Centre for Climate Change Economics and Policy

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October 2016

Centre for Climate Change Economics and Policy Working Paper No. 281

Grantham Research Institute on Climate Change and the Environment Working Paper No. 252

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Tales from the tails: Sector-level carbon intensity distribution

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November 2016

(first version: September 2016)

Abstract

The decomposition of changes in a country's carbon emissions into contributions from changes in the sector-level carbon intensity, value-added share of sectors and level of GDP illustrates their relative importance for observed emissions. Using data from 34 sectors in 39 countries covering 1995-2009, I find that shifting composition of output towards low-carbon sectors and improvements in sector-level carbon intensity were instrumental in constraining emissions in most countries. In contrast, increases in economic activity pushed emissions up in all countries. These observations suggest structural change can be as important as cleaning up carbon intensive sectors and motivate a closer look at high (HCI) and low (LCI) carbon intensity sectors. I document the large cross-country variation in the average carbon intensity of HCI and LCI sets and of individual HCI and LCI sectors. HCI sectors tend to (i) account for a smaller share of employment; (ii) be more capital intensive; and (iii) employ a workforce with a lower average skill level. In the full sample, and in subsamples by level of development, employment declined in HCI sectors and increased in LCI sectors with its composition shifting towards high-skilled workers in both. Capital intensity growth was faster but multifactor productivity growth was slower in HCI sectors. Moreover, the pace of change was typically greater in the LCI sectors of the developing country subsample.

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1 Overview

Reductions in carbon emissions are essential for an effective response to the challenges posed by climate change. In an economy consisting of many sectors which differ in the amount of carbon emitted per unit of value generated, i.e. carbon intensity, these reductions can come from improvements in sectors' carbon intensity or from a reallocation of production away from relatively carbon intensive sectors. In this paper, I use data from 34 sectors in 39 countries over 1995-2009 to provide empirical evidence on the historical importance of these two channels and on the economic characteristics of the sectors which are at the tails of the carbon intensity distribution. The results of this analysis are summarized in five stylized facts.

I find that without the observed improvements in carbon intensity and the favorable changes in the composition of output cumulative emissions would have been substantially higher (fact 1). In most countries, including the USA, both intensity and structure channels contribute to constraining emissions. However, there are examples, most prominent among them China and Russia, where they operate in opposite directions. In particular, emissions in China would have been lower absent changes in the composition of GDP, but higher absent changes in the carbon intensity of sectors. In the case of Russia, the opposite result obtains, namely changes in the structure of the economy restrained emissions while changes in the carbon intensity of sectors increased them.

A novel contribution of the current paper is to systematically evaluate the contribution of changes in carbon intensity and composition of GDP to changes in cumulative emissions for a large group of countries. The dataset also allows a closer look at those sectors the tails of the of the carbon intensity distribution. I propose a rule to construct country-specific HCI and LCI sets, populate them and document the cross-country heterogeneity that exists in carbon intensity (fact 2). I find that HCI sectors tend to account for a smaller share of employment, be more capital intensive and employ a smaller share of high-skilled workers than LCI sectors. In order to capture the broad differences in the level of development, I divide the sample into two groups by the observed level of output per worker in 2009. I find that in advanced countries HCI sectors also employ a greater share of low-skilled workers (fact 3).

These observations are cross-sectional in essence and vary little across the different years in the sample. Adopting a longer term perspective, I show that employment declined in HCI sectors and increased in LCI sectors with its composition shifting towards high-skilled workers in both. Capital intensity growth was faster but multifactor productivity growth was slower in HCI sectors (fact 4). Using the developing and advanced country subsamples, I show that the preceding observations regarding long term changes are valid in both subsamples. Moreover, I find that the pace of change was typically greater in the developing country subsample, especially in the LCI sectors. Put differently, the LCI sectors, particularly in developing countries, are among the most dynamic and can provide a cushion for low-skilled workers becoming unemployed in HCI sectors (fact 5).

Voigt et al (2014) and Schymura and Voigt (2014) are two recent studies which use the same dataset and a similar analytical approach. The focus of Voigt et al (2014) is *energy intensity* changes across countries and sectors using multiplicative index decomposition analysis (IDA). The authors identify substantial heterogeneity across sectors within a country and across countries within a sector, and show that the latter is greater. This is consistent with fact 2 of the current paper. Using an approach that relies on energy use, rather than cumulative emissions which is behind the current paper's fact 1, Voigt et al also find that changes in the composition of GDP and the energy intensity of sectors have been crucial factors driving aggregate intensity changes.

