Structural Transformation and Pollution[1]

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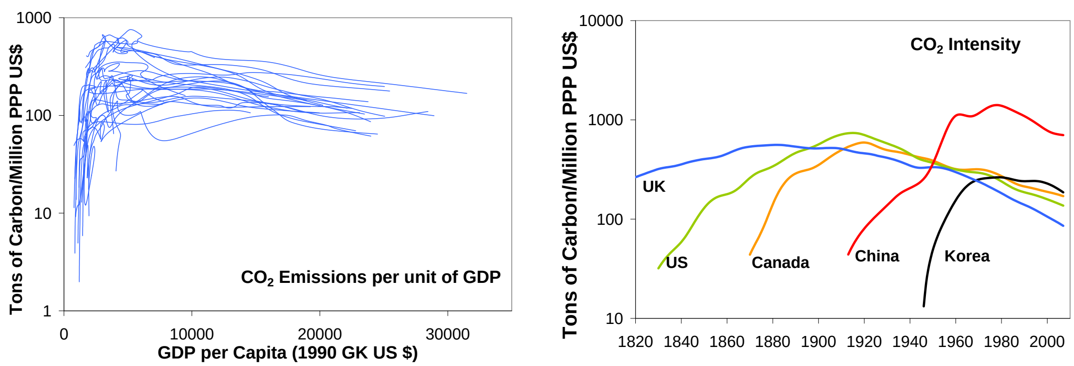
Abstract

It has been argued that CO_2 emissions of poorer nations should rise above the developed world's on a per capita basis due to their ongoing industrialization. This can only occur if poorer countries have higher emission intensities than rich countries. As such, I assess how different starting dates of structural transformation affect a country's emission intensity. I document two facts: Countries exhibit hump shaped CO_2 emission-intensities, but energy-intensities that fall. These facts are explained by a changing fuel-mix associated with a shift from clean agriculture to dirty non-agriculture as well as improvements in energy-efficiency. I construct and calibrate a two-sector, general-equilibrium model of structural transformation that reproduces these facts by generating an endogenously changing fuel mix. I then use the model to show that timing of structural-transformation matters for emission intensity and hence emission profiles: emission intensities of late developers: a) peak later; b) peak at lower levels and c) tend to be lower than in earlier developers. Industrialization is thus no excuse for relatively higher emissions. Instead, I show that higher levels of emission intensity in developing countries are symptomatic of distortions in either energy prices or the non-agricultural sector.

[1] PRELIMINARY DRAFT. I would like to thank Thierry Brechet, Torfinn Harding, Fabrizio Perri, Rick van der Ploeg and Tony Venables as well as seminar participants at the University of Minnesota International Trade Workshop and the University of Oxford Macro workshop for helpful comments and discussion. I have also benefited from comments of seminar participants at the Overlapping Generations Days Meetings (Vielsalm) and the World Congress of Environmental and Resource Economists (Montreal). All errors are my own. Contact: radek.stefanski@economics.ox.ac.uk

1 Introduction

Structural transformation is the shift in the composition of an economy away from agriculture towards industry and services, that accompanies growth. Governments of poorer, industrializing countries, such as China, have argued that due to this change in structure, their per capita CO_2 emissions should be allowed to rise above those of the developed world.[2] The argument goes that richer countries had the opportunity to emit unhindered when they were industrializing, so poorer countries should be allowed to follow a similar path. These claims, however, rest on the assumption that each industrialization is the same and that the starting date of industrialization plays no role in carbon emissions. This paper assesses this claim and investigates how different starting dates of structural transformation affect a country's CO_2 emission profile.



(a) OECD CO_2 Emission Intensity, 1751-2007

(b) Timing and Emission Intensity

Figure 1: Carbon Dioxide Emission Intensity Patterns

The total per capita emissions of an economy, p_t, depend on how much per capita output is produced, y_t, and on how dirty that output is, N_t, also known as emission intensity:

$$p_t = y_t N_t. \tag{1}$$

Poorer countries - by definition - have lower GDP per capita. In order for them to have higher emissions than rich countries, it is necessary that they have higher emission intensities. Figure 1(a) plots total CO_2 emissions per dollar of GDP for 26 OECD countries versus each country's GDP per capita, for 1820-2007. The graph seems to suggest that middle income, industrializing countries produce dirtier output than other nations. The hump shaped pattern of emission

[2] According to Pan Jiahua, an adviser to the Chinese government on climate change, "China's emissions must be allowed to rise above the developed world's on a per capita basis. The rich world has built the infrastructure it needs and must now make major cuts to emissions. We need to develop so we need lots of energy. Our emissions must continue to go up. Developed countries must bring their emissions down, perhaps even to zero. So we should be allowed to emit more than the rich world." (BBC, 2009).

intensity for carbon dioxide is relatively well known in the environmental and economic history literature.[3] This simple representation however, abstracts from the *timing* of industrialization. Figure 1(b), shows the emission intensities of five countries that began industrialization at different times. Each country exhibits a hump shaped emission intensity over time. Furthermore, all countries except China, follow a similar pattern - emission intensity rises over time until it roughly reaches the level of the 'leader' (the UK or the US) and then declines at approximately the same rate as the leader, forming an 'envelope' of emission intensities. This paper argues that this envelope in CO_2 emission intensity is a consequence of different starting dates of structural transformation. Whilst industrialization does generate a hump shaped emission intensity, the peak of late industrializers will be below the intensity of the leader. Instead, I show that the higher levels of emission intensity found in China are symptomatic of distortions in that economy - either in the form of energy price subsidies or in the form of broadly understood wedges in the non-agricultural sector. As such, the thrust of the paper is that economic distortions - rather than industrialization - are the driver of high per capita emissions in poorer countries.

The main contribution of the paper is the formalization of a mechanism that links the hump shaped intensity to structural transformation. A decomposition of data shows that increasing emission intensity at low income levels is driven by rising energy impurity caused by changing fuel mix, whilst falling emission intensity at higher income levels is driven by falling energy intensity. I propose structural transformation as a simple mechanism of endogenously changing fuel-mix that can generate the rising part of emission intensity. In the data agricultural economies tend to use "clean" renewable, carbon-neutral fuels as the main source of energy, whilst non-agriculture dominated economies use predominantly "dirty" fossil fuels. The shift of an economy from agriculture to non-agriculture changes the mix of fuel in use, which results in rising emission intensity. In a longer horizon, falling energy intensity results in falling emission intensity, despite the dirtier fuel mix. I propose two factors that are potentially responsible for the long run decline in energy intensity that are independent of the state of industrialization, but depend on the current state of technology and hence on time - energy saving technological progress and complementarity between energy and non-energy inputs.

I build and calibrate a simple two-sector, general equilibrium growth model of structural transformation similar to Gollin et al. (2002), Rogerson (2007), Duarte and Restuccia (2007) and Echevarria (1997) but with energy as an intermediate input. Agriculture is assumed to be a clean sector, whilst non-agriculture is assumed to be dirty. Energy efficiency improves exogenously in both sectors but the ability to substitute between energy and non-energy inputs may vary

[3] Tol et al. (2009) shows the existence of the relationship for the US. Lindmark (2002), Kander (2002) and Kander and Lindmark (2004) demonstrate that this relationship holds for Sweden. Bartoletto and Rubio (2008) find evidence of a similar pattern in Italy and Spain. Finally, Lindmark (2004) shows that the hump is a feature in most of his 46 country sample.

across sectors. As productivity improves, labor shifts across sectors due to an assumption of non-homothetic preferences in agriculture. Since each sector consumes a different energy type, structural transformation generates endogenously changing fuel mix, which - coupled with improving energy efficiency - generates an inverted-U emission intensity and a falling energy intensity as labor moves from agriculture to non-agriculture.

The key experiment of the paper is to vary starting dates of structural transformation. In the model, countries with lower productivity in agriculture devote a larger share of their work force to satisfying subsistence needs. By varying this productivity I can change the share of employment in that sector and hence the effective starting date of industrialization.[4] The main finding is that, in as far as low agricultural productivity delays the beginning of structural transformation, it is key in influencing the emission profile of countries over their development process. Countries that begin industrialization later, will have access to more energy efficient (and hence cleaner) technology than countries that industrialized earlier. At each point in time, late transformers will optimally emit *less* pollution per unit of GDP (and per capita) than earlier transformers. I test the implications of the model and show that in the data emission intensities of countries that begin industrializing later: a) peak later; b) peak at lower levels and c) tend to be lower than in countries that industrialized earlier.

Finally, I show that - in the context of the model - the high emission intensity found in some industrializing countries like China, is explained by two types of distortions in that economy - energy price subsidies or wedges in the non-agricultural sector. Whilst both policies have the same impact on emission intensity, the impact on total emissions of either policy is very different. Subsidies on dirty energy, will result in higher energy use and hence higher emissions. Non-agricultural wedges however, result in low overall output but the same level of energy use and emissions that would occur without the wedges. The two lessons from the paper are as follows: 1) industrialization is not an excuse for high per capita emissions and 2) high emission intensities, whilst driven by distortions, may - but do not have to - be indicative of countries that are polluting 'too much'.

