) Norm. Sectoral Productivity vs. Resource Export Share

Figure 4: Heterogenous Consumers: Data Deciles and Model.

Productivity and Employment 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 panel on the left shows that the model predicts rising employment in non-manufacturing and falling employment in manufacturing as resource wealth increases.[27] In general, the fit of employment shares is good, although the model over-predicts the size of the shift towards non-manufacturing in the top decile. The panel on the right demonstrates the change of sectoral productivity with resource wealth.[28] We see that the model is very good at matching the slight decline in non-manufacturing productivity and the large increase in manufacturing productivity as explained by Proposition 4. Finally, Table 5 compares the empirical windfall elasticities of employment and sectoral productivity from Table 2 with the corresponding elasticities implied by the model. A doubling of natural resource windfalls in the model results in 0.99 percentage point decline in manufacturing employment, a 0.75 percent decline in non-manufacturing productivity and 2.48 percent increase in manufacturing productivity. Although other channels may also be driving the facts, the message from the calibration is that our specialization mechanism is strong enough to explain 59% of the reallocation of labor in the data, 61% of differences in non-manufacturing productivity and 38% percent of the differences in manufacturing productivity between resource-rich and resource-poor countries.

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

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

Windfall Elasticities	Data	Model	Model/Data
M. Emp., L_m	-1.69	-0.99	0.59
NM. Prod., D_s	-1.22	-0.75	0.61
M. Prod., D_m	6.54	2.48	0.38
NM. price, p_s	6.34	3.99	0.63

Table 5: Changes in sectoral employment and sectoral productivity associated with resource wealth in the Data and Model.

The Resource Curse In our model there is no first-order effect of windfalls on non-resource aggregate productivity, whilst the direction of higher order effects depends entirely on the pricing scheme used to measure output in the construction of productivity. To see this, notice that in an economy without oil, the equilibrium price and employment of non-manufacturing is given by $\bar{p}_s = \nu^{\frac{\sigma}{1-\theta-\sigma}}$ and $\bar{L}_s = \nu^{\frac{\sigma\theta}{1-\theta-\sigma}}/(1+\nu^{\frac{\sigma\theta}{1-\theta-\sigma}})$ respectively. Since there is a unit of workers, non-oil aggregate productivity measured with the above price is simply given by non-oil output:

$$Y_{NO}(L_s) = \bar{p}_s Y_s + Y_m = \nu^{\frac{\sigma}{1-\theta-\sigma}}\Gamma(1-1/\theta)L_s^{1-\frac{1}{\theta}} + \Gamma(1-1/\theta)(1-L_s)^{1-\frac{1}{\theta}}. \tag{23}$$

The above is a concave function on $0 \leq L_s \leq 1$ and has a unique maximum given by $L_s^{NO} = \nu^{\frac{\sigma\theta}{1-\theta-\sigma}}/(1+\nu^{\frac{\sigma\theta}{1-\theta-\sigma}})$. Notice that the employment that maximizes output is also the equilibrium employment in the no oil case, $L_s^{NO} = \bar{L}_s$. Since the equilibrium employment in a country with resources will necessarily be different to $\bar{L}_s$, the aggregate non-oil productivity (measured in resource-poor country's prices) will necessarily be lower in the resource-rich economy. This effect however will be negligibly small. Taking a first-order Taylor expansion of equation 23 around L^{NO} we can show that $Y_{NO}(L_s) \approx (1+\nu^{\frac{\sigma\theta}{1-\theta-\sigma}})^{-1}$ and is thus constant to a first-order approximation. The higher order effects are very small. Given our calibration, the model predicts the highest decile of resource exporters will have a non-oil aggregate productivity that is only 0.016% smaller than the lowest decile. Notice also, that the direction of this effect is entirely a consequence of the pricing scheme chosen to measure real GDP. If we expressed aggregate productivity using the resource-rich country's prices, *we would get exactly the opposite result.*[29] Kehoe and Ruhl (2008) make a similar point about the importance of different pricing schemes. Thus, in our model, windfall induced sectoral labor reallocation does not generate a resource curse that acts to lowers aggregate non-oil productivity - at least to a first-order approximation.

[29] In that case, the employment allocation that would maximize output would be exactly the equilibrium labor allocation from the oil-rich country and the model would then predict that the highest decile of exporters would have a non-oil aggregate productivity that is 0.016% *larger* than the lowest decile.

	$\log(p_s)$	$\log(p_s)$	$\log(p_s)$	$\log(p_s)$
$\log(NRE)$	0.026***	0.027***	0.063***	0.070***
	(0.007)	(0.007)	(0.007)	(0.012)
$\log(D)$	0.718***	0.692***	0.616***	0.388***
	(0.038)	(0.038)	(0.035)	(0.062)
τ_e			-0.712***	
			(0.052)	
Time FE	no	yes	yes	no
Country FE	no	no	no	yes
Obs.	806	806	806	806
R^2	0.319	0.349	0.476	0.812

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

Table 6: Changes in relative price of non-manufacturing to manufacturing goods associated with resource wealth in the Data and Model.

8 Evidence: Prices

A key implication of the model is Proposition 1 which states that the relative price of non-manufacturing goods is higher in resource-rich than in resource-poor economies. To test this hypothesis, we construct a panel of sectoral price level data by combining ICP cross-country sectoral price levels with sectoral price indices from the UN. The first column of Table 6 shows the results from a regression of relative non-manufacturing price levels on our measure of resource windfalls and aggregate productivity. The second column adds controls for time-fixed effects.[30]

We find that a doubling of natural resource windfalls is associated with a 2.7% increase in the price of non-traded goods. This however, may be an underestimation of the impact of windfalls on prices. As was discussed before, a potential issue with the ICP price data is that they reflect consumer rather than producer prices - which are the focus of our model. This may be particularly important in resource-rich economies, where consumer subsidies are prevalent. To address this issue, we perform two additional tests in columns 3 and 4 of Table 6. First, we control for the size of energy subsidies using data from the WEO.[31] This is an indirect attempt at controlling for the overall level of subsidies in a country's economy. Second, we control for country-fixed effects instead of time-fixed effects. This may be a better way to capture the impact of windfalls on prices if subsidies vary predominantly across countries rather than over time. Doubling of natural resource windfalls is associated with a 6.3%-7% increase in the price of non-manufacturing goods. The corresponding number in the model, as shown in Table 5, is found to be 3.99%. The model thus accounts for between 57% and 63% of the observed increase in the price of non-traded goods associated with natural resource windfalls.

[30] Notice that we include aggregate productivity to control for the so-called Penn effect - the observation that richer countries have higher non-traded goods prices than poorer countries.

[31] Subsidy data is an average of 2008-2010 data. We assume that these subsidies are country specific and fixed over the 1980-2007 period.

(a) Brawn/Brain req. by sector

	M	NM	M/NM
Brawn	0.25	0.24	1.04
Brain	0.39	0.50	0.78
Brawn/Brain	0.64	0.48	1.33

(b) Male/Female wages and employment by sector

	Productivity		Employment Shares	
	NM	M	NM	M
Female	5.03	4.89	80%	20%
Male	7.78	7.94	71%	29%

(c) Male/Female employment by sector and oil wealth

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

Table 7: Productivity and employment by sector and sex. (Source: IPUMS) Sectoral employment share (disaggregated by gender): oil rich vs. oil poor counties

9 Evidence: Brain vs. Brawn

Whilst in general it is difficult to observe differences in innate ability across individuals due to skill endogeneity, one potential way of doing this is to consider differences in physical strength or brawn endowments between men and women. A standard view in the development literature is that men and women are equally endowed with mental ability but men tend to have more physical strength than women.[32] This implies that men will tend to have a comparative advantage in brawn-intensive tasks, whilst women will tend to have a comparative advantage in brain intensive tasks. In what follows, we show that the US manufacturing sector is composed of occupations that are predominately brawn intensive, whilst the non-manufacturing sector is composed of occupations that are predominately brain intensive. Men will thus tend to have comparative advantage in manufacturing tasks and women in non-manufacturing tasks. Since variation in gender is exogenous, this allows us to test our theory. We expect a disproportionately greater share of women to be employed in the non-manufacturing sector in resource-rich regions. We show that this is indeed the case using the previous section's micro data. Finally, we also show that the decline in manufacturing employment in oil rich counties is higher within female-intensive manufacturing industries, which further supports our mechanism.

Brain and Brawn of Sectors The Dictionary of Occupational Titles (DOT) classifies more than twelve thousand occupations in the US based on 38 characteristics along dimensions such as aptitudes, temperaments, physical strength requirements, reasoning ability and so on. We follow Ingram and Neumann (2006) and Rendall (2010) and use factor analysis to collapse these 38 features into three main characteristics of each occupation - brain, brawn and motor skills

[32] See for instance Galor and Weil (1996), Galor and Weil (1999), Fan and Lui (2003) or Rendall (2010).