Schymura and Voigt (2014) use a more detailed decomposition which accounts for changes in emissions factors and fuel mix in addition to changes in structure, intensity and activity to extend the analysis of Voigt et al (2014) to *carbon intensity*. They confirm the that the main conclusions of Voigt et al (2014) remain valid. However, neither paper investigates the economic characteristics of high and low intensity sectors, which is a key contribution here.

IDA is a simple, flexible and popular tool often used to describe the relative contribution of changes in the components of an aggregate variable to that variable's evolution over time. In recent years, the aggregate variable of choice has often been greenhouse gas emissions. The survey by Xu and Ang (2013) provides a rich overview of the studies using this method which focus on carbon emissions.[1] In arriving at fact 1, the current paper uses additive log-mean divisia index described in detail in Ang (2005) and its desirable properties are established in Ang (2004).

The data for the current paper's empirical analysis are from the recently compiled WIOD database. By providing consistent sector-level data on several key economic variables as well as emissions and energy use for the world's largest advanced and developing countries over 1995-2009, the database permits empirical analyses which until recently would have been infeasible.[2] In addition to the studies cited above, Xu and Dietzenbacher (2014) and Ferrarini and de Vries (2015) apply structural decomposition analysis to shed light on the effect of international trade as a driver of carbon emissions. In their econometric analysis of the effect of imports of investment and intermediate goods on energy intensity, Hübler and Glas (2014) find that international trade contributes to reducing the North-South gap in energy intensity. Using a different dataset, Douglas and Nishioka (2012) analyse the relationship between carbon intensity and international trade from the opposite direction, i.e. they investigate whether differences in carbon intensities determine the patterns of trade. They find that while carbon intensities differ systematically across countries, they are not a significant source of comparative advantage driving trade flows.

Delivering on the ambitious promises of the Paris Agreement (2015) needs significant policy action in the decades to come. As a matter of accounting identity, it will require the cleaning-up of

[1] Hoekstra and van der Bergh (2003) compares the pros and cons of IDA relative to its main alternative, namely structural decomposition analysis.

[2] See http://www.wiod.org/new_site/published.htm for an overview of the emerging literature which uses WIOD database.

dirty sectors, and the relocation economic activity and productive inputs to cleaner sectors of the economy. The evidence provided in this paper suggests that in most, but not all, countries over the 1995-2009 period there was already much action on both fronts, even without stringent policy intervention. In a sense this is good news because policymakers will need enhance, rather than reverse, pre-existing trends.

The same evidence also provides a cautionary note. With such pre-existing trends, it is difficult to attribute the recent encouraging developments in carbon intensity and composition of GDP to policy action alone. In this context, it is important to note that the period under consideration *precedes* the introduction of stringent climate change policies in most countries, particularly in the USA and China.

In formulating climate change policies it is important to get the policy stringency right and to find the appropriate balance between policy instruments targeting reductions in carbon intensity on the one hand and those that aim to guide labor and capital to cleaner sectors on the other. In light of this paper's evidence this balance need not be the same in advanced and developing countries. It is also essential to account for the interaction between policy in different areas. Specifically, policies affecting the pace and direction of structural change, which often differ at different stages of development process, are likely to have implications for the operation of climate change polices.

The rest of the paper is organized as follows. The dataset is described in more detail in the next section. Section 3 presents empirical evidence on the contribution of changes in carbon intensity and the composition of GDP to a country's aggregate emissions. In section 4, I introduce the rule for defining HCI and LCI sectors, and explore their key characteristics. Sections 5 concludes and provides a brief discussion of these findings for climate change policy. All tables and figures can be found at the end.