2 Stylized Facts

This section establishes three facts for UK data. I show that: 1) CO_2 emission intensity follows an inverted-U shape over time; 2) that the initial increase in emission intensity is driven by rising energy impurity, whilst the subsequent decline is driven by falling energy intensity; 3) and that

[4] Gollin et al. (2002) use these productivities as a shorthand method of capturing a wide range of cross-country differences in agriculture productivity including, but not limited to, differences in taxation, educational attainment, endowments, technological differences, enforcement of property rights or regulations.

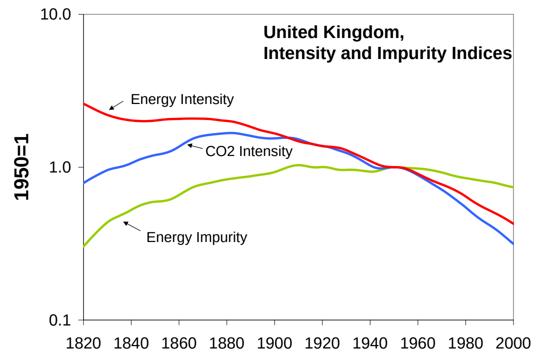
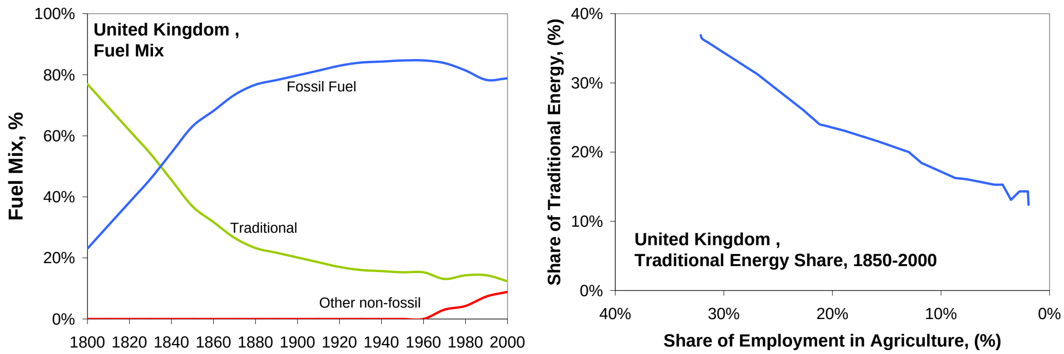


Figure 2: Pollution intensity, energy intensity and energy impurity in UK.

there has been large shift in the fuel mix away from traditional, biomass fuels towards predominantly fossil fuels that has been associated with structural transformation. In the Appendix I show that a similar set of facts holds for a panel of more then 200 countries for the year 1960-2009 and for historical time series data for Sweden, Holland, Italy, Spain and the United States. I finish by arguing that falling energy intensity can be attributed to energy saving technological progress in conjunction with complimentarity between energy and non-energy inputs.

Emission Intensity Fossil fuel energy production accounts for approximately 80% of all anthropogenic carbon dioxide emissions with the remaining twenty percent stemming largely from changes in land use - such as deforestation or urbanization (Schimel et al., 1996). As such, in this paper I will focus on carbon emissions that stem entirely from energy consumption. Since historical energy production and consumption is relatively well documented, this allows for the estimation of long run emissions of carbon dioxide using historical energy consumption, production and trade data. In this way Andres et al. (1999) have constructed long time series data of carbon emissions for a number of countries. The data and construction is discussed in the Appendix. Using GDP expressed in purchasing power parity terms (1990 Geary-Khamis dollars) from Maddison (2007), the curve labeled 'CO_2 intensity' in Figure 2 shows that CO_2 emission intensity follow an inverted-U shape over time over the 1820-2009 period.

Pollution Accounting Next, I find the source of the inverted-U emission intensity curve through a simply decomposition exercise. Since I focus on carbon emissions that come from energy production, the total amount of emissions in an economy can be expressed through the following identity, $P_t = \eta_t E_t$, where P_t is the amount of carbon emissions, E_t is the total use of energy and η_t represents the contribution of one unit of energy to emissions and can thus be interpreted as the impurity of energy. Dividing both sides of the identity by GDP, gives a



(a) Change in fuel mix in UK

(b) Fuel mix and structural transformation in UK

Figure 3: Fuel mix in the United Kingdom.

relationship between pollution intensity, energy intensity and energy impurity:

$$\frac{P_t}{Y_t} = \eta_t \frac{E_t}{Y_t}. \tag{2}$$

In order to perform the decomposition, I need data on a country's total energy use which includes fossil fuel based energy, renewable non-combustibles (such as wind, hydro or nuclear power) and renewable combustibles (such as wood or biomass). Given data for pollution intensity and energy intensity, I can deduce energy impurity. The source of the energy data is discussed in the Appendix. Figure 2 shows the results of the decomposition: energy impurity rises almost over the entire period (with a slight decline at the end of the series), whilst energy intensity falls, where both series have been normalized to 1950. The implication of this is that the increases in emission intensity observed initially is driven predominantly by rising impurity, whereas falling emission intensities later on are driven predominantly by falling energy intensity.

Fuel mix, Energy Impurity and Structural Transformation A number of factors can potentially account for changes in energy impurity: technology, type and quality of fuel, cleanliness of the combustion process, extent of carbon sequestration, government regulations and so on. It seems reasonable however, that technology, quality, cleanliness and sequestration should - if anything - increase or improve over time, resulting in falling energy impurity. This leaves changes in the fuel mix as the most likely candidate to explain rising energy impurity. Suppose that there are a number of fuels and that each type of fuel, i, emits a fixed quantity of pollution, so that total energy impurity is given by, $\eta_t = \sum_i \eta_i E_{i,t}$, where $E_{i,t}$ is energy produced by fuel type i and η_i is the amount of pollution produced by each fuel type. Emission intensity is then given by:

$$\frac{P_t}{Y_t} = \left(\sum_i \eta_i \frac{E_{i,t}}{E_t} \right) \frac{E_t}{Y_t}. \tag{3}$$

In the above, $\frac{E_{i,t}}{E_t}$ is thus the share of type i fuel in total energy production. Figure 3(a) shows how the fuel mix used to generate energy has changed over time. There has been a shift from "clean" combustible renewable fuels towards "dirty" fossil fuels. The transition from renewable to fossil fuels has an important effect on CO_2 emissions. The burning of biomass materials for energy, only releases the carbon accumulated by the plant-matter during its lifecycle. Since such emissions do not add to the atmospheric concentrations of carbon dioxide, most international protocols - including that of the Intergovernmental Panel on Climate Change (IPCC) - consider biomass emissions to be neutral. The US Energy Information Administration, also follows the IPCC guidelines and recommends that "reporters may wish to use an emission factor of zero for wood, wood waste, and other biomass fuels".[5] The burning of fossil fuels for current energy use however, releases large quantities of CO_2 that had previously been removed or 'fixed' from the biosphere over millions of years and locked under ground in the form of coal, oil or natural gas. Burning these fuels releases stored carbon back into the biosphere, whereas burning biomass recycles carbon that is already in the biosphere.

I argue that the change in fuel mix is closely linked to structural transformation. Figure 3(b) plots the share of traditional fuels versus the share of employment in agriculture in the UK. Higher employment in agriculture is associated with a higher use of traditional fuels. Intuitively, these fuels are relatively abundant in an agricultural and rural setting. When a large share of the labor force is employed in agriculture, energy will be derived predominantly from materials such as wood, biomass or muscle power (which in turn is powered by food). In the same, non-agriculture will derive most of their energy needs from non-biomass fuels such as coal, oil or natural gas. Intuitively, many industrial processes and services require modern types of energy. For instance industries that use, produce or process metals require dependable fuel supplies and the greater flexibility associated with fuels like coal or oil, than renewable combustibles. Fossil fuels also provide a degree of control, ease and energy density that allow for greater quantities of effective power - coal, for instance, burns hotter than wood since it is more compact and has more combustible material. Many modern services also require a constant flow of energy which can - to a large extent - only be supplied by modern sources of energy such as fossil fuels. Finally, most factories and services are localized in urban areas, were easy access to biomass is limited. As the composition of the broader economy shifts from agriculture towards the industry and service sectors, the production of energy will also shift from the agricultural sector to the non-agricultural sector. This, will induce a change in the mix of fuel used to generate energy -

[5] For details see, *Emissions of Greenhouse Gases in the United States 2000* (November 2001).

from renewable biomass materials to (predominantly) fossil fuels such as coal, oil or gas. Notice also that due to their small role in energy generation in most countries, I will abstract from modern non-fossil fuels such as nuclear, wind or solar.