- each of which is measured on a scale from zero to one.[33] Using CPS data from the Inter-university Consortium for Political and Social Research (ICPSR), we obtain the distribution of occupations by sector. Combining this with our estimated factors, we calculate the average brain and brawn requirements in manufacturing and non-manufacturing in the US. For construction details see Appendix 11. The results are shown in Table 7(a). Notice that manufacturing requires 4% more brawn than non-manufacturing and 22% less brain. Thus manufacturing is 33% more brawn-intensive than non-manufacturing. Given this, we expect men to have a comparative advantage in manufacturing tasks and women in non-manufacturing tasks. This is confirmed in Table 7(b) which shows the sectoral productivity (as measured by hourly wages) of male and female workers. Whilst female productivity is lower in both non-manufacturing and manufacturing sectors, females are *relatively* more productive in non-manufacturing whilst males are *relatively* more productive in manufacturing sector work. The last two columns show that this productivity difference occurs despite a higher fraction of females being employed in non-manufacturing.

Gender and Employment Since women have a comparative advantage in non-manufacturing sector work, our mechanism suggests that females are more likely to leave the manufacturing sector and enter the non-manufacturing sector in resource-rich regions then men. We would thus expect a disproportionately greater fraction of women employed in non-manufacturing in resource-rich regions. As evidence of that, Table 7(c) shows the differences in the structure of employment between resource-rich and resource-poor counties for men and women. Whilst more of both men and women are employed in non-manufacturing in resource-rich regions, employment in non-manufacturing for women is disproportionately greater: 6% more women are employed in non-manufacturing in resource-rich than in resource-poor counties, but only 1% more men. In response to higher oil endowments, part of the labor force moves from the manufacturing to the non-manufacturing sector. Given the comparative advantage of women in non-manufacturing relative to men, female workers are more likely to move to non-manufacturing than men.

10 Conclusion

In this paper, we use macro cross-country data and micro US county-level data to show that resource-rich regions have small and productive manufacturing sectors and large and unproductive non-manufacturing sectors. We propose and test a mechanism, derived from the growth and development literature, that explains these productivity differences through a process of self-selection. Windfall revenue induces labor to move from the (traded) manufacturing sector to the

[33] We can think of occupations with zero as using zero percent of a particular characteristics and with one as using 100 percent of a characteristic.

(non-traded) non-manufacturing sector. A self-selection of workers takes place. Only those most skilled in manufacturing sector work will remain in manufacturing. Workers that move to the non-manufacturing sector however, will be less skilled at non-manufacturing sector work than those who were already employed there. Resource-induced structural transformation thus results in higher productivity in manufacturing and lower productivity in non-manufacturing. A calibrated version of the model can account for much of the cross-country productivity and employment differences in manufacturing and non-manufacturing sectors found between resource-rich and resource-poor countries.

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

11 Data Appendix

11.1 Macro Data

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

Labor Shares To calculate the last two measures of productivity, we need to find expressions for labor shares, $1-\alpha_s$, for each sector s. Although these shares can potentially vary across countries, due to a lack of comprehensive cross-country sectoral data, we make use of OECD data to calculate the average annual share of employee compensation for each sector in OECD countries for the longest period of time that data is available. We calculate the labor share as the ratio of total compensation of employees (wages and salaries before taxes, as well as employer's social contributions) over sectoral value-added.[34] Table 8 presents the results. We find labor share in manufacturing is 0.57 whilst in non-manufacturing it is 0.53. Notice that these are lower bound estimates since national accounts data does not include incomes generated from self-employment under total compensation. One commonly used technique to correct for this is to re-scale the shares by the ratio of total employment to total employees. In effect, the self-employed are then assumed to be paid the same average rate of compensation as employees and the same marginal rate of productivity is assumed for dependent and independent workers. Doing this with the above data results in higher average labor shares of 0.64 in non-manufacturing and 0.62 in manufacturing. Quantitatively and qualitatively however, this adjustment leaves our results almost unchanged. Since we are uncertain of exactly how compensation of self-employed workers varies across countries and sectors, we choose to retain our first estimates of labor shares.

Sectoral Employment We obtain sectoral employment data for 1980-2006 from the ILO KILM online database. To obtain the largest set of employment data, we combine ISIC revision 2 and ISIC revision 3 employment data.[35]

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

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

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

Table 8: Shares of labor compensation relative to sectoral value added in agriculture, construction, services, manufacturing, mining and utilities as well as (non-resources) non-manufacturing (which consists of agriculture, construction and services), the non-resource sector (agriculture, construction, services and manufacturing) as well as total value added (agriculture, construction, services, manufacturing, mining and utilities) in OECD countries for the periods indicated. (Source: OECD, 2007)

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

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

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

Table 9: ICP Disaggregated Categories

to that of the US) is given by:

$$P_s^i/P_s^{PPP} = E_s^i/E_s^{PPP}. \tag{24}$$

The publicly available ICP expenditure data disaggregates expenditure into 19 sectors. These however, do not map very well into ISIC sectors. On request however, it is possible to obtain proprietary ICP data that is further disaggregated into approximately 129 sectors. We make use of this disaggregated data to construct expenditure data at market exchange rates and at PPP for five sectors: agriculture, manufacturing, mining & utilities, construction and services. Our mapping of ICP to ISIC data is shown in Table 9. Notice that the last columns refers to categories that are not classified and hence excluded from our price indices. We then use equation 24 to calculate sector specific price levels in each country (relative to the US) for each of the five sectors. Finally, we can combine the above 2005 price level data with sectoral price indices for the 1980-2008 period from the UN to obtain a panel of price *levels*. In particular, we obtain one digit ISIC v.3 sectoral value-added data in constant 1990 USD prices ($VA_{s,t}^{1990}$) and current prices ($VA_{s,t}$) which can be used to calculate an index of sectoral prices relative to a base year: $P_{s,t}/P_s^{1990} = VA_{s,t}/VA_{s,t}^{1990}$. We then rebase this index so that it is equal to 1 in 2005 and multiply the result by the ICP price levels calculated above. The resulting series gives the price level of a particular sector in each country relative to the price of the same sector in the US in 2005.

Although the ICP study is especially built to provide accurate cross-country measures of price differences, it does have some well known limitations. For our purposes, the main objection is that expenditures are valued at the actual transaction prices paid by purchasers and hence may include delivery charges and any taxes payable (or subsidies received) on purchased products. This may be an issue if taxes/subsidies vary systematically with resource wealth. We recognize this fact, but our hands are tied for lack of better data. In the main body of the paper, we use a simple version of our model to show that to account for observed productivity differences, unrealistically large subsidies would be necessary. Notice also that this re-basing is not driving our results and we see similar productivity differences when value-added is left in constant US dollars. Table 15 in Appendix 12.1, shows that when we re-run our regressions controlling for energy subsidies (as an indirect way of capturing non-traded sector subsidies) all previous results go through. Notice also that our measure provides only a potential cross-country bias. Since our findings also hold over time, subsidies are not driving our results.

Sectoral value-added in International Dollars We obtain one digit ISIC v.3 sectoral value-added data from the UN. UN data is given in constant 1990 USD prices and current prices.[36] First, we re-base the 1990 data to 2005 prices by calculating (for each sector) the ratio between the 2005 current and constant value-added. This gives us a relative sectoral price between 2005 and 1990: P_s^{2005}/P_s^{1990}. Multiplying the constant 1990 value-added series for each sector by this sector-specific price we obtain constant price sectoral value-added data in 2005 prices. Next, we need to convert the constant price (2005) sectoral vale added data into one measured in international (or PPP) dollars. To do this, we divide constant (2005) price sectoral value-added data by the relative price levels, P_s^i/P_s^{PPP}, from expression 24. This converts sectoral value-added calculated in constant (2005) country specific prices into sectoral value-added calculated at international (2005) prices that are (in principle) invariant across countries and time. We recognize that these are imperfect price indices, however they are the best available, given data constraints. Finally, it is important to note that our empirical results do not - in any way - hinge on this procedure.

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

$$K_{t+1} = (1 - \delta)K_t + I_t, \tag{25}$$

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, g or initial capital stock.

The above process gives us sequences of capital stocks derived from PWT data. Notice however, that since we will be using UN PPP value-added data to calculate sectoral total factor productivity (and not PWT data), we want the capital values to be consistent with our UN total value-added data. As such, we use the PWT data to calculate the (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

[36] value-added by Economic Activity at constant 1990 prices, USD and value-added by Economic Activity at current prices, USD.

[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.

UN measure of total value-added in 2005 international dollars, calculated previously.