2 Data

I rely on the Socio-Economic and Environmental accounts of the WIOD database which are described in Gouma et al (2014), Erumban et al (2012) and Genty et al (2012). Data are available for 35 sectors described in Table 1. The four columns in the table provide the intuitive sector code this paper uses, the code that is in underlying WIOD data, the description of sectors and their corresponding NACE codes. For example, the sector AGR+ corresponds to AtB in WIOD which combines data from sectors with NACE codes 01, 02 and 05, namely Agriculture, Hunting, Forestry and Fishing. The sector TOT is the sum for all 35 sectors, i.e. the entire economy. It includes the sector "Private Households with Employed Persons", but this sector is excluded from the analysis below.[3]

[3] This sector "includes the activities of private households employing all kinds of domestic personnel such as maids, cooks, waiters, valets, butlers, laundresses, gardeners, gatekeepers, stablehands, chauffeurs, caretakers, gov-

Table 2 lists the countries and variables included in the dataset. The 39 countries include all members of the EU, the remaining OECD countries and key emerging markets are in the dataset.[4] In what follows I refer to a country by its name or three letter code which can be found in Table 2. In Socio-Economic Accounts gross output (GO) and all its components (II,VA, COMP, etc.) are typically available for all sectors and cover 1995-2009. Labour input to production is provided in number of workers as well as hours. Moreover, hours worked are subdivided into hours worked by high-, medium- and low-skilled workers based on the education of level workers as described in Erumban et al (2012). Real fixed capital stock (K_GFCF) data for 2008-9 are missing for several countries including the UK.

All values are expressed in nominal national currency units (ncu) in the underlying data files. To allow comparison over time, the analysis in section 3 uses sector-specific price indexes to convert data expressed in nominal ncu to constant ncu. Similarly, to allow comparison across countries, section 4 converts all variables in constant ncu units to constant 1995 US dollars (us$). The exchange rates used are the same ones that WIOD database uses in constructing its world input-output tables. The key data from Environmental Accounts are the total carbon emissions (CO2).

In the analysis below it is sometimes useful to distinguish between advanced and developing countries. For the purposes of this paper, the 'developing' country subsample includes those countries whose economy-wide output per worker in 2009 is less than the median across all countries in the same year. Based on this criterion, the 20 developing countries in the sample are country BGR, BRA, CHN, CYP, CZE, EST, HUN, IDN, IND, LTU, LVA, MEX, MLT, POL, PRT, ROU, RUS, SVK, SVN and TUR.

3 Sector-level carbon intensity and composition of GDP

Carbon intensity of production is defined as

$$ci_{cit} = \frac{e_{cit}}{va_{cit}}$$

where e_{cit} is carbon emissions measured in kilotons and va_{cit} is value-added measured in constant national currency units in country c, sector i and year t. Given this definition a country's aggregate emissions can be written as

erness, baby-sitters and tutors, secretaries, etc." In the case of UK it is tiny. It is excluded because data is not consistently available in all countries.

[4]Luxembourg is dropped from the sample because data are patchy, especially in sectors with high carbon intensity.

$$E_{ct} = \sum_i \left[ci_{cit} \times \frac{va_{cit}}{Y_{ct}} \times Y_{ct} \right] = \sum_i \left[ci_{cit} \times s_{cit} \times Y_{ct} \right]$$

where $Y_{ct} = \sum_i va_{cit}$ is the sum of value-added across sectors (i.e. the country's GDP) and s_{cit} is sector i's share in Y_{ct}. I use index decomposition analysis (IDA) to compute the contribution of changes in each component to changes in observed aggregate emissions $\Delta E_{ct} = E_{ct} - E_{ct-1}$.

Dropping the country subscript for brevity, this results in

$$\Delta E_t = \Delta E_{int,t} + \Delta E_{str,t} + \Delta E_{act,t}$$

where subscripts *int*, *str* and *act* identify the contribution of intensity, structure and activity changes. I use the additive log-mean divisia index (LMDI) method to calculate each component. This decomposition method has desirable properties as described in Ang (2004), and its implementation is straightforward so I omit the formulas here and refer the reader to Ang (2005) for a clear exposition.

The output of the LMDI in the current sample is $\{\Delta E_{int,t}, \Delta E_{str,t}, \Delta E_{act,t}\}$ for each country over 1996-2009 and can be used to construct counterfactual emissions scenarios using different assumptions about the evolution of the components. This section evaluates how different a country's emissions would look under these scenarios.

In particular, I close one of these channels at a time to isolate its effect. For example, in the *no intensity change* (NIC) scenario, the intensity channel is shut down by setting $\Delta E_{int,t} = 0$ in each t but allowing the changes in the structure of the economy (i.e. structure channel) and in the level of economic activity (i.e. activity channel) to contribute to E_t^{NIC} as observed in the data. The following table provides the formulas for calculating aggregate emissions under alternative scenarios.