Technology, Complementarity and Falling Energy Intensity In the paper I focus on two channels to drive changes in energy intensity patterns: technology and complementarity. First, the key characteristic of energy is that it is an intermediate input. As such, energy benefits from technological progress at two stages in the production process: during the production of energy itself (economies become better at creating more energy given other inputs) and when energy is combined with other factors to produce final goods (economies become better at using less energy to produce a given unit of output). Whilst other intermediate products may benefit from targeted technological progress at various stages of their use, since energy is an input at virtually every stage of production, it will always benefit from technological progress at an additional stage.

Second, complementarity between energy and non-energy inputs can induce a lower demand for energy. Suppose energy and non-energy inputs are perfect complements that must be used in relatively fixed proportions in production. Since, by the above argument, an economy is better at producing a higher effective amount of energy, an economy will devote relatively more resources to the slower growing non-energy inputs over time to maintain relatively fixed proportions between energy and non-energy inputs. If there is enough complementarity between energy and non-energy inputs, the outflow of resources from energy production can contribute to falling energy use and hence to falling energy intensity. If, on the other hand, energy and non-energy inputs are substitutes, the efficiency gains of energy, will encourage more resource to move towards energy production and may result in rising energy use and intensity.

At this stage, I do not specify which of the two channel or to what extent either channel operates. Instead, I assume that both channels may potentially be active but I leave the pinning down of the parameters to the calibration, when a structural model is specified.

3 The Model

Preferences There is an infinitely lived representative agent endowed with a unit of time each period. Period utility is defined over agricultural goods a_t and non-agricultural goods c_t. To generate structural transformation, I follow Gollin et al. (2002) by assuming a simple type of Stone-Geary period utility:

$$U(a_t, c_t) = \begin{cases} \bar{a} + u(c_t) & \text{if } a_t > \bar{a} \\ a_t & \text{if } a_t \leq \bar{a}, \end{cases} \tag{4}$$

with lifetime utility being given by:

$$\sum_{t=0}^{\infty} \beta^t U(a_t, c_t), \tag{5}$$

where $0 < \beta < 1$, is the discount factor. From this setup, we see that once per capita output in the agricultural sector has reached the level $\bar{a}$, all remaining labor moves to the non-agricultural sector.

Technologies Non-agricultural output (Y_{Ct}) is produced using labor (L_{Ct}) and a modern energy inputs (E_{Ct}):

$$Y_{Ct} = B_C \left(\alpha_C (B_{lCt} L^y_{Ct})^{\frac{\sigma-1}{\sigma}} + (1-\alpha_C)(B_{Et} E_{Ct})^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} \tag{6}$$

In the above equation, α_C is the weight of labor in production, whilst σ is the elasticity of substitution between labor and energy, B_C is a productivity parameter whilst labor and energy augmenting productivity at time t are given by B_{lCt} and B_{Et} respectively. Modern energy, is produced using labor (L^e_{Ct}):

$$E_{Ct} = B_{eCt} L^e_{Ct}, \tag{7}$$

where B_{eCt} is productivity at time t. The modern energy sector can be taken to be the mining or drilling sector and as such total employment in the non-agricultural sector is given by the sum of employment in both sub-sectors, $L_{Ct} \equiv L^y_{Ct} + L^e_{Ct}$.

Agricultural output (Y_{At}) is produced using labor (L_{At}) and a traditional energy input(E_{At}):

$$Y_{At} = B_{At} {L^y_{At}}^{\alpha_A} {E_{At}}^{1-\alpha_A}. \tag{8}$$

In the above equation, α_A is the weight of labor in production and B_{At} is productivity at time t. Unlike the non-agricultural sector I assume an elasticity of substitution of one between energy and labor, so that the production function is Cobb-Douglas. This is in line with the argument put forward by Lucas (2003) that "traditional agricultural societies are very like one another". I take this to mean that the structure of time and labor spent across activities in traditional agricultural societies remains the same, which would imply a production function like the above. Traditional energy, is produced using labor (L^e_{At}):

$$E_{At} = B_{eAt} L^e_{At}, \tag{9}$$

where B_{eAt} is productivity at time t. The traditional energy sector can be taken to be the gathering of fuel wood or charcoal production etc. and as such total employment in the agricultural sector is given by the sum of employment in both sub-sectors, $L_{At} \equiv L^y_{At} + L^e_{At}$. Finally, I assume that the total amount labor in the economy is given by, $L^y_{At} + L_{Ct} = g^t_N$, where $g_N - 1$ is the exogenous growth rate of the total labor force.

Pollution A unit of energy consumed in the production of output in sector $s = A, C$ is assumed to release a proportional amount of pollution, P_{st}:

$$P_{st} = \eta_s E_{st} \tag{10}$$

where, η_s, is the coefficient of proportionality and captures the total amount of pollution released per unit of each type of energy. Since I assume that the source of energy used varies by sector, $\eta_A \neq \eta_C$. Finally, notice that pollution is a prefect complement of output production but has no influence on either utility or productivity.

Solution I focus on the competitive equilibrium of this economy, and in particular I show how different productivity parameters in agriculture, B_A, affect emission intensities and hence emissions over structural transformation. The problem is solved in two parts. The first step, takes employment across agriculture and non-agriculture as given and allocates labor within each sector between energy and output subsectors. From the first order conditions of output firms, I obtain a wage to energy price ratio which I set equal to the wage to energy price ratio obtained from the corresponding energy sector. This implies the following distribution of labor across subsectors within agriculture:

$$L_{At}^e = (1 - \alpha_A)L_{At} \text{ and } L_{At}^y = \alpha_A L_{At}. \tag{11}$$

and within non-agriculture:

$$L_{Ct}^e = \left(\frac{1}{1 + x_{Ct}}\right) L_{Ct} \text{ and } L_{Ct}^y = \left(\frac{x_{Ct}}{1 + x_{Ct}}\right) L_{Ct} \tag{12}$$

where $x_{Ct} \equiv \left(\frac{\alpha_C}{1-\alpha_C}\right)^\sigma \left(\frac{B_{Et}B_{eCt}}{B_{lCt}}\right)^{1-\sigma}$. The second step, determines the division of labor across agriculture and non-agriculture. Preferences imply that $Y_{At} = \bar{a}g_N^t$ and so combining this with equations (8), (9) and (11) employment in agriculture and non-agriculture is given by:

$$L_{At} = \frac{\bar{a}g_N^t}{B_{At}\alpha_A{}^{\alpha_A}\left(B_{eAt}(1-\alpha_A)\right)^{1-\alpha_A}} \text{ and } L_{Ct} = g_N^t - L_{At}. \tag{13}$$

Given the above, equations (7), (9) and (10) then determine energy use and emissions of each sector.

4 Calibration

I calibrate the model by choosing a specification that largely matches the development process of the United Kingdom over the last 200 years. First, population growth is chosen to match the average population growth between 1870 and 1950 so that $g_N = 1.006$. Next, without loss of

Parameter	Values	Target
g_N	1.006	Population growth 1870-1950
$B_{A0}, B_C, B_{eC0}, B_{eA0}$	1	Normalization
$\bar{a}$	0.175	Agriculture Empl. Share, 1870
g_A	1.023	Agriculture Empl. Share, 1950
g_{eA}	1.009	Growth in wage to fuelwood price ratio, 1820-1870
$1-\alpha_A$	0.08	Share of time spent gathering fuel wood
$1-\alpha_C$	0.06	Mining VA Share, 1870
σ	0.80	Mining VA Share, 1950
g_E	1.036	Change in total energy intensity, 1870-1950
B_{et}	data	Growth in wage to oil price ratio
g_{lC}	1.02	GDP per capita growth, 1950-2008
η_A	0	Emissions from biomass
η_C	1	Emissions from modern energy

Table 1: Calibrated parameters

generality, I normalize $B_{A0} = B_C = B_{eC0} = B_{eA0} = 1$. I also assume that $B_{At} = g_A^t$, $B_{Ct} = g_C^t$, $B_{eAt} = g_{eA}^t$ - so that these productivity terms grows at a constant, exogenous rate. Notice that $B_{eAt} = \frac{w_t}{p_{Et}^A}$ and $B_{eCt} = \frac{w_t}{p_{Et}^C}$ where w_t is the wage rate and p_{Et}^A and p_{Et}^C are the prices of traditional and modern energy respectively. As such, I set $g_{eA} = 1.009$ which is the average growth rate of farm wages to fuelwood price between 1820 and 1870 and I choose B_{eCt} to match craft wage to modern energy price ratio period-by-period directly from the data. The reason for this second choice is that the relative price of modern energy has not grown at constant rate over the last two hundred year, especially after 1970. For data construction and details see the Appendix.