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

$$\alpha_s \frac{P_s^D Y_s}{K_s} = \alpha_{s'} \frac{P_{s'}^D Y_{s'}}{K_{s'}}, \tag{26}$$

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

$$\sum_s K_s = K, \tag{27}$$

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:

$$K_s = \left(\frac{\alpha_s P_s^D Y_s}{\sum_i \alpha_i P_i^D Y_i} \right) K. \tag{28}$$

Finally, to calculate the above expression we take labor shares, $1 - \alpha_s$, for each sector s from Table 8. Given these shares, we can use equation 28 for each sector and the aggregate capital stock (calculated previously) to obtain an estimate of sectoral capital.

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

$$h = e^{\phi(x)}, \tag{29}$$

Sector	<HS	HS	<C	C(A)	C(B)	M	D	Ave. Y.	Ave. Years/Mfg
	Education Distribution								
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 10: 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)

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

$$\phi(x) = \begin{cases} 0.134 \cdot s & \text{if } x \leq 4 \\ 0.134 \cdot 4 + 0.101 \cdot (x-4) & \text{if } 4 < x \leq 8 \\ 0.134 \cdot 4 + 0.101 \cdot 4 + 0.068 \cdot (x-8) & \text{if } 8 < x \end{cases} \tag{30}$$

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

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

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

Instead, we base our sectoral educational estimates on US schooling data. In particular, using BLS data, we estimate the average years of schooling of those working in each ISIC one digit sector in the United States in 2008. The results are shown in Table 10. We then assume that the relative number of years of education between any two sectors remains constant (and the same as the US) across countries and time which allows us to infer sectoral education levels in all countries. To construct Table 10 from the BLS we obtain a distribution of occupations within each ISIC sector that specifies what fraction of employees within that sector work in a given occupation.[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) through (7) take 8, 12, 14, 14, 16, 18 and 21 years respectively to achieve, allows us to calculate the average number of years of education of people working within each ISIC sector.

Sectoral Human Capital To calculate sectoral human capital we assume that the relative number of years of education between any two sectors remains constant (and the same as the US) across countries and time. More specifically, we define η_s^{US} as the ratio of average years of schooling in sector s relative to the years of schooling in the manufacturing in 2008 in the US (from Table 10):

$$\eta_s^{US} = x_s^{US}/x_m^{US}. \tag{31}$$

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:

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

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:

$$\sum_s l_s^i x_s^i = x^i, \tag{33}$$

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

[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 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.

years of schooling and η_s^{US}, the above expressions yield five equations in five unknowns, which can be solved for years of schooling in each sector and country, x_s^i. For each country, we can then relate the years of schooling in each sector to sectoral human capital through the 'standard' Mincerian returns formula in equation 30.

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

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

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

Summary Statistics Table 11, presents summary statistics for our main macro economic variables: sectoral employment shares, sectoral labor productivity, sectoral TFP (physical capital only), sectoral TFP (physical and human capital), value-added per worker (this is 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.

Disaggregated Manufacturing We disaggregate our manufacturing employment, value-added as well as physical capital estimates using ISIC 3.1 United Nations Industrial Development Organization data for the years 1990-2006.[41] This data comes at the 3 and 4 digit level, but to maintain tractability, we aggregate it up to the two digit level- giving us 23 manufacturing sub-sectors. We then calculate the employment and current price value-added shares of each sub sector in total manufacturing in every country and at every point in time. We then multiply these shares by the (previously calculated) aggregate manufacturing employment and (PPP) value-added respectively. We do this in order to maintain consistency with our aggregate data. To calculate labor shares in each subsector, $1-\alpha_s$, we calculate the ratio of sectoral wages and salaries (from the same data source) relative to the sectoral value-added and then - for each sector - we average over all countries and years to obtain the average sectoral wage and salary share. The UNIDO data however, does not contain employers social contributions as did our aggregate data. Thus, to maintain consistency with our aggregate data, we rescale these wage and salary shares so that the implied aggregate manufacturing UNIDO shares are equal to the

[41] The exact table is: INDSTAT4, Industrial Statistics Database 2011 at the 3- and 4-digit level of ISIC Code (Revision 3).

labor shares calculated before. In particular, for each sector we calculate the ratio of sector's wage and salary share relative to the wage and salary share in aggregate manufacturing. Then, we multiply this by the labor share found previously (0.57).[42] Next, using the same methods as in the previous section, we can calculate physical capital stock in each manufacturing sub-sector. Finally, human capital stock requires estimating education in each subsector of manufacturing in the US. This proves to be more challenging, as the education data in the US is of the ISIC 4 classification which is hard to map to ISIC 3 data at this level of aggregation. As such, for simplicity, we maintain the assumption that each sub-sector of manufacturing has the same (per-capita) education as aggregate manufacturing itself. Given this assumption, human capital in each manufacturing sector is calculated as before.

11.2 Micro Data

Resource Wealth We divide US counties into oil-rich and oil-poor following the methodology of Michaels (2011). We use the *Oil and Gas Journal Data Book* (2000) to identify major US oil fields - those with ultimate oil recovery exceeding 100 million barrels of oil - and determine in which county/-ies these fields are located using the *Oil and Gas Field Master List* (2001). We define a county as oil-rich if it lies above one or more of these oilfields. Most of the oil-rich counties are located in three states: Texas (106 counties), Oklahoma (24 counties) and Louisiana (18 counties). We exclude from our analysis the two other oil-abundant states, Alaska and California for reasons discussed in the main text. Our control countries are those located within 200 miles of the oil-rich.[43] This leaves us with the sample of 775 counties, 168 of which are oil-rich and are shown in Figure 5.

Sectoral Labor Productivity Next, we use 1980 US census data from the Integrated Public Use Microdata Series or IPUMS (Ruggles et al., 2008) to determine sectoral labor productivity within counties.[44] 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[45] and use hourly wage as a measure of labor productivity of each

[42] Notice, that all the results go through without this rescaling.

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

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

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

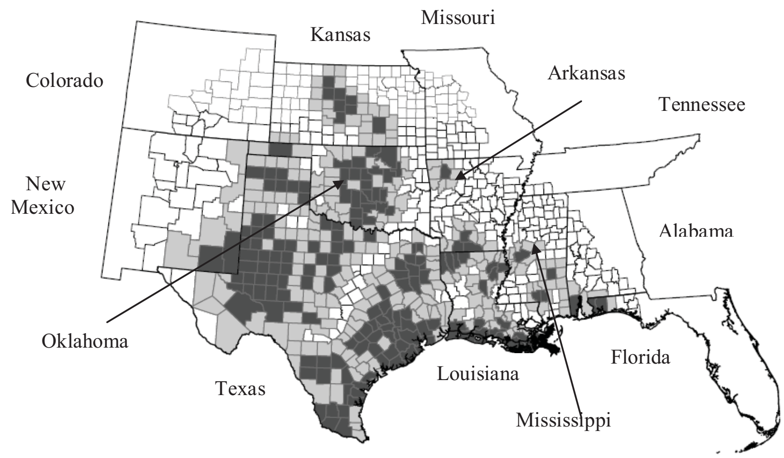


Figure 5: Counties in Micro Sample. Oil-rich counties (black), adjacent counties (grey) and other nearby counties (white). (Source: Michaels (2011))

person.[46]

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

Brain and Brawn We estimate sectoral brain and brawn requirements using US census occupation and industry classifications from the 1977 Dictionary of Occupational Title (DOT). This DOT survey set is particularly useful since it is readily available in an electronic format and has been merged with the 1971 Current Population Survey (CPS) allowing for civilian employment population weighted results.[47] The 1977 DOT reports 38 job characteristics for

[46] 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.

[47] Data including documentation is available from the Inter-university Consortium for Political and Social Research (ICPSR).

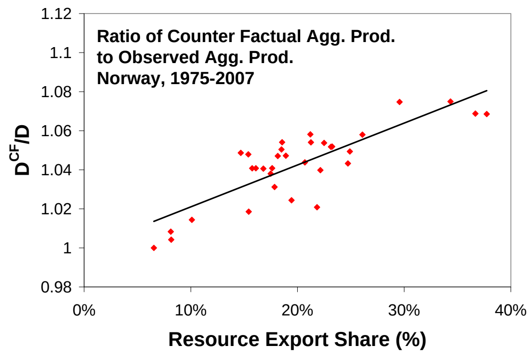
over 12,000 occupations. We use factor analysis to reduce this large number of characteristics into three unobserved variables, called factors. The main idea behind grouping a set of different job characteristics into fewer categories is that many characteristics are highly correlated and are likely to be influenced by the same underlying factor. The following gives an outline of our procedure. Notice, that since we follow Ingram and Neumann (2006) and Rendall (2010) closely, we refer the reader to those papers for more details.