Counterfactual Scenario	**Formula for computing emissions**
No Intensity Change (NIC)	$E_t^{NIC} = E_0 + \sum_{s=1}^{t} [\Delta E_{str,s} + \Delta E_{act,s}]$
No Structure Change (NSC)	$E_t^{NSC} = E_0 + \sum_{s=1}^{t} [\Delta E_{int,s} + \Delta E_{act,s}]$
No Activity Change (NAC)	$E_t^{NAC} = E_0 + \sum_{s=1}^{t} [\Delta E_{int,s} + \Delta E_{str,s}]$

Take the experiences of the top two emitters in the sample, USA and China, as examples. The two panels of Figure 1 show the observed and counterfactual emissions profiles under the scenarios described above. Also note that while observed emissions in the USA have been broadly constant over this period, Chinese emissions more than doubled.

As a general rule, the further a given counterfactual emissions series is from observed emissions, the more important is the channel which is closed by assumption in its construction. Focusing on the USA first, the deviation of NAC from observed emissions is the largest. Moreover, NAC emissions are everywhere below the observed emissions. This suggests absent changes in the level of economic activity American emissions would have been much lower. Conversely, NSC emissions are greater than observed emissions implying that the structure channel worked to restrain emissions.

The multiple crossings between observed and NIC emissions in the first half of the sample make similarly unambiguous statements impossible regarding the contribution of the intensity channel. Over this period the NIC series deviated relatively little from observed emissions. However, after the early 2000s NIC emissions are progressively greater than those observed so similar to the structure channel, the intensity channel tended to restrain American emissions more recently.[5]

For China, changes in the level of the economic activity also constituted the dominant channel for the observed increases in emissions. However, the evolution of NIC and NSC series are quite different from the USA. The structure of the economy unambiguously shifted towards relatively carbon intensive sectors. Without such changes emissions would have been lower as indicated by the NSC series. Conversely, the intensity channel constrained emissions in China. In 2009 Chinese emissions would have been about 30% higher if the intensity channel did not operate.

The USA and China are two important emitters so the detailed discussion of their individual experiences is justified. Yet there are 37 other countries in the sample and developing a graphical analysis country by country is cumbersome. Moreover, as the crossings between NIC and observed series in the American case illustrate, the net contribution of a given component may change qualitatively from one year to another. Against this background, another metric for comparing the contribution of intensity, structure and activity channels would be useful.

In the climate change context such a metric, namely cumulative emissions, is readily available because carbon dioxide is extremely persistent in the atmosphere. In other words, if a particular channel adds a million tonne of carbon emissions in a given year and reduces them by the same amount in the following year, its climate change impact over the two years is approximately nil. Put more starkly, it is the the cumulative emissions of carbon that determine the climate change impact.[6]

[5] Based on direct econometric estimates of the size of structure and intensity effects, albeit for six non-CO2 pollutants, Levinson (2015) finds the former accounted for most of the decline in aggregate emissions from the US manufacturing sector.

[6] See, for example, Allen (2016).

To operationalize this idea in the current context, I define the *relative* cumulative emissions associated with scenario $S \in \{NIC, NSC, NAC\}$ as

$$rce^S = \frac{\sum_t E_t^S}{\sum_t E_t} - 1.$$

If $rce^S > 0$, then the cumulative emissions under S are greater than those observed, implying their climate change impact would have been greater as well. Note also that it is possible to interpret the magnitude of rce_c^S across scnearios. Using the USA as an example once again, $rce_{USA}^{NAC} = -0.258$ meaning cumulative emissions would have been almost 26% lower under NAC scenario. The shift towards less carbon intensive sectors implied that $rce_{USA}^{NSC} = 0.148$, i.e. shutting down the structure channel would have implied 15% higher cumulative emissions. Similarly, $rce_{USA}^{NIC} = 0.054$ so that the intensity channel also constrained cumulative emissions over the sample period.

For China, $rce_{CHN}^{NAC} = -0.534$, $rce_{CHN}^{NSC} = -0.101$ and $rce_{CHN}^{NIC} = 0.338$ which can be compared to the USA. Specifically, in China the activity channel was about twice as important in determining cumulative emissions. In contrast to the USA, the composition of the Chinese economy's output shifted towards more carbon intensive sectors. Finally, the contribution of the intensity channel was much larger than in the USA. From a global perspective it is important to note that over the sample period the cumulative American emissions were about 20% greater than in China so the overall climate change impact of the various components need to be adjusted for this difference.