The parameter $1-\alpha_A$ determines what fraction of their time workers spend producing energy in the agricultural sector. Ideally, this parameter would be calibrated to the share of hours devoted to energy production in the pre-industrial agricultural sector in the United Kingdom. Since this data is unavailable, I use data for another pre-industrial country for which data is available - Nepal. I set $1 - \alpha_A = 0.92$ to match the fact that agricultural families devote 8% of their time to fuel wood gathering. See the Appendix for details. I set parameters $\bar{a} = 0.175$ and $g_A = 1.023$ so that the model matches employment shares in the UK agriculture in 1870 and 1950 (with $t = 0$ for 1870 and $t = 80$ for 1950) of 23% and and 6% respectively.

For the non-agricultural sector, I set $1 - \alpha_C = 0.06$, $\sigma = 0.80$ and $g_E = 1.036$. These are chosen simultaneously to match the share of value added in mining in 1870 and 1950 (employment shares are unavailable) and the rate of decline of total energy intensity for 1870-1950. See the Appendix for data and construction details. The elasticity parameter is broadly consistent with previous literature and lies in the mid-range of the values usually estimated for Allen partial elasticities between energy and labor in manufacturing. For example Berndt and Wood (1975) estimate the elasticity of substitution in US manufacturing between energy and labor to be 0.65.

Griffin and Gregory (1976) estimates this elasticity for numerous advanced European countries and the US to be between 0.72 and 0.87. Kemfert (1998) as well as Kemfert and Welsch (2000) estimate this elasticity for Germany to be 0.871.

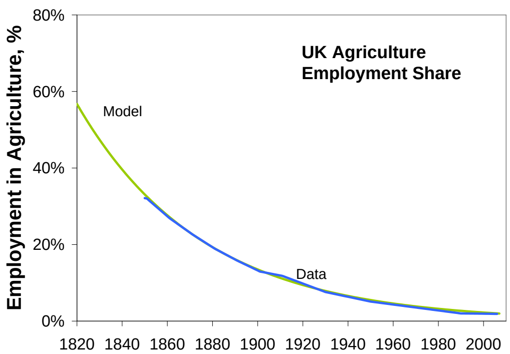
Given $\sigma < 1$, it can be shown that the asymptotic growth rate of (per capita) output in the model economy is g_{lC}. As such, I choose $g_{lC} = 1.02$ to match the observed GDP growth rate in the model since 1950 as reported by Maddison. Finally I choose the pollution parameter for agriculture to be $\eta_A = 0$. Emissions from traditional, biomass fuels do not add carbon dioxide to the biosphere and only recycle the carbon that is already there. Given this fact I can set $\eta_C = 1 > 0$ without loss of generality.

5 Results

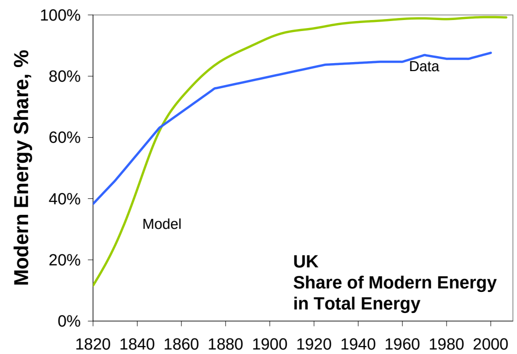
United Kingdom Figure 4 shows the baseline simulations. The falling employment share in agriculture in the data and the model is presented in Figure 4(a). Increasing productivity in agriculture results in less workers needed to produce the subsistence level of food. Figure 4(b) shows the change in the fuel mix. As the economy shifts from the clean sector to the dirty sector, the share of dirty fuel increases. Finally, Figures 4(c) and 4(d) show changes in pollution and energy intensity. Pollution intensity follows a hump shape, whilst emission intensity declines over time. Finally, Figure 5 shows the result for total emissions, GDP per capita and value added share in mining and utilities.

Counterfactuals When performing the following counterfactuals, I replace the period-by-period productivity growth in the modern energy sector by the 1870-1950 average productivity growth in the UK. In particular, I assume that $B_{eCt} = g_{eC}^t$ where, $g_{eC} = 1.021$. In the first counterfactual, I show how different productivity parameters in agriculture, B_A, affect emission intensities and emissions over structural transformation. Following Gollin et al. (2002), I take these productivity differences across countries as catchalls for any number of cross-country differences such as taxation, regulation, assignment and enforcement of property rights, institutions such as collective bargaining, and soil and climate conditions. I choose $B_{A0} = 0.370; 0.112; 0.0365$ in order to create industrializations that begin in 1850 and 1900 and 1948, whilst keeping $B_C = 1$ for all countries. The last parameter is chosen so that the model matches China's employment share in agriculture of 89% in 1952. Figure 6 shows the results for agricultural employment, emission intensities, modern fuel shares and total emissions.[6] Notice that GDP for each economy is computed using year 2000 prices from the baseline (UK) economy. Lower productivity in agriculture keeps more workers in that sector and results in a higher proportional use of clean

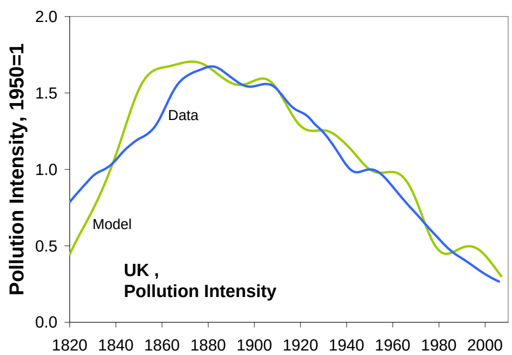
[6] The data for agricultural employment share in China comes from Evans and Stavetieg (2009) for 1952-1973 and from Brandt and Zhu (2010) for 1978-2007. The data in between is linearly interpolated.



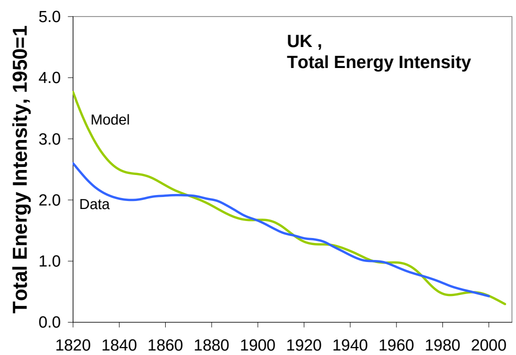
(a) UK Agricultural Employment Share



(b) UK Modern Energy Share

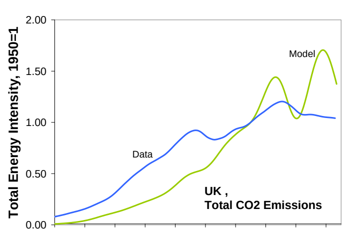


(c) UK CO_2 Emission Intensity

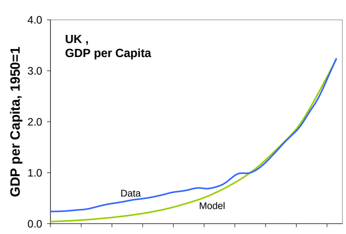


(d) UK Total Energy Intensity

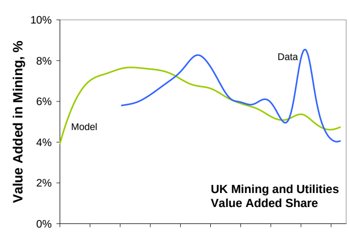
Figure 4: Simulations and data for UK employment shares, fuel mix, emission intensity and energy intensity, 1820-2010



(a) Total Emissions



(b) GDP per Capita



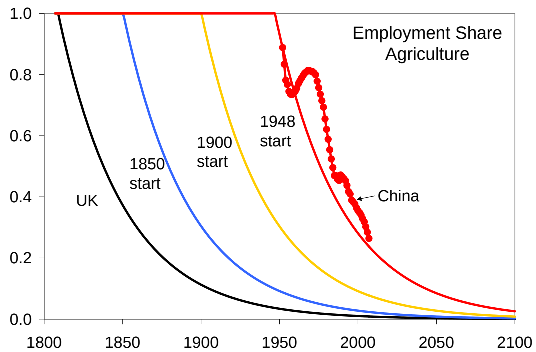
(c) Mining VA Share

Figure 5: Data and model, UK

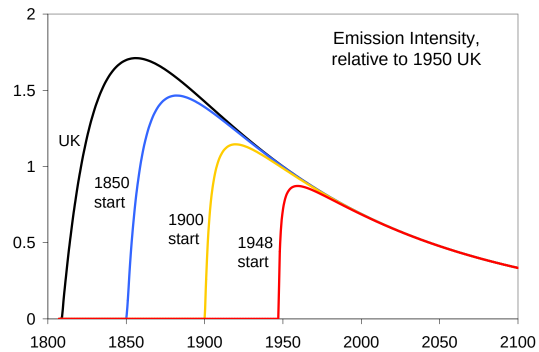
fuel. As countries begin to industrialize, they shift towards dirty non-agriculture. However, since there is technological progress in energy efficiency (coupled with an elasticity of substitution less than one, between energy and non-energy inputs), countries that begin industrialization later, move into a non-agricultural sector that is more energy efficient and hence less emission intensive. The takeaway from the first counterfactual is that the process of industrialization does not result in higher emission intensity (and hence emissions) in industrializing countries than in countries that have already industrialized. Instead, an envelope like pattern of emission-intensities emerges.