First, following Vijverberg and Hartog (2005) we convert job characteristics into numerical scales, as some of the values assigned by the DOT are not useable in the format in which they are reported. Second, following Rendall (2010), we merge six characteristics of environmental conditions into one measure which captures general exposure to the environment. This brings down the number of job characteristics from 38 to 33. Third, we perform an initial factor analysis on all the 33 job characteristics and find - like Rendall (2010) - that three factors do well in explaining their covariance structure - explaining 83% of the covariance. Like Rendall (2010) however we find that the first factor is positively related to intellectual characteristics and negatively correlated with both motor coordination and physical characteristics, making it difficult to interpret the factor consistently. As such, we re-estimate the factors assuming they are correlated, similarly to Ingram and Neumann (2006). However, for identification purposes, we assume that job characteristics that explain one factor are restricted and cannot explain another factor. Given the particular grouping of characteristics (for details of which see Rendall (2010)) we call the three factors brain, motor coordination, and brawn. Finally, to estimate brain and brawn requirements in manufacturing and non-manufacturing in the US, we match the estimated factors with the employment shares of each sector from the appended CPS data. We restrict our sample to including individuals aged 18-65 and who worked at least 35 hours per week. Next, given the level of brain and brawn of each occupation-industry pair and the distribution of each occupation-industry pair in a given sector we calculate the average brain/brawn demand requirements of manufacturing and non-manufacturing.

12 Empirical Appendix

12.1 Macro Results

Robustness In this section we check the robustness of our macro results. In the main text we considered a restricted sample which we took to be our baseline. Our first robustness check in Table 12 includes all the data. Whilst the fit is unsurprisingly not as tight as with the restricted sample, all established results for employment shares and sectoral productivity go



(a) Scatter Plot

	D^{CF}/D	D^{CF}/D
$\log(NRE)$	0.040***	0.021***
	(0.004)	(0.006)
Time Trend	no	yes
Obs.	33	33
R^2	0.744	0.822

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

(b) Regressions

Figure 6: A growth-accounting exercise for Norway. The graph and regressions show how much higher the counterfactual measure of aggregate productivity, D^{CF}, would be relative to observed aggregate productivity, D, in resource-rich economies.

through.[48] Second, in an effort to control for unobserved cross-country heterogeneity - in Table 13 - we restrict our baseline sample even further to only the thirty richest countries and show that quantitatively and qualitatively all results go through.[49] Third, 14 reproduces the results for countries where windfalls are smaller than 10% of GDP. This drops the ultra-resource-rich countries like Saudi Arabia where data may not be as reliable. Again we find that all results go through.[50] Next, Table 15 adds controls for energy subsidies, OPEC membership, average hours worked per worker and the unionization rate in a country to the baseline regressions. Again, all results go through.[51]

Variation over time: Norway Next, we show that similar results hold in one country over time. We chose to focus on Norway, since it has good quality data that spans a longer period of time and it has experienced a significant resource boom. Focusing on one country is also another way of controlling for unobserved cross-country heterogeneity and helps to avoid possible issues with ICP price data. We extend our data back to 1975 - and hence capture the large increase in the oil price in the second half of that decade. Pre-1980 employment share data comes from Meyer-zu Schlochtern (1988). To extend our resource wealth measure we make use of PPP GDP in current prices from the Penn World Tables (instead of the WDI). The rest of the data comes

[48] For the employment results with the full sample we have 119 countries. For each of the productivity measures we have 85, 70 and 69 countries respectively.
[49] We have also experimented with restricting the data to the richest 100, 75, 50, 25 and 20 countries, without changes to the results. Regressions available on request.
[50] We have also experimented with restricting the data to countries where resource exports are less than 15% and 5%, without changes to the results. Regressions available on request.
[51] For brevity, we have only shown results for our third measure of productivity, but results also go through with the other two measures. Regressions available on request.

(a) Changes in mfg. employment share and resource wealth (all data)

	(1) M. Emp.	(2) M. Emp.	(3) M. Emp.	(4) M. Emp.
log(NRE)	-0.57***	-0.98***	-0.92***	-0.67***
	(0.13)	(0.11)	(0.11)	(0.15)
logLprod		52.11***	48.95***	93.32***
		(3.07)	(2.92)	(4.83)
sqlogLprod		-2.43***	-2.26***	-4.96***
		(0.15)	(0.14)	(0.24)
Time FE	no	no	yes	no
Country FE	no	no	no	yes
Obs.	1,287	1,287	1,287	1,287
R^2	0.01	0.30	0.39	0.89

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

(b) Changes in non-mfg. productivity and resource wealth (all data).

	(1) $\log(A_s)$	(2) $\log(A_s)$	(3) $\log(A_s)$	(4) $\log(B_s)$	(5) $\log(B_s)$	(6) $\log(B_s)$	(7) $\log(D_s)$	(8) $\log(D_s)$	(9) $\log(D_s)$
$\log(NRE)$	-0.011***	-0.011***	-0.009***	-0.008***	-0.008***	-0.010***	-0.009***	-0.008***	-0.011***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)
$\log(A)$	1.002***	1.004***	0.887***						
	(0.003)	(0.003)	(0.004)						
$\log(B)$				0.943***	0.948***	0.882***			
				(0.004)	(0.004)	(0.007)			
$\log(D)$							0.944***	0.947***	0.906***
							(0.005)	(0.004)	(0.009)
Time FE	no	yes	no	no	yes	no	no	yes	no
Ctry FE	no	no	yes	no	no	yes	no	no	yes
Obs.	1,287	1,287	1,287	1,139	1,139	1,139	1,134	1,134	1,134
R^2	0.992	0.992	0.999	0.981	0.982	0.995	0.975	0.977	0.993

(c) Changes in mfg. productivity and resource wealth (all data).

	(1) $\log(A_m)$	(2) $\log(A_m)$	(3) $\log(A_m)$	(4) $\log(B_m)$	(5) $\log(B_m)$	(6) $\log(B_m)$	(7) $\log(D_m)$	(8) $\log(D_m)$	(9) $\log(D_m)$
$\log(NRE)$	0.051***	0.051***	0.003	0.051***	0.051***	0.020**	0.055***	0.055***	0.025***
	(0.009)	(0.009)	(0.009)	(0.007)	(0.007)	(0.009)	(0.007)	(0.007)	(0.009)
$\log(A)$	1.118***	1.114***	1.427***						
	(0.016)	(0.016)	(0.022)						
$\log(B)$				1.379***	1.367***	1.547***			
				(0.026)	(0.027)	(0.035)			
$\log(D)$							1.329***	1.320***	1.471***
							(0.031)	(0.031)	(0.044)
Time FE	no	yes	no	no	yes	no	no	yes	no
Ctry FE	no	no	yes	no	no	yes	no	no	yes
Obs.	1,287	1,287	1,287	1,139	1,139	1,139	1,134	1,134	1,134
R^2	0.805	0.807	0.980	0.720	0.724	0.959	0.638	0.646	0.944

Table 12: The impact of windfalls on sectoral employment and productivity. A, B and D refer to our three measures of sectoral productivity (with subscript) and aggregate productivity (without subscript). NRE refers to the natural resource export share. Results for all data.

(a) Changes in mfg. employment share and resource wealth (30 richest).

	(1) M. Emp.	(2) M. Emp.	(3) M. Emp.	(4) M. Emp.
$\log(NRE)$	-1.83***	-2.03***	-1.58***	-0.49**
	(0.15)	(0.14)	(0.14)	(0.21)
$\log(A)$		77.53**	149.65***	146.14***
		(37.16)	(34.04)	(37.49)
$(\log(A))^2$		-3.83**	-6.82***	-7.40***
		(1.69)	(1.55)	(1.72)
Time FE	no	no	yes	no
Country FE	no	no	no	yes
Obs.	440	440	440	440
R^2	0.26	0.36	0.54	0.89

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

(b) Changes in non-mfg. productivity and resource wealth (30 richest).

	(1) $\log(A_s)$	(2) $\log(A_s)$	(3) $\log(A_s)$	(4) $\log(B_s)$	(5) $\log(B_s)$	(6) $\log(B_s)$	(7) $\log(D_s)$	(8) $\log(D_s)$	(9) $\log(D_s)$
$\log(NRE)$	-0.017***	-0.010***	-0.007**	-0.012***	-0.010***	-0.010***	-0.012***	-0.009***	-0.015***
	(0.002)	(0.002)	(0.003)	(0.001)	(0.001)	(0.003)	(0.002)	(0.001)	(0.004)
$\log(A)$	0.930***	1.032***	0.786***						
	(0.011)	(0.013)	(0.008)						
$\log(B)$				0.908***	0.980***	0.763***			
				(0.012)	(0.011)	(0.014)			
$\log(D)$							0.959***	1.004***	0.785***
							(0.013)	(0.011)	(0.019)
Time FE	no	yes	no	no	yes	no	no	yes	no
Ctry FE	no	no	yes	no	no	yes	no	no	yes
Obs.	440	440	440	440	440	440	440	440	440
R^2	0.945	0.962	0.989	0.925	0.953	0.971	0.926	0.958	0.967

(c) Changes in mfg. productivity and resource wealth (30 richest).