Table 3 provides the rce_c^S for all countries, indicating developing countries with an asterisk. Average values for rce_c^S under each scenario are given at the bottom of the table for the full sample and the subsamples by level of development. The table ranks countries in increasing order of rce_c^{NIC} and highlights $rce_c^S < 0$ in each case. There are two important patterns in the table.

First, rce_c^{NAC} is negative for every country in the sample. That is, if the activity channel were closed emissions would have been lower. Moreover, the activity activity channel was quantitatively the most important driver of carbon emissions in a large majority of countries with notable exceptions in Taiwan and Germany as well as in a number of Eastern European countries which experienced economic upheaval following the collapse of the Soviet Union.

Second, in 25 of the 39 countries both the intensity and structure channels constrained the emissions increases implied by the activity channel. This pattern is apparent in Figure 2 which provides a visual summary of the information in the first two columns of Table 3 by plotting rce_c^{NIC} versus rce_c^{NSC}. Not surprisingly, several Eastern European countries feature the largest $rce_c^{NIC} > 0$ and/or $rce_c^{NSC} > 0$. The positive quadrant of Figure 2 also contains most of the advanced countries in the sample.

Among these, Ireland, Finland and Sweden, are the only three advanced countries which simultaneously have rce_c^{NIC}, rce_c^{NSC} and $|rce_c^{NAC}|$ greater than the respective averages for these statistics in the advanced country subsample. That is, the intensity and structure channels constrained emissions in these economies more than the average advanced country. At the same time, these countries experienced strong growth which pushed emissions up through the activity channel. It is interesting to note, but not read too much into, the fact that Finland and Sweden are the first two countries to introduce an explicit carbon tax.

There are some important exceptions to the broad pattern of positive rce_c^{NIC} and rce_c^{NSC}. For example in Figure 2, the pattern $rce_c^{NIC} < 0$ and $rce_c^{NSC} > 0$ is observed in seven countries including Russia, and the opposite pattern $rce_c^{NIC} > 0$ and $rce_c^{NSC} < 0$ prevailed in five countries, which includes, most prominently, China. Finally, both cumulative emissions statistics are negative in Indonesia and Brazil themselves large emitting developing countries. In these two countries, changes in the carbon intensities of sectors and composition of GDP complemented the activity channel in increasing cumulative emissions.

The figure also highlights advanced (blue) and developing (red) countries in the sample.[7] The observation from Taiwan notwithstanding, developing countries tend to be overrepresented in both tails of the distributions of rce_c^{NIC} and rce_c^{NSC}. This suggests structural and technological changes were larger in developing countries and have not always contributed towards emissions reductions. The preceding observations are summarized in the first stylized fact of this paper.

Fact 1. *Intensity and structure channels both constrained emissions in most countries. In contrast, the activity channel increased emissions for all countries in the sample. Developing countries were overrepresented in the tails of the cross-country distributions for the cumulative effects of intensity and structure channels.*

In passing, observe that in Figure 2 there appears to be a negative, albeit noisy, relationship between rce_c^{NIC} and rce_c^{NSC} suggesting a trade-off between the two channels. The correlation coefficient, based on the full sample, is -0.479 and has a p-vlaue of 0.002. However, with only 39 observations and in the presence of some large outliers this can statistic can be misleading. Excluding the countries with the largest $|rce_c^{NIC}|$ and $|rce_c^{NSC}|$, i.e. Bulgaria, Estonia and Taiwan, the correlation coefficient is -0.174 but no longer significant with a p-value of 0.318.

Two aspects of Fact 1 are novel. First, it introduces rce^S as a new metric to compare the contribution of changes in intensity, structure and activity levels. Second, based on this metric, it identifies economically interesting regularities in the sign, magnitude and distribution of the intensity and structure channels in the cross-country panel. This motivates a closer look at the sectors which have particularly high and low carbon intensity and is provided in the next section.

[7] Recall that the 'developing' country definition used in this paper is non-standard and described in Section 2.

4 Tales from the tails: High and low carbon intensity sectors

I start by proposing a flexible rule to identify the HCI and LCI sectors

1. Order sectors in decreasing order of ci_{cit} in each country and year, so the sector with the highest carbon intensity is ranked first, the sector with second highest is ranked second etc.