The second counterfactual, examines the importance of the assumption of identical non-agricultural productivities across countries. I continue to examine the country which started industrializing in 1948 but also assume that it has a lower productivity in non-agriculture, $B_C = 0.34$, chosen to match the Chinese-UK ratio of GDP per capita in 2006. As in the first counterfactual, these differences are taken to capture various distortions in the non-agricultural sector. The long run GDP per capita of this economy will be 34% of the long run UK GDP as shown in Figure 7(a). A lower B_C however does not affect the reallocation of labor between agriculture and non-agriculture, as seen in equation (13). More importantly it does not change the reallocation of labor between non-agricultural energy production and non-agricultural output production, as seen in equation (12). As such, the total amount of modern energy and emissions produced remains the same as in the first counterfactual. Since emissions are unaffected but GDP is lower, we observe a permanently higher emissions intensity shown in Figure 7(b). The takeaway from the second counterfactual is that a large part of high emission intensity in developing countries like China, stems from distortions in the non-agricultural economy. The counter-intuitive implication of this is that to lower emission intensity, countries like China need to focus on increasing their GDP (by alleviating non-agricultural wedges) and *not* on cutting emissions.

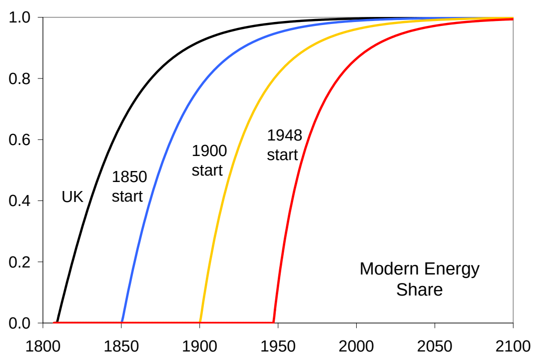
The final counterfactual tests the importance of modern fuel subsidies on emissions and emission intensity. In particular, I continue to examine the country from the second counterfactual, which started industrializing in 1948 and had $B_C = 0.34$. In addition I assume that non-agricultural final good producers benefit from a subsidy on modern energy, $(1 - \tau_{et})$, financed by a lump sum tax on consumer income. With the subsidy, x_{Ct} from equation (12) becomes, $x_{Ct} \equiv \left(\frac{\alpha_C}{1-\alpha_C}\right)^{\sigma} \left(\frac{B_{Et}B_{eCt}}{B_{lCt}}\right)^{1-\sigma} (1 - \tau_{et})^{1-\sigma}$, whilst all remaining equations stay the same. A higher τ_{et} makes the modern energy sector more attractive to workers, resulting in higher production of modern energy and emissions. I choose τ_{et} to match China's emission intensity at each point in time. The implied subsidy rates are shown in Figure 9. Between 1955 and the mid-1980's subsidies are approximately 40%, after which they decline to approximately 12% in 2006. Larsen and Shah (1992) estimate that energy subsidies in China were 84% for coal



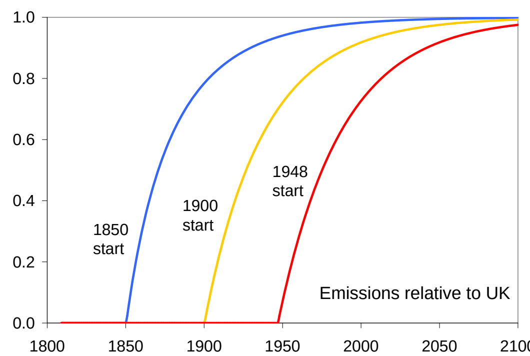
(a) Agricultural Employment Shares



(b) Emission Intensities Relative to 1950 UK

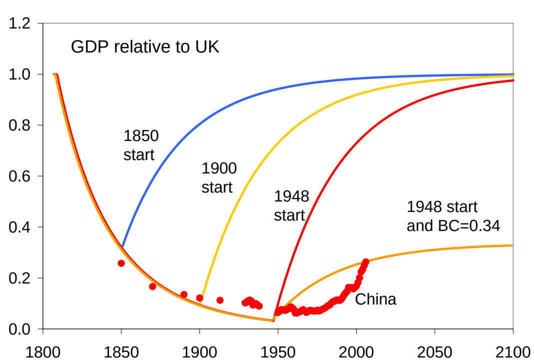


(c) Modern Energy Shares

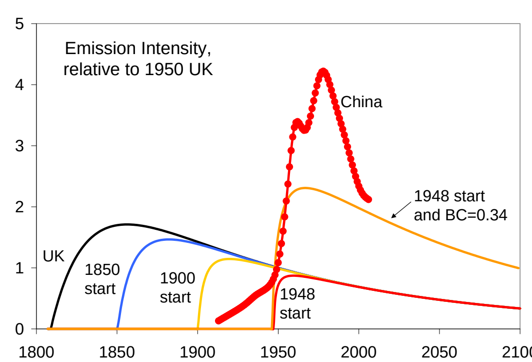


(d) Emissions Relative to the UK

Figure 6: Counterfactual One, varying B_A.

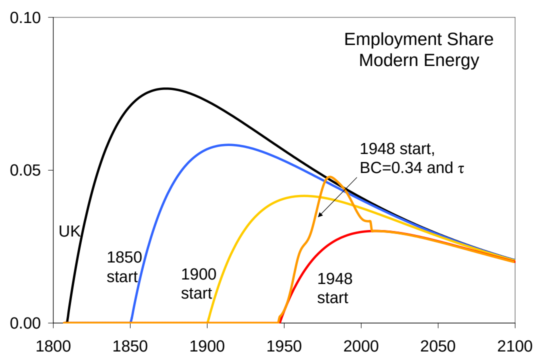


(a) GDP relative to UK

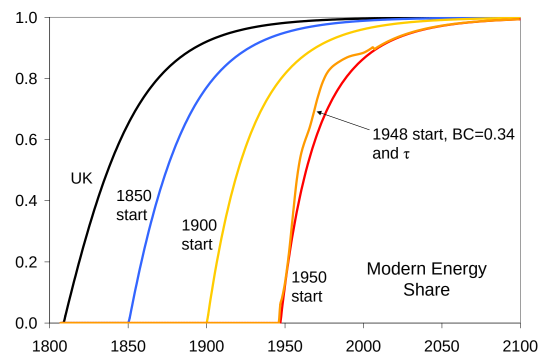


(b) Emission Intensities Relative to 1950 UK

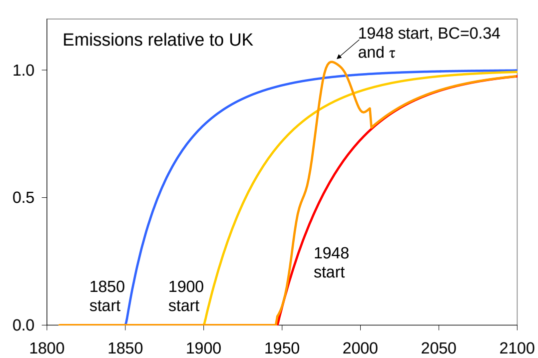
Figure 7: Counterfactual Two, varying B_C.



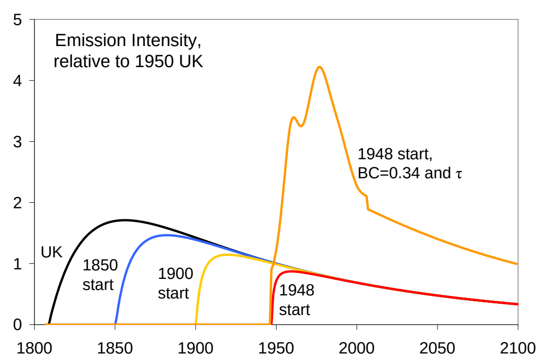
(a) Modern Energy Employment Shares



(b) Modern Energy Shares



(c) Emissions Relative to the UK



(d) Emission Intensities Relative to 1950 UK

Figure 8: Counterfactual Three, varying τ_e.