	(1) $\log(A_m)$	(2) $\log(A_m)$	(3) $\log(A_m)$	(4) $\log(B_m)$	(5) $\log(B_m)$	(6) $\log(B_m)$	(7) $\log(D_m)$	(8) $\log(D_m)$	(9) $\log(D_m)$
$\log(NRE)$	0.079***	0.043***	0.041***	0.055***	0.043***	0.050***	0.056***	0.043***	0.073***
	(0.009)	(0.009)	(0.014)	(0.007)	(0.006)	(0.014)	(0.007)	(0.006)	(0.016)
$\log(A)$	1.263***	0.816***	1.859***						
	(0.052)	(0.060)	(0.037)						
$\log(B)$				1.432***	1.119***	2.022***			
				(0.058)	(0.055)	(0.061)			
$\log(D)$							1.261***	1.054***	1.977***
							(0.061)	(0.053)	(0.083)
Time FE	no	yes	no	no	yes	no	no	yes	no
Ctry FE	no	no	yes	no	no	yes	no	no	yes
Obs.	440	440	440	440	440	440	440	440	440
R^2	0.576	0.692	0.923	0.612	0.734	0.869	0.531	0.700	0.816

Table 13: The impact of windfalls on sectoral employment and productivity. A, B and D refer to our three measures of sectoral productivity (with subscript) and aggregate productivity (without subscript). NRE refers to the natural resource export share. Results for 30 richest countries.

(a) Changes in mfg. employment share and resource wealth (NRE¡10%).

	(1) M. Emp.	(2) M. Emp.	(3) M. Emp.	(4) M. Emp.
log(NRE)	-1.38***	-1.51***	-1.44***	-0.48***
	(0.15)	(0.14)	(0.14)	(0.18)
log(A)		86.57***	76.80***	128.93***
		(8.12)	(7.77)	(6.88)
$(\log(A))^2$		-4.18***	-3.69***	-6.62***
		(0.39)	(0.38)	(0.33)
Time FE	no	no	yes	no
Country FE	no	no	no	yes
Obs.	740	740	740	740
R^2	0.10	0.22	0.34	0.85

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

(b) Changes in non-mfg. productivity and resource wealth (NRE¡10%).

	(1) log(A_s)	(2) log(A_s)	(3) log(A_s)	(4) log(B_s)	(5) log(B_s)	(6) log(B_s)	(7) log(D_s)	(8) log(D_s)	(9) log(D_s)
log(NRE)	-0.020***	-0.020***	-0.014***	-0.013***	-0.013***	-0.016***	-0.013***	-0.013***	-0.019***
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
log(A)	0.975***	0.980***	0.861***						
	(0.004)	(0.004)	(0.006)						
log(B)				0.908***	0.915***	0.847***			
				(0.006)	(0.006)	(0.010)			
log(D)							0.904***	0.910***	0.868***
							(0.007)	(0.007)	(0.013)
Time FE	no	yes	no	no	yes	no	no	yes	no
Ctry FE	no	no	yes	no	no	yes	no	no	yes
Obs.	740	740	740	740	740	740	740	740	740
R^2	0.988	0.989	0.998	0.971	0.973	0.991	0.960	0.963	0.986

(c) Changes in mfg. productivity and resource wealth (NRE¡10%).

	(1) log(A_m)	(2) log(A_m)	(3) log(A_m)	(4) log(B_m)	(5) log(B_m)	(6) log(B_m)	(7) log(D_m)	(8) log(D_m)	(9) log(D_m)
log(NRE)	0.087***	0.086***	0.072***	0.061***	0.061***	0.086***	0.064***	0.063***	0.103***
	(0.011)	(0.011)	(0.011)	(0.009)	(0.009)	(0.011)	(0.009)	(0.009)	(0.011)
log(A)	1.134***	1.121***	1.528***						
	(0.021)	(0.021)	(0.027)						
log(B)				1.401***	1.382***	1.654***			
				(0.033)	(0.034)	(0.044)			
log(D)							1.407***	1.389***	1.579***
							(0.040)	(0.040)	(0.057)
Time FE	no	yes	no	no	yes	no	no	yes	no
Ctry FE	no	no	yes	no	no	yes	no	no	yes
Obs.	740	740	740	740	740	740	740	740	740
R^2	0.807	0.814	0.974	0.713	0.721	0.947	0.641	0.653	0.928

Table 14: The impact of windfalls on sectoral employment and productivity. A, B and D refer to our three measures of sectoral productivity (with subscript) and aggregate productivity (without subscript). NRE refers to the natural resource export share. Results for countries with natural resource export share that is smaller than 10% of GDP.

(a) Changes in mfg. employment share and resource wealth (restricted sample).

	(1) M. Emp.	(2) M. Emp.	(3) M. Emp.	(4) M. Emp.	(5) M. Emp.
$\log(NRE)$	-1.69***	-1.39***	-1.41***	-1.67***	-2.70***
	(0.11)	(0.11)	(0.11)	(0.14)	(0.19)
$\log(A)$	72.50***	68.99***	64.44***	72.55***	116.18***
	(7.46)	(7.27)	(7.54)	(16.41)	(25.96)
$(\log(A))^2$	-3.48***	-3.34***	-3.13***	-3.50***	-5.68***
	(0.36)	(0.35)	(0.36)	(0.76)	(1.22)
Time FE	yes	yes	yes	yes	yes
Energ. Subsidy	no	yes	yes	yes	yes
OPEC	no	no	yes	yes	yes
Hours Wrked	no	no	no	yes	yes
Union. Rate	no	no	no	no	yes
Obs.	806	806	806	570	243
R^2	0.40	0.43	0.44	0.47	0.70

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

(b) Changes in non-mfg. productivity and resource wealth (restricted sample).

	(1) $\log(D_s)$	(2) $\log(D_s))$	(3) $\log(D_s)$	(4) $\log(D_s)$	(5) $\log(D_s)$
$\log(NRE)$	-0.012***	-0.014***	-0.014***	-0.009***	-0.010***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
$\log(D)$	0.910***	0.914***	0.913***	0.954***	0.957***
	(0.006)	(0.006)	(0.006)	(0.013)	(0.020)
Time FE	yes	yes	yes	yes	yes
Energ. Subsidy	no	yes	yes	yes	yes
OPEC	no	no	yes	yes	yes
Hours Wrked	no	no	no	yes	yes
Union. Rate	no	no	no	no	yes
Obs.	806	806	806	570	243
R^2	0.965	0.966	0.966	0.931	0.947

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

(c) Changes in mfg. productivity and resource wealth (restricted sample).

	(1) $\log(D_m)$	(2) $\log(D_m))$	(3) $\log(D_m)$	(4) $\log(D_m)$	(5) $\log(D_m)$
$\log(NRE)$	0.065***	0.070***	0.070***	0.041***	0.040***
	(0.007)	(0.008)	(0.008)	(0.009)	(0.011)
$\log(D)$	1.410***	1.400***	1.400***	1.289***	1.342***
	(0.038)	(0.038)	(0.038)	(0.069)	(0.098)
Time FE	yes	yes	yes	yes	yes
Energ. Subsidy	no	yes	yes	yes	yes
OPEC	no	no	yes	yes	yes
Hours Wrked	no	no	no	yes	yes
Union. Rate	no	no	no	no	yes
Obs.	806	806	806	570	243
R^2	0.681	0.682	0.682	0.651	0.807

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

Table 15: The impact of windfalls on sectoral employment and productivity. A, B and D refer to our three measures of sectoral productivity (with subscript) and aggregate productivity (without subscript). NRE refers to the natural resource export share. Results for the restricted sample with control variables for energy subsidies, OPEC membership, number of hours worked per worker and the unionization rate.

(a) Manufacturing Employment Share (Norway)

	(1) M. Emp.	(2) M. Emp.	(3) M. Emp.
log(NRE)	-7.71***	-3.12***	-1.50***
	(0.78)	(0.59)	(0.41)
logLprod		-825.19***	-230.98*
		(151.50)	(120.88)
sqlogLprod		37.28***	11.76**
		(6.96)	(5.39)
Time Trend	no	no	yes
Obs.	33	33	33
R^2	0.76	0.95	0.98

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

(b) Changes in non-mfg. productivity and resource wealth (Norway)

	(1) $\log(A_s)$	(2) $\log(A_s)$	(3) $\log(B_s)$	(4) $\log(B_s)$	(5) $\log(D_s)$	(6) $\log(D_s)$
$\log(NRE)$	-0.026***	-0.019***	-0.020***	-0.019***	-0.018***	-0.019***
	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)
$\log(A)$	1.009***	1.158***				
	(0.013)	(0.056)				
$\log(B)$			1.052***	1.067***		
			(0.011)	(0.022)		
$\log(D)$					1.073***	1.070***
					(0.013)	(0.019)
Time Trend	no	yes	no	yes	no	yes
Obs.	33	33	33	33	33	33
R^2	0.998	0.998	0.999	0.999	0.998	0.998

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

(c) Changes in mfg. productivity and resource wealth (Norway)

	(1) $\log(A_m)$	(2) $\log(A_m)$	(3) $\log(B_m)$	(4) $\log(B_m)$	(5) $\log(D_m)$	(6) $\log(D_m)$
$\log(NRE)$	0.103***	0.099***	0.097***	0.098***	0.091***	0.099***
	(0.029)	(0.033)	(0.024)	(0.026)	(0.022)	(0.025)
$\log(A)$	0.904***	0.807**				
	(0.071)	(0.342)				
$\log(B)$			0.688***	0.706***		
			(0.063)	(0.130)		
$\log(D)$					0.603***	0.665***
					(0.077)	(0.116)
Time Trend	no	yes	no	yes	no	yes
Observations	33	33	33	33	33	33
R^2	0.957	0.957	0.952	0.953	0.916	0.917

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

Table 16: The impact of resource wealth on sectoral employment and productivity in Norway over time for 1975-2007. A, B and D refer to our three measures of sectoral productivity (with subscript) and aggregate productivity (without subscript). NRE refers to the natural resource export share.