2. Calculate the average rank of each sector over all years and order sectors in increasing order of average rank for each country.

3. Define the set containing the top (bottom) five sectors as the HCI_c (LCI_c) set.

A number of points are worth highlighting. First, the sets HCI_c and LCI_c are country-specific but always contain five sectors because the rule relies on within-country ordering of carbon-intensity. By implication, the remaining twenty-four sectors have intermediate carbon intensity. Below I show that these intermediate sectors typically employ most of a country's productive inputs and generate most of its value-added. Second, HCI_c and LCI_c are time-invariant themselves even though the rule uses information from all years in populating them. Third, it is possible to create *global* HCI_G and LCI_G sets which include sectors that are members of HCI_c and LCI_c in at least k countries. In other words, as k becomes larger, HCI_G and LCI_G shrink.

Table 4 lists the sectors in HCI_c and LCI_c for a select group of countries: two advanced European, two advanced non-European and two large developing countries. The average carbon intensity levels in 2009 are also provided. Finally, the table lists the members of HCI_G and LCI_G sectors for $k = 5$. For each sector in the global lists, the figures in the parenthesis indicate the number of countries in which the sector is in HCI_c and LCI_c. For example, even though CHEM is *not* an HCI sector in any of the six countries in the table, it is identified as an HCI sector in nine countries in the sample.

In the top panel of Table 4, the HCI sectors are broadly similar across countries: utilities (PWR+), manufacture of non-metallic minerals (MINnm), refined fuels (RFUEL) and metals (MINm) as well as domestic air (TRAair) and water transport (TRAwat). This is true for those six countries considered in detail and more generally for the 39 countries in the sample as demonstrated by the nine HCI_G sectors. In the lower panel, financial (FIN), real estate (REST), and telecommunications services (TCOM) sectors are most frequently in the LCI_G. However, their frequencies are lower than those for the HCI sectors and there are eleven sectors in LCI_G sectors. These suggest LCI sectors are somewhat more diverse.

The average carbon intensity levels in HCI_c and LCI_c show much variation across countries despite the fact that the members of these sets are similar across countries. For example, the HCI sectors of France emit less than 20% of what the HCI sectors in China do to produce a unit of economic value. This is partly due to the composition of the respective HCI_c. RFUEL tops the French set while it is not even in the Chinese set. More importantly, individual sectors are heterogeneous themselves. In France a large portion of electricity is generated in nuclear power stations whose carbon emissions are negligible. In contrast, Chinese power generation is extremely coal, and therefore carbon, intensive. Similar variation, albeit around much lower average carbon intensity levels, exists across LCI_c.

Table 4 is organized around the ranking of sectors by ci_{cit}. Accordingly, it does not provide information on the magnitude of an individual sector's carbon intensity or how it compares to others. I explore this in Figures 3 and 4 which show the 2009 carbon intensity of production for the three most common sectors in HCI_G and LCI_G, which are {PWR+, MINnm, RFUEL} and {REST, FIN, TCOM}, respectively.

In Figure 3 the countries are sorted in decreasing order of carbon intensity in their PWR+ sector. As in Figure 2 advanced and developing countries are identified using blue and red country names along the horizontal axis. For example, the most carbon intensive PWR+ sector is in Estonia and the least intensive one in Brazil, both developing countries. The ratio between the two is 162. It is difficult to conclude whether this figure is too high. Estonia is a small country but appears to be a large outlier since the carbon intensity level of PWR+ is almost twice as large as the runner up country. It also relies heavily on fossil fuels, and mostly coal among them, for generating about 90% of its power. Conversely in Brazil, which has important hydroelectric potential, only about 20% of power is generated using fossil fuels with natural gas most significant in the mix. Indeed, in Table 4 PWR+ is not even an HCI sector in Brazil.