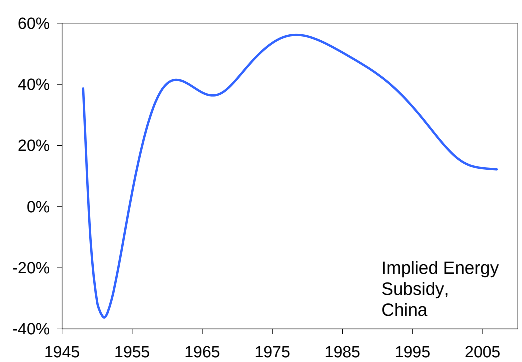


Figure 9: Implied Energy Subsidies in China

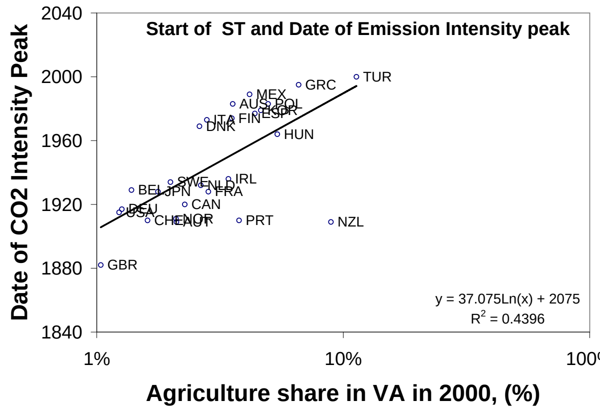
(in 1989), 48% for oil (in 1985) and 40% for natural gas (in 1986) and they argue that after a series of reforms in the mid-80's subsidies began to decline. The resulting higher share of modern energy workers is shown in Figure 8(a), whilst the higher modern energy output and a higher share of modern fuel is seen in Figure 8(b). Whilst, the higher emissions are shown in Figure 8(c). Finally, higher levels of emissions but roughly the same level of GDP, results in a higher emission intensity shown seen in Figure 8(d). The takeaway from this counterfactual is that all distortions are not created equal. Whilst general low levels of non-agricultural productivity observed in the second counterfactual have no impact on total emissions, distortive wedges like price subsidies on fuel result in both higher emission intensities *and* higher total emissions.

There are thus two messages from the counterfactuals. First, industrialization in poor countries is *not* an excuse for emissions that are higher than those of rich countries. Second, distortions in the economy can generate high energy intensities. The source of these inefficiencies however is crucial to determine whether high intensities translate to higher emission levels. If inefficiencies are distortionary, they can generate higher modern energy use and higher emissions. If inefficiencies are non-distortionary and reflect an overall low level of productivity, then they will have no effect on the overall emission levels.

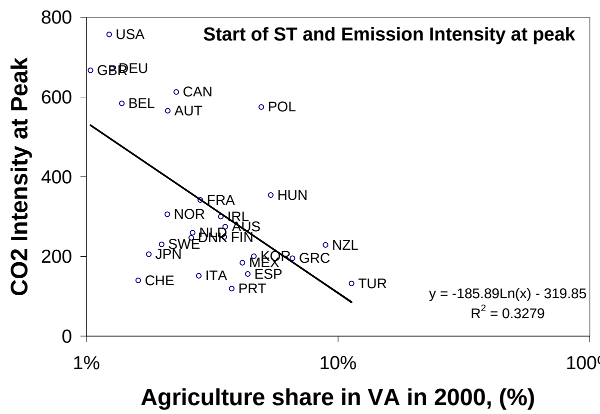
6 Evidence

The model assumes that the inverted-U shape of emission intensity is intimately linked with structural transformation. A key implication of the model is that the starting point of a structural transformation is crucial to determining the actual emission path of a country. In this section I show evidence using 26 OECD countries supporting the results of the model - in particular, I demonstrate how different starting dates of structural transformation impact the inverted-U shape of emission intensity.

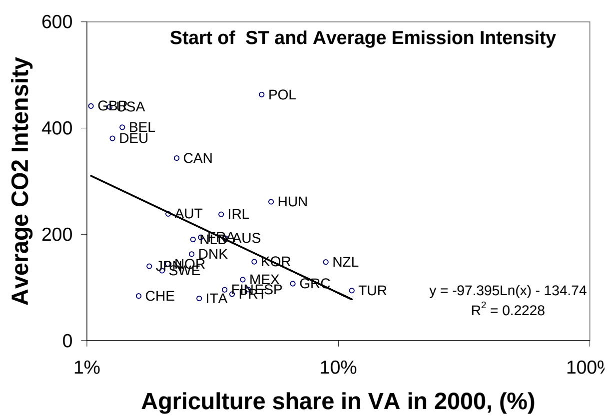
I use the year 2000 share of agriculture in value added in a given country as a yardstick of when a country begins its industrialization process. The implicit assumption is that the earlier a country began industrializing, the lower its share of agriculture in total value added at every point in time relative to countries that began industrializing later. This assumption is based on the observation that the share of agricultural value added in countries tends to fall over time once countries begin the industrialization process. According to this measure, countries that industrialized later, will have a higher shares in the year 2000. Although this is clearly an imperfect measure, I use it for lack of better data. The results - shown in Table 3 - suggest that the UK, the US and Germany were the first countries to industrialize, whilst Poland, Greece, New Zealand and Turkey were the last to industrialize in the sample. The table also shows the date when emission intensity peaked for each country, the average emission



(a) Countries that begin structural transformation later, peak in emission intensity later.



(b) Countries that begin structural transformation later, peak at lower levels of emission intensity.



(c) Countries that begin structural transformation later, exhibit lower average emission intensities.

Figure 10: The impact of different starting dates of structural transformation on emission intensity.

intensity at the peak (in tons of carbon/million USD) for each country and the average intensity over the entire period. Finally, Figure 10, shows how different starting dates of structural transformation influence emission intensity. In particular, the emission intensities of countries that begin industrializing later: a) peak later (10(a)); b) peak at lower levels (10(b)) and c) tend to be lower than in countries that industrialized earlier (10(c)). This supports the findings of the model.

7 Conclusion

Countries exhibit emission intensities that follow a hump shape with income. This paper shows that different starting dates of structural transformation generate an 'envelope pattern' in country's emissions intensity of carbon dioxide. Emission intensities of late developers: a) peak later; b) peak at lower levels and c) tend to be lower than in earlier developers. Industrialization is thus no excuse for relatively higher pollution levels. Instead, I show that the higher levels of emission intensity found in some developing countries could be symptomatic of distortions in that economy - either in the form of energy price subsidies or in the form of broadly understood wedges in the non-agricultural sector. The source of these inefficiencies however is crucial to determine whether high intensities translate to high emission levels. If inefficiencies are distortionary, they can generate higher modern energy use and higher emissions. If inefficiencies are non-distortianary and reflect an overall low level of productivity, they will have no effect on the overall emission levels.

8 Appendix

	hrs/person/day			hrs/HH/day	
Activity	Men	Women	Children	Household†	HH Shares
Field Work	3.10	2.75	0.05	6.00	27.33%
Grazing	0.00	0.00	1.80	5.40	24.60%
Cooking	0.38	2.10	···	2.48	11.28%
Grass Collection	0.35	0.98	0.28	2.15	9.79%
Water	0.10	1.15	0.23	1.93	8.77%
Fuel Wood Collection	0.13	1.15	0.13	1.65	7.52%
Employment	0.80	0.13	···	0.93	4.21%
Food processing	0.20	0.70	···	0.90	4.10%
Leaf Fodder	0.10	0.35	0.03	0.53	2.39%
TOTAL	5.15	9.30	2.50	21.95	100.00%

Source: Kumar and Hotchkiss (1988), Table 5.
†Data constructed by assuming five people/household.

Table 2: Patterns of time allocation in Nepal for Men, Women, Children and Households.

Energy Share, Agriculture Table 2 shows time allocation information for men, women and children for the year 1982 in Nepal. The table is constructed from numbers reported by Kumar and Hotchkiss (1988) and is based on data collected by the Nepalese Agriculture Projects Service Center; the Food and Agricultural Organization of the United Nations and the International Food Policy Research Institute.[7] In particular, the first three columns of the table show the number of hours per person per day devoted to a particular activity. Kumar and Hotchkiss (1988) present the data disaggregated by season - the data in the above table, is aggregated by taking inter-seasonal averages and hence represents an annual average. To see what fraction of total hours worked in agriculture is devoted to fuel collection, I construct hours spent per activity for a "typical" Nepalese household/agricultural producer. According to the Nepalese Central Bureau of Statistics,[8] the average size of an agricultural household in Nepal is approximately 5 people - a man, a woman and three children. Thus, to obtain the total hours devoted to each activity for an average household, the men, women and children columns are summed with the children's column weighed by a factor of three. This gives total hours per day spent by a typical Nepalese agricultural household/producer in each one of the above activities. From this, the fraction of time spent on fuel wood collection is approximately eight percent, which implies that, $1 - \alpha_A = 0.08$.

[7] "Nepal Energy and Nutrition Survey, 1982/83," Western Region, Nepal.
[8] http://www.cbs.gov.np/nlfs_%20report_demographic_characteristics.php.