(a) Sectoral employment and resource wealth

	(1) A. Emp.	(2) C. Emp.	(3) S. Emp.
log(NRE)	-0.012***	-0.002***	0.031***
	(0.002)	(0.001)	(0.002)
logLprod	-1.519***	0.252***	0.542***
	(0.115)	(0.037)	(0.120)
sqlogLprod	0.066***	-0.012***	-0.019***
	(0.006)	(0.002)	(0.006)
Time FE	yes	yes	yes
Obs.	806	806	806
R^2	0.742	0.164	0.716

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

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

	(1) D_a	(2) D_c	(3) D_s
log(NRE)	0.020**	0.022***	-0.033***
	(0.009)	(0.008)	(0.003)
log(D)	0.750***	0.499***	0.588***
	(0.049)	(0.040)	(0.015)
Time FE	yes	yes	yes
Obs.	806	806	806
R^2	0.360	0.260	0.687

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

Table 17: The impact of resource wealth on sectoral TFP (K,H) and employment in disaggregated non-manufacturing. D and D_s refers to our third measure of sectoral and aggregate productivity respectively. NRE refers to the natural resource export share.

from the same sources as before.[52] Table 16, shows the impact of resource wealth on sectoral employment and productivity. All results go through and - if anything - are stronger than in the cross-country data. We also include regressions that control for a time trend, to capture any other possible systematic trend in the data. The results also go through. Finally, in Figure 6, we repeat the counterfactual aggregate productivity exercise from the main body of the paper for the Norwegian case. We construct a counterfactual measure of aggregate productivity, D^{CF}, that Norway would have if its sectoral productivity remained the same, but its sectoral sizes were those it had in 1975 - when it was a relatively resource-poor country. We also show the corresponding regressions with and without a time trend. As in the main body of the paper, the results seem to suggest that a windfall induced decline of the small but productive manufacturing sector could be causing a relatively low aggregate productivity in Norway. Our model suggests that this is due to the over-simplicity of the growth-accounting exercise.

Disaggregation of Non-Manufacturing Next, we show how productivity and employment in sub-sectors of the non-manufacturing sector (Agriculture, Construction and Services) change with resource wealth. The panel on the left of Table 17 shows changes in sectoral employment with resource wealth. Employment in agriculture and construction both increase. The aggregate results are thus driven by the service sector, where resource wealth has a significant positive impact on employment. The panel on the right shows how our third measure of sectoral productivity changes with resource wealth. We see that a strong positive effect is found in agriculture and construction and a strong negative effect is found in services. The overall negative result

[52] Also notice, that although we have extended the data backwards this is *not* driving our time series results for Norway. We find similar outcomes using only data that starts from 1980.

(a) Employment Shares, mfg. sub sectors (restricted sample).

Sectoral Employment Share	$\log(NRE)$	$\log(A)$	$(\log(A))^2$	Time FE	Obs.	R^2
15 Food & bev.	**-0.11**** (0.04)	16.98*** (3.43)	-0.83*** (0.16)	yes	426	0.23
16 Tobacco prod.	0.00 (0.00)	-0.00 (0.31)	-0.00 (0.02)	yes	316	0.13
17 Textiles	**-0.18***** (0.02)	0.65 (2.03)	-0.06 (0.10)	yes	427	0.42
18 Wearing apparel, fur	**-0.90***** (0.10)	6.51 (9.15)	-0.43 (0.44)	yes	405	0.40
19 Leather & prod. & footwear	**-0.09***** (0.02)	4.43*** (1.51)	-0.23*** (0.07)	yes	400	0.35
20 Wood prod. (excl. furn.)	0.09*** (0.02)	6.29*** (1.31)	-0.30*** (0.06)	yes	430	0.16
21 Paper & prod.	0.06*** (0.02)	3.18** (1.49)	-0.15** (0.07)	yes	424	0.23
22 Printing & publishing	0.06*** (0.02)	7.94*** (1.41)	-0.36*** (0.07)	yes	418	0.36
23 Coke,ref. petr. prod.,nuc.	**-0.01*** (0.01)	-0.07 (0.60)	-0.00 (0.03)	yes	331	0.21
24 Chemicals & chem. prod.	-0.02 (0.02)	-2.90* (1.61)	0.14* (0.08)	yes	409	0.16
25 Rubber & plastics prod.	**-0.08***** (0.01)	-3.35*** (1.12)	0.17*** (0.05)	yes	431	0.15
26 Non-metal. min. prod.	**-0.14***** (0.02)	0.01 (1.20)	-0.01 (0.06)	yes	420	0.19
27 Basic metals	0.11*** (0.02)	-4.77*** (1.50)	0.22*** (0.07)	yes	424	0.26
28 Fabricated metal prod.	**-0.10***** (0.02)	1.84 (1.95)	-0.05 (0.09)	yes	413	0.30
29 Mach. & equip. n.e.c.	-0.07 (0.05)	-5.80 (3.76)	0.29 (0.18)	yes	430	0.12
30 Office, acc. & comp. mach.	**-0.05***** (0.02)	-6.79*** (1.51)	0.32*** (0.07)	yes	383	0.13
31 Elec. machinery & app.	**-0.07***** (0.02)	5.76*** (2.03)	-0.26*** (0.10)	yes	411	0.14
32 Radio,tv & comm. equip.	**-0.17***** (0.03)	2.96 (3.20)	-0.13 (0.15)	yes	395	0.09
33 Medical, prec. & optical instr.	**-0.04***** (0.01)	-4.10*** (1.38)	0.21*** (0.07)	yes	406	0.25
34 Mtr veh., trail. etc.	**-0.05*** (0.03)	-7.76*** (2.61)	0.38*** (0.12)	yes	424	0.12
35 Other transp.equip.	0.12*** (0.02)	2.10 (1.99)	-0.09 (0.09)	yes	398	0.17
36 Furn.; mfg n.e.c.	**-0.06***** (0.02)	3.32*** (1.22)	-0.17*** (0.06)	yes	430	0.14
37 Recycling	0.00* (0.00)	-0.41** (0.17)	0.02** (0.01)	yes	303	0.14

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

(b) Productivity, mfg. sub sectors (restricted sample).

$\log(D_{m,i})$	$\log(NRE)$	$\log(D)$	Time FE	Obs.	R^2
15 Food & bev.	**0.026**** (0.013)	1.319*** (0.060)	yes	407	0.582
16 Tobacco prod.	-0.006 (0.024)	1.457*** (0.082)	yes	273	0.582
17 Textiles	**0.065***** (0.020)	1.695*** (0.094)	yes	400	0.495
18 Wearing apparel, fur	**0.091***** (0.021)	1.916*** (0.104)	yes	374	0.530
19 Leather & prod. & footwear	**0.070***** (0.022)	1.815*** (0.106)	yes	368	0.496
20 Wood prod. (excl. furn.)	**0.075***** (0.015)	1.724*** (0.072)	yes	406	0.636
21 Paper & prod.	**0.058***** (0.014)	1.587*** (0.066)	yes	396	0.643
22 Printing & publishing	0.007 (0.015)	1.653*** (0.068)	yes	399	0.625
23 Coke,ref. petr. prod.,nuc.	**0.066**** (0.027)	1.459*** (0.121)	yes	298	0.430
24 Chemicals & chem. prod.	**0.037**** (0.018)	1.680*** (0.074)	yes	375	0.629
25 Rubber & plastics prod.	**0.032***** (0.012)	1.602*** (0.058)	yes	407	0.684
26 Non-metal. min. prod.	**0.047***** (0.013)	1.577*** (0.052)	yes	394	0.741
27 Basic metals	**0.063***** (0.014)	1.542*** (0.068)	yes	401	0.645
28 Fabricated metal prod.	**0.030**** (0.014)	1.751*** (0.064)	yes	393	0.691
29 Mach. & equip. n.e.c.	0.023 (0.016)	1.995*** (0.075)	yes	399	0.675
30 Office, acc. & comp. mach.	-0.061 (0.056)	3.047*** (0.238)	yes	347	0.352
31 Elec. machinery & app.	**0.061***** (0.014)	1.850*** (0.087)	yes	379	0.589
32 Radio,tv & comm. equip.	0.008 (0.020)	1.841*** (0.117)	yes	363	0.437
33 Medical, prec. & optical instr.	**0.093***** (0.019)	1.791*** (0.088)	yes	372	0.579
34 Motor veh., trailers, semi-trailers	0.025 (0.017)	1.856*** (0.081)	yes	393	0.620
35 Other transp.equip.	0.024 (0.023)	2.000*** (0.135)	yes	366	0.412
36 Furn.; mfg n.e.c.	**0.054***** (0.015)	1.934*** (0.072)	yes	410	0.676
37 Recycling	**0.041**** (0.020)	1.977*** (0.108)	yes	267	0.634

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

Table 18: The impact of resource windfalls on employment shares and productivity in sub-sectors of manufacturing. A and D refer to our first and third measure of sectoral productivity (with subscript) and aggregate productivity (without subscript). NRE refers to the natural resource export share. Results for the restricted sample.

for productivity in the non-manufacturing sector is thus also primarily driven by changes in service sector productivity.[53] Finally, we have also experimented by re-calibrating the model (and re-running the regressions) only considering the manufacturing and service sectors (excluding construction and agriculture) - and find that very similar results (quantitatively and qualitatively) go through. These results are available on request.

Disaggregation of Manufacturing Here we test whether individual manufacturing sub-sectors are driving the observed results. Table 18 shows the employment and productivity results for 23 two-digits ISIC manufacturing sub-sectors. Resource windfalls are associated with smaller manufacturing sub-sectors in over 60% of the cases and with more productive manufacturing sub-sectors in nearly 70% of the cases. The results thus do not seem to be driven by individual sub-sectors.

12.2 Micro Results

Table 19 shows how manufacturing employment shares and sectoral labor productivity change with resource wealth across counties. We present results with and without controls for average, sector-specific (non-oil) wages.[54] From the tables we see that resource-rich counties have smaller employment shares in manufacturing (and hence implicitly larger employment shares in non-manufacturing.). They are also more productive in manufacturing and less productive in non-manufacturing than resource-poor counties. Finally, notice that - like in the macro data - the change in productivity is greater in manufacturing than in non-manufacturing.

Disaggregation of Manufacturing Table 20 shows employment shares and productivity (relative to aggregate productivity) of manufacturing sub-sectors. Fourteen and fifteen out of twenty sub-sectors exhibit lower employment and higher productivity in manufacturing (relative to aggregate productivity) respectively. Lower productivity sectors employ only approximately 30% of manufacturing workers. This provides evidence that higher manufacturing productivity is not driven by higher productivity in resource processing sectors.

[53] 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.

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

(a) Employment

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

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

(b) Labor productivity

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

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

Table 19: Employment shares, labor productivity and oil wealth

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

Table 20: Employment shares and labor productivity (rel. to agg. prod.) in manufacturing sub-sectors for oil rich/poor counties.

13 Theory Appendix

13.1 Physical Capital and Labor Productivity

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

Capital First, suppose we introduce capital into the homogenous worker model of section 4, so that the production function of the manufacturing and non-manufacturing sector become:

$$Y_{m,t} = A_{m,t} L_{m,t}^{1-\theta} K_{m,t}^{\theta}, \text{ and } Y_{s,t} = A_{s,t} L_{s,t}^{1-\alpha} K_{s,t}^{\alpha} \tag{34}$$

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:

$$\frac{w_t}{r_t} = \frac{1-\theta}{\theta}\frac{K_{m,t}}{L_{m,t}}, \text{ and } \frac{w_t}{r_t} = \frac{1-\alpha}{\alpha}\frac{K_{s,t}}{L_{s,t}}. \tag{35}$$

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

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

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

$$\frac{p_{m,0}Y_{m,t}}{L_{m,t}} = p_{m,0}A_{m,t}\left(\frac{K_{m,t}}{L_{m,t}}\right)^{\theta}, \text{ and } \frac{p_{s,0}Y_{s,t}}{L_{s,t}} = p_{s,0}A_{s,t}\left(\frac{K_{s,t}}{L_{s,t}}\right)^{\alpha}, \tag{37}$$

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 (36), if capital labor ratio rises/falls in one sector, it rises/falls in the other and hence according to equation (37), labor productivity in both sectors rises/falls. A model with capital predicts that sectoral labor productivities move in the same direction and hence cannot account for the asymmetric changes in labor productivity observed in the data. Notice however, that the above model can generate a non-constant *relative* productivity, $y \equiv \frac{p_{s,0}Y_{s,t}}{L_{s,t}} / \frac{p_m Y_{m,t}}{L_{m,t}}$, if capital shares vary across sectors. Productivity then changes in in both sectors but it changes *more* in one sector than another. Furthermore, within this framework, TFP (in contrast to labor productivity) still remains exogenous and unaffected by labor moving across sectors.

Subsidies A second possibility, would be to force a homogenous worker model with capital to match sectoral labor productivity by introducing subsidies to the rental rate of capital inputs in the manufacturing sector (financed by lump sum taxes) that increase exogenously with resource wealth. This would lead to a greater proportion of capital shifting towards the manufacturing sector in resource-rich countries making labor more productive in those countries. We have experimented with a simple calibration of such a model and found that the subsidies needed to achieve the observed asymmetric labor productivity differences between the 10-th and 90-th percentile of exporters are implausibly high.[55] Whilst some resource-rich countries may have high subsidies, we observe similar patterns in productivity and employment in resource-rich members of the OECD like Australia, Norway and Canada and in oil rich US counties where capital subsidies are unlikely to be high.

Fixed Factors The third possibility would be to introduce specific or fixed factors into our homogenous worker model. Then labor moving from one sector to another would encounter diminishing returns. Each additional worker to a sector would have a lower marginal productivity than the last, resulting in declining sectoral labor productivity in a worker's new sector and an increase in labor productivity in the worker's old sector. The problem with this model is the interpretation of the fixed factors. There are generally two accepted explanations in the literature. First, fixed factors may be fundamentally different and very difficult to use across sectors, for example land plays a key role in agriculture. This interpretation makes less sense in our context. What is a fixed factor in manufacturing? The second interpretation, as in Neary (1978), views capital as sector-specific in the short run but becoming interchangeable with the passage of time. In our context, this interpretation also runs into trouble. The facts presented above, demonstrate that sectoral labor productivity differences occur across a wide cross-section of countries. Cross-sectional data however, captures the long run adjustments that time series data does not. This suggests that differences in productivity across sectors are persistent over time and do not disappear as the specific factor view would predict. Finally, in this setup, just like in the mobile capital case, only labor productivity changes whilst TFP remains exogenous and unaffected by the movement of labor.

Our data showed that there exist asymmetric differences in TFP between resource-rich and resource-poor countries. Models where TFP is exogenous and unaffected by labor reallocation, cannot account for asymmetric differences. There is however, some reason to approach our TFP measures with caution.

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

13.2 Learning and ability

It could be argued that our model describes the short run due to our assumption of exogenous skill endowments: in the long run agents could potentially acquire skills to eliminate talent differences. There are two reasons to think why this is not the case and our model is a good approximation of the long run. First, our empirical analysis controls for acquired human capital: our facts reflect productivity differences above and beyond those driven by different levels of education. Consequently, we interpret skills in our model as innate abilities that are exogenous and impossible (or at least very costly) to acquire. Importantly, in the previous section we only focused on brain/brawn skill variation since it was relatively easy to identify subsections of the population across which brawn endowment conceivably varied in an exogenous fashion (i.e. men vs. women). In reality, manufacturing and non-manufacturing sector tasks could vary along a number of other dimensions (for example, creativity, inventiveness, motor skills, sociability, dexterity etc.) - it is however much harder to identify subgroups of the population across which these innate abilities would vary exogenously. As such, we emphasize that the brain/brawn division of the last section is only one of many innate skill differences that may play a role in our framework. Second, the volatility of natural resource prices coupled with the cost of retraining can act as a barrier to acquiring sector specific skills. Changes in the value of endowments of resources shift labor between sectors. Whilst agents could retrain, this may be costly or take time. Resource prices however, tend to be very volatile,[56] driving labor back and forth between sectors and making repeated re-training expensive.