United Kingdom Prices Wage data for for craftsmen and farmers (1820-1914) comes from Greg Clark, on the Global Price and Income History Group web site.[9] The wage data for craftsmen is extended to 2010 using Officer (2011). The data for fuel wood prices also comes from Greg Clark in the same data file for the year 1820-1970. For modern energy prices, I combine two different price series: price of town gas for 1820-1900 and the oil price after 1900. The price data on town gas comes from Fouquet (2011). The data there is given in 2000 GBP. I convert it back into nominal GBP using the CPI from Officer (2011). The oil price after 1900 comes from (BP, 2008). Since this data is in US dollars, it is converted into British pounds using data from Officer (2011). The reason for choosing gas and oil rather than coal, is that the types of coal across the UK and over time in the UK vary significantly in fuel content and type. Although oil and town gas can vary along this dimension as well, the variation is much smaller. Notice however that as long as one unit of modern energy costs the same irrespective of source, we expect the price of energy to be equalized across modern fuel types.

GDP and GDP per capita data GDP and GDP per capita are expressed in purchasing power parity terms (1990 Geary-Khamis dollars). Both series for all countries are obtained from Maddison (2007) for the years 1820-2006. This is extended for the 2006-2007 period using *World Development Indicators* (2009) data. Both the emissions data and the GDP per capita data is smoothed using an HP filter, with smoothing parameter $\lambda = 100$.

Emissions OECD data This paper focuses on CO_2 emissions derived from energy use. Since historical energy production and trade is well documented, this allows for the estimation of long run emissions of both types of pollutants using historical energy consumption and production data. Andres et al. (1999) make use of historical energy statistics and estimate fossil fuel CO_2 emissions from 1751 to the present for a wide selection of countries. In this exercise, they obtain historical coal, brown coal, peat, and crude oil production data by nation and year for the period 1751-1950 from Etemad et al. (1991) and fossil fuel trade data over this period from Mitchell(1983, 1992, 1993, 1995).[10] This production and trade data is used to calculate fossil fuel consumption over the 1751-1950 period. Carbon dioxide emissions are imputed following the method first developed by Marland and Rotty (1984) and Boden et al. (1995). The 1950-2007 CO_2 emission estimates reported by Andres et al. (1999) are derived primarily from energy consumption statistics published by the United Nations Nations (2006) using the methods of Marland and Rotty (1984). The data is now maintained and updated by the Carbon Dioxide Information Analysis Center.[11]

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[9] Available at http://gpih.ucdavis.edu/Datafilelist.htm, in the file 'England prices and wages since 13th Century (Clark)'

[10] Mitchell's work tabulates solid and liquid fuel imports and exports by nation and year.

[11] The data is available for download at http://cdiac.ornl.gov/trends/emis/overview.html.

Figure 1(a) plots total CO_2 emissions per dollars of GDP for 26 OECD countries versus each country's GDP per capita, for the years 1820-2007. The countries and the years under consideration are: Canada (1870-2007), Mexico (1900-2007), United States (1870-2007), Japan (1875-2007), Korea, Rep. (1945-2007), Australia (1875-2007), New Zealand (1878-2007), Austria (1870-2007), Belgium (1846-2007), Denmark (1843-2007), Finland (1860-2007), France (1820-2007), Germany (1850-2007), Greece (1921-2007), Hungary (1924-1942; 1946-2007), Ireland (1924-2007), Italy (1861-2007), Netherlands (1846-2007), Norway (1835-2007), Poland (1929-1938; 1950-2007), Portugal (1870-2007), Spain (1850-2007), Sweden (1839-2007), Switzerland (1858-2007), Turkey (1923-2007) and the United Kingdom (1830-2007). The Czech and Slovak Republics, Iceland and Luxembourg were not considered due to the lack of data. Emissions of CO_2 are measured in thousands of metric tons of carbon and the data comes from Andres et al. (1999).

Energy Intensity OECD data Whilst historical data on fossil fuel consumption is well documented (which allows for the construction of carbon emissions data) the consumption of traditional, biomass fuels and other energy sources is not as well documented. I make use of three sources for historical energy data. For the United Kingdom I obtain modern energy data from Fouqet and Pearson (1998) for 1800-1960 and from the Digest of United Kingdom energy statistics for 1970-2009. I obtain the share of biomass energy used by the UK from the Social Ecology Data Base. I combine the two, to construct total energy used by the UK. Second, Gales et al. (2007) "construct the first national series of energy consumption data to include the full set of traditional energy carriers" such as firewood, charcoal, human and animal traction, and stationary (nonelectric) hydropower along with modern sources for: Sweden (1820-2000), Holland (1846-2000), Italy (1861-2000) and Spain (1850-1935; 1940-2000). Third, I use energy consumption data from Wright (2006) and Grubler (2003) for the United States (1800-2001). In their case, energy consumption consists of wood, coal, petroleum, natural gas, hydroelectric power, nuclear electric power and geothermal energy, and is hence not directly comparable to the Gales et al. (2007) and the UK data.

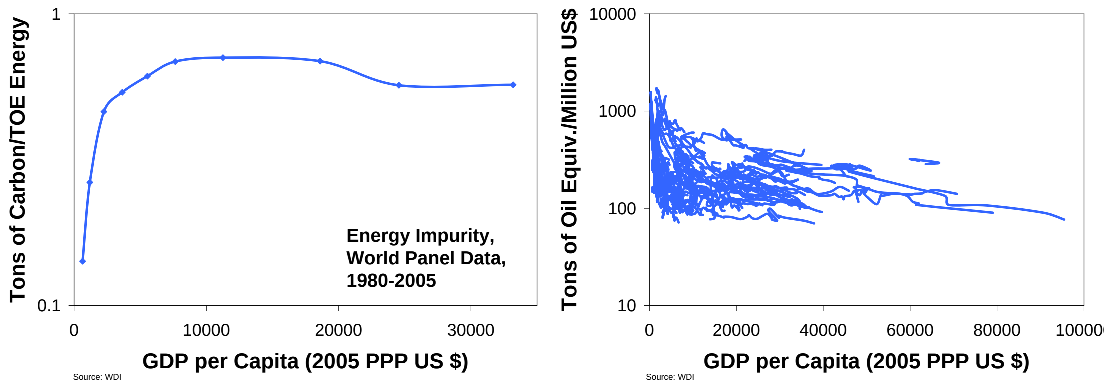
Emissions, Energy and GDP - WDI data For the contemporary panel of modern data I use *World Development Indicators* (2009) for all countries (over two hundred countries) and years available. Energy here is defined as the use of primary energy before transformation to other end-use fuels and is in tons of oil equivalent. Carbon dioxide emissions are those stemming from the burning of fossil fuels and the manufacture of cement. They include carbon dioxide produced during consumption of solid, liquid, and gas fuels and gas flaring. GDP and GDP per capita is in 2005 PPP US dollars.

Pollution Decomposition in World, EU and US Figure 11 presents the result of the growth accounting exercise. Energy impurity in the world, the EU and the US increases with GDP per capita, whilst energy intensity falls. The increase in impurity predominantly takes place at low levels of income, whereas falling energy intensity seems to be a more continuous process. The implication of this is that the increases in emission intensity observed in low income countries is driven predominantly by rising impurity, whereas falling emission intensities in richer countries are driven predominantly by falling energy intensity.

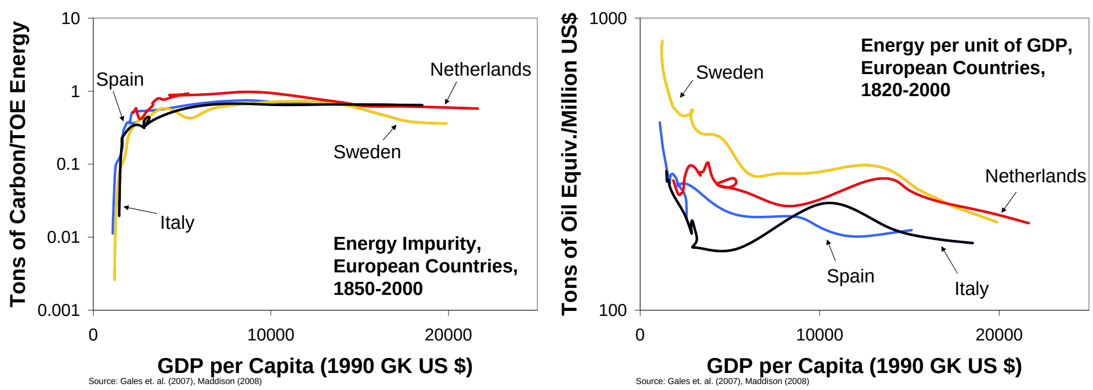
Fuel Mix and Structural Transformation I show evidence that structural transformation - the shift of an economy from agriculture to non-agriculture - is associated with changing fuel mix. I take the share of labor force employed in agriculture as a measure of the progress of structural transformation - countries with a lower shares of agriculture are further along in their structural transformation. For the world panel employment and value added data comes from the *World Development Indicators* (2009). If employment data is unavailable in a given country or year, the observation is dropped in the particular sample.[12] For European countries the sources for agriculture employment data are: Smits and van Zanden (2000) for the Netherlands (1849-1950), de la Escosura (2006) for Spain (1850-1950), Kuznets (1971) for Italy (1866-1891) and Edvinsson (2005) for Sweden (1850-1955), whilst 1956-2000 data for all countries comes from the *OECD* (2009). Employment data for the US comes from Wright (2006) (1800-1890), Kendrick (1961) (1890-1960) and *OECD* (2009) (1960-2000).