13.3 Extension to Dependence and Variable Dispersion

In the baseline model, we assumed skill draws were independent. We also assumed that skills were drawn from a distribution with the same dispersion parameter. As such, we ignored the possibility that ability is correlated across sectors and that it is potentially dispersed unevenly across sectors. In this section, we introduce the possibility of correlated skill draws and different skill dispersions across sectors and show that these changes quantitatively add little to our model. If anything, increasing correlation between sectoral draws makes our results stronger. We follow Lagakos and Waugh (2012) by introducing dependance between skill distribution in the form of a copula function. In particular, we set the joint distribution of abilities to be:

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

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

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

ρ	Imp. Corr.	L_s	L_m	Y_s/L_s	Y_m/L_m	$(Y_s/L_s)/(Y_m/L_m)$	$(p_sY_s/L_s)/(Y_m/L_m)$
-	0.00	1.15	0.39	0.94	1.53	0.61	1.00
0	0.00	1.16	0.40	0.94	1.50	0.63	1.00
2	0.32	1.17	0.35	0.94	1.53	0.61	0.94
3.5	**0.51**	**1.19**	**0.30**	**0.94**	**1.59**	**0.59**	**0.87**
4	0.55	1.19	0.28	0.93	1.62	0.58	0.85
6	0.71	1.21	0.21	0.93	1.76	0.53	0.76

Table 21: The impact of changing dependence between skill draws. Entries reflect the predicted ratio between the top 10th and bottom 90th percentile resource exporters.

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

The function $C[F(z_s), H(z_m)]$, is known as a Frank copula, which allows for dependence between draws from the distributions $F(z_s)$ and $H(z_m)$, which themselves, are Frechet, with dispersion parameter, θ_m and θ_s. The dependence parameter ρ may assume any real value. Values of ρ below and above zero generate negative and positive correlations between z_s and z_m respectively. With $\rho = 0$, the variables are independent. If in addition we assume that $\theta_s = \theta_m$, we are back to the baseline case.[57] The Frank copula is popular in empirical applications because unlike some other copulas, it permits negative dependence between the marginals and the dependence is symmetric in both tails (Trivedi and Zimmer, 2005).

In what follows, we investigate the impact of varying the correlation parameter between skill draws, ρ, from 0 to 6. Each time we adjust ρ, we re-calibrate ν to maintain employment share in the non-manufacturing sector in resource-poor countries at 79%, θ_s and θ_m to maintain observed standard deviations in sector-specific wages and endowments of oil to match the resource export share of the top 10th percentile of resource exporters.

In Table 21, we show the predicted percentage change in sectoral employment and productivity between the top 10th and bottom 90th percentile of resource exporters. Since ρ is itself difficult to interpret, we also report the Spearman correlation coefficient from a simulation of 50,000 draws of the random variable for each choice of ρ. In the top of the table we report the results for our baseline calibration. We then keep the assumption that draws are uncorrelated (i.e. $\rho = 0$) and re-estimate the model allowing dispersion parameters to vary across sectors. This has almost no impact on the results. The reason for this is that, in the data, the standard deviation of log wages in manufacturing and non manufacturing are almost the same: 0.57 and 0.58 respectively. Next, we increase ρ from 0 to 6 which results in an increase in correlation between talent draws from 0 to 0.71. This results in an even greater decline in employment in

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

manufacturing in resource-rich countries and an accompanying larger increase in productivity in manufacturing. Non-manufacturing productivity is almost unaffected by the change.[58] From this exercise we see that, if anything, increasing correlation between sectoral talent draws will result in an even greater role for our mechanism.

We pin down ρ by observing that this parameter influences the change in relative productivity *measured in local prices* between resource-rich and resource-poor countries. In the baseline model with independent skills, the ratio $(p_s Y_s/L_s)/(Y_m/L_m)$ is equal to one irrespective of the size of the windfall. In the data however this ratio tends to fall with windfalls and is approximately 13% lower in the top ten percent of natural resource exporters than in the bottom ten percent. By choosing an appropriate ρ however, we can match this decline. Intuitively, a windfall generates a change in the structure of demand within a country - with more locally produced non-traded goods being demanded. For markets to clear, labor needs to reallocate towards the non-traded sector and the relative price must change to induce labor to move across sectors. The greater the correlation of skills across sectors, the more indifferent workers are in which sector they work, and so the less prices need to change in order to induce workers to move from one sector to the other. Higher values of ρ thus cause the relative productivity of non-manufacturing to manufacturing measured in domestic prices to increases less: with a high ρ, p_s is lower in the resource-rich country and so $(p_s Y_s/L_s)/(Y_m/L_m)$ will also be lower. Setting $\rho = 3.5$ we can match the 13% lower relative domestic price productivity between the top and the bottom tenth percentile of exporters. Notice, that adding correlation between skill draws increases the complexity of model but largely leaves the quantitative and qualitative results unchanged. As such, we stick with the simpler independent talents model as our baseline.

13.4 Heterogenous Firms

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

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

the economy wide level of TFP.[59] The benefit for agent i of becoming an entrepreneur is given by the profit agent i's firm would earn, $\Pi_e^i = \max\{\max_{n_s^i} p_s Y_s^i - wn_s^i, \max_{n_m^i} Y_m^i - wn_m^i\}$. If an agent i chooses not to become an entrepreneur (since his entrepreneurial ability is low and hence his profits from running a firm would not be high enough), he will choose to become a worker and earn a sector independent wage w. The final income earned by agent i will thus simply be $w^i = \max\{\Pi_e^i, w\}$. The remainder of the setup is similar to our heterogenous worker model and remains unstated. Next, we argue that we can nest both the homogenous and heterogenous worker cases in the above framework by varying the span of control parameter and without having to assume different skill distributions.

If $\nu \to 0$, we are in the world of our heterogenous agent model. There is complete decreasing returns to scale at the firm level and it is unfeasible for entrepreneurs/firms to hire any workers. Everyone is thus a self-employed entrepreneur and the economy consists only of very small firms. This is a world of corner shops and garage industries. If $\nu \to 1$ however, a measure one of agents (almost everybody in the probabilistic sense) are workers hence (almost) everyone is homogenous. Since there are constant returns to scale at the firm level, only the most productive (i.e. the most managerially talented) individual in each sector becomes an entrepreneur and between them they hire all the remaining workers. Thus, each sector simply has an aggregate productivity equal to the product of the economy wide TFP, A, and the productivity of the most talented worker in each sector.

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

13.5 Proof of Proposition 1

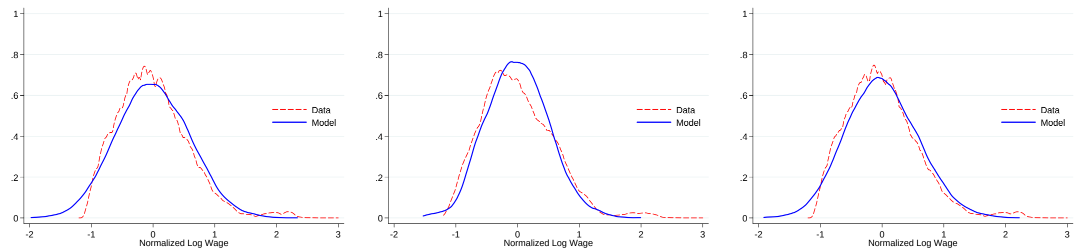
Proof. Assume, by contradiction, that $p_{s,H} \leq p_{s,L}$. Notice, from (12), that the ratio of manufacturing to non-manufacturing (aggregate) good consumption is given by $\nu^\sigma p_{s,H}^\sigma$ in the high endowment economy and $\nu^\sigma p_{s,L}^\sigma$ in the low endowment economy, hence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

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

where, $C_{m,k} = \int_i c_{m,k}^i$ 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:

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

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



(a) Distribution of Wages, Log-normal (b) Distribution of Wages in Mfg., Log-normal (c) Distribution of Wages in Non-Mfg., Log-normal

Figure 7: Distribution of wages in model and data, by sector with log-normal talent draws.

Notice however, that by Equation (11), the higher the price of non-manufacturing goods, the larger the set of consumers working in the non-manufacturing sector (and the smaller the number of people working in manufacturing), and hence the higher the total output of services (and the smaller the total output of non-services).[60] Consequently, (since we've assumed that $p_{s,H} \leq p_{s,L}$), $Y_{s,H} \leq Y_{s,L}$ and $Y_{m,L} \leq Y_{m,H}$. Using this, we can re-write the above inequality as

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

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

13.6 Log-normal version of the model

In this section, we show the implied sectoral and aggregate distribution of a version of the model where talent draws are assumed to be log-normal instead of Frechet. We assume that individual productivities are drawn independently from log-normal distribution with standard deviation $\sigma = 0.652$ chosen to match standard deviation of observed log wages. Figures 7 shows the results. Whilst in general the fit is good, the lower and upper tails are more compressed in the model with log-normal skill distributions than the in data. This mirrors the findings of Lagakos and Waugh (2012) and Heckman and Sedlacek (1985), who also conclude that a log-normal model performs poorly in matching the tails of the U.S. wage distribution.

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

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