Figure 12, shows the extent to which the progress of structural transformation in a country is related to it's fuel mix. From the graphs it is clear that countries at earlier stages of structural transformation, derive a larger share of their energy from renewable combustibles. Countries at later stages, derive a greater share of their energy needs from fossil fuels.

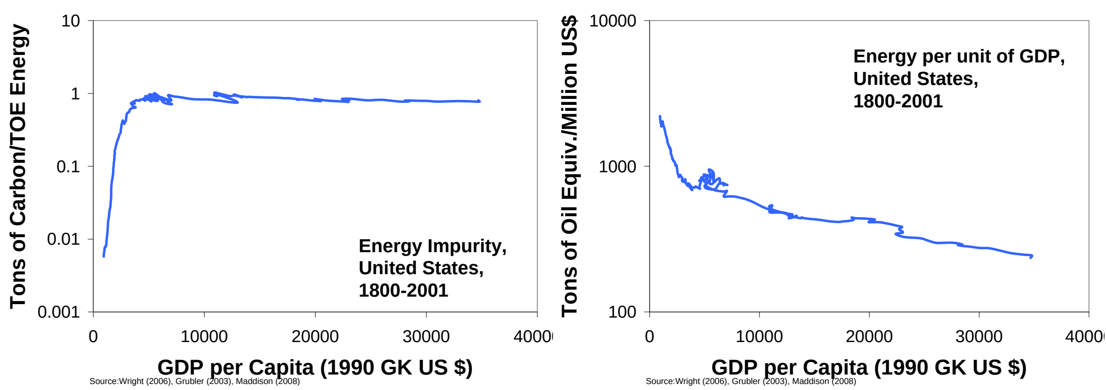
[12] Notice also, that the following countries exhibit very erratic behavior in their employment data: Argentina, Armenia, Bolivia, Colombia, El Salvador, Honduras, Morocco, Paraguay, Peru, Philippines, Uruguay. For example, in 1988 employment in agriculture in Bolivia is 47% of the labor force, in 1989 it is 2% , whilst in 2001 it is 41%. As such, I use data from Timmer and de Vries (2007) for Argentina, Bolivia, Colombia, Peru and the Philippines and I drop the other countries (for which alternative data is unavailable) from the employment panels.



(a) Energy Impurity and Intensity in the World (1960-2006)

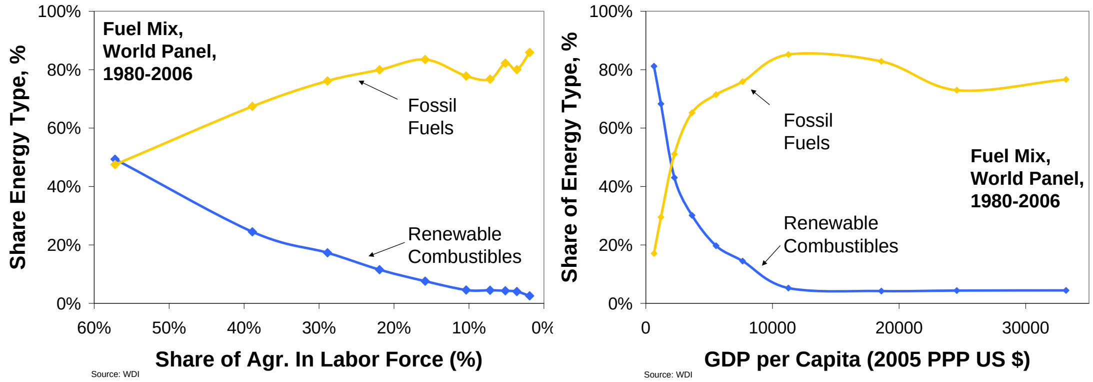


(b) Energy Impurity and Intensity of Selected European Countries, 1820-2000

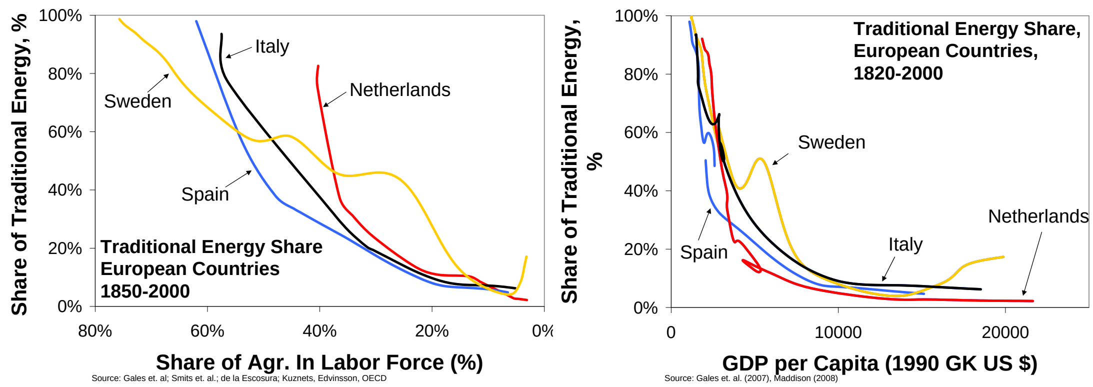


(c) Energy Impurity and Intensity of the US, 1800-2001

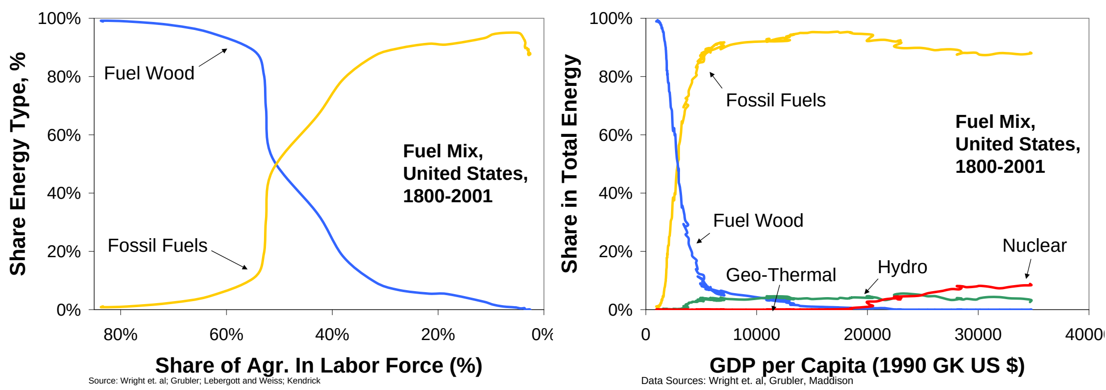
Figure 11: Decomposition of emission intensity into energy impurity and energy intensity terms for the World (1980-2005), selected EU countries (1820-2000) and the US (1800-2001).



(a) World panel (1980-2006)



(b) EU (1820-2000)



(c) US (1800-2001)

Figure 12: Changes in fuel mix versus GDP per capita and agricultural employment share.

	Agr. Value Added Share, 2000 (%)	Emission Intensity Peak (year)	Intensity at Peak (tons of carbon/million USD)	Average Intensity (tons of carbon/million USD)
UK	1.04%	1882	667	441
US	1.23%	1915	757	440
Germany	1.26%	1917	672	381
Belgium	1.38%	1929	584	401
Switzerland	1.61%	1910	140	84
Japan	1.77%	1928	206	140
Sweden	1.99%	1934	230	132
Norway	2.10%	1911	306	144
Austria	2.11%	1909	566	238
Canada	2.28%	1920	613	343
Denmark	2.61%	1969	247	163
Netherlands	2.64%	1932	259	190
Italy	2.80%	1973	151	79
France	2.84%	1928	342	194
Ireland	3.42%	1936	300	238
Finland	3.53%	1974	249	96
Australia	3.56%	1983	274	192
Portugal	3.78%	1910	119	87
Mexico	4.17%	1989	184	115
Spain	4.38%	1977	156	96
Korea, Rep.	4.63%	1979	200	148
Poland	4.96%	1983	575	463
Hungary	5.40%	1964	354	261
Greece	6.59%	1995	195	107
New Zealand	8.92%	1909	229	148
Turkey	11.31%	2000	132	94

Table 3: Table of Evidence

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