Putting these extremes aside there remains substantial variation in the carbon intensity of PWR+ sector even among seemingly similar countries like the UK and the USA where the carbon intensity of the latter is about three times greater that of the former. In 2009, these two advanced economies have broadly similar fossil fuel shares in their power generation mix. Specifically, the UK's fossil fuel share in power generation is 72% of which 45% is natural gas, and in the USA the corresponding statistics are 66% and 23%. That is, the UK was more reliant on fossil fuels but used less of the more carbon intensive fossil fuel, coal. Even allowing for the fact that per unit of energy input carbon emissions from coal are twice as much as those from natural gas, much difference remains to be explained in the relative carbon intensities of PWR+.[8]

The top panel of Table 5 which provides the summary statistics for ci_{cit} shows that the carbon intensity in these three HCI sectors have different means and exhibit large variations across countries. Based on the the unweighted mean values reported in the table PWR+ is by far the dirtiest sector per unit of economic value generated. With different mean values, the coefficient of variation

[8]There may be several reasons for these differences: technology differences induced in part by fuel input quality and price differences, power price differences, exchange rate misalignment, phase of the economic cycle, policy differences, market structure etc. Also note that the fracking revolution in the US has significantly altered the coal-natural gas mix. In 2013, the fossil fuel share in US power generation is 68% of which 40% is natural gas.

is a better statistic for comparing variability. By this metric RFUEL is the most variable sector and MINnm is the least variable one.[9]

Analogous information on the LCI sectors, which come from the opposite tail of the carbon intensity distribution, are shown in Figure 4 and the lower panel of Table 5. The figure sorts the countries in decreasing order of carbon intensity in the REST sector. An important difference from the previous figure is the scale of the vertical axis making it difficult to interpret the levels and ratios of variables so close to zero. For example, the ratio between the most and least carbon intensive REST sectors in the sample, those in Russia and Austria respectively, is 680. However, the magnitudes of both the numerator and the denominator in this ratio are negligible compared to the carbon intensities of HCI sectors. Moreover, as discussed in more detail below, the data from the REST sector may not be as informative or reliable as data from other sectors.

A common feature of Figures 3 and 4 is that developing countries tend to cluster in the left end of both figures. In other words, the carbon intensity of HCI or LCI sectors are on average higher in developing countries. This can be due to their production and emissions abatement technologies being less efficient than in advanced countries. It could also be the result of weaker regulation of carbon emissions, or in some cases outright subsidies supporting the use of fossil fuels as an energy source. Whatever the underlying cause, an effective response to the climate change challenge necessitates substantial change in developing countries especially in their HCI sectors. Some evidence that this is already happening is presented below. The paper's second stylized fact summarizes these observations.

Fact 2. *There is substantial cross-country variation in the average carbon intensity of HCI and LCI sets, and of individual HCI and LCI sectors. The carbon intensity of a given HCI or LCI sector tends to be higher in developing countries.*

Such variation is to be expected due to the heterogeneity within HCI_c and LCI_c as well as within sectors. However, it is not clear whether there are systematic differences along other relevant characteristics of these sectors as carbon intensity changes. For example, do the shares of a country's productive inputs, namely its workers, physical and human capital, vary by carbon intensity? If so, one is most likely to find evidence of this in the HCI and LCI sectors.

Table 6 uses the USA as an example to shed light on this question. In 2009, HCI sectors of the US accounted for just over 1% of aggregate employment, used almost 5% of the country's capital stock. These figures mask much heterogeneity across HCI sectors however. PWR+ is the most capital intensive, i.e. each worker has much more capital to produce with. Similarly, there is much heterogeneity in labour productivity as measured by output per worker, with the RFUEL sector workers generating the greatest value per worker.

[9] Estonia has a disproportionate influence in the statistics for PWR+ and RFUEL because it is a large outlier. Excluding the observations from Estonia the mean and standard deviation in PWR+ declines to 13.939 and 13.423, and in RFUEL the analogous figures are 9.297 and 11.242.

The LCI sectors, on the other hand, employed more than 11% of the country's workers and used 53% of its capital stock. The latter figure is so high because the economy's housing capital is included in the REST sector by accounting convention. This is clearly visible in the value of capital per worker being extremely high in REST. REST sector is *special* for another reason. Its value-added includes the imputed value of services from owner-occupied houses, making its labour productivity appear exceptionally high. This accounting convention also makes the carbon intensity figures hard to interpret and sensitive to imputation methods. Indeed, The sector is such an outlier that excluding REST from LCI_c average renders the group much less capital intensive and productive.[10]

Table 6 shows that HCI sectors employ a smaller share of the US workers and use more capital intensive technologies. Table 7 provides more detail on the skill composition of the workforce employed in these sectors. Specifically, it reports the share of hours supplied by high-, medium- and low-skilled workers for each sector in HCI_{USA} and LCI_{USA}. The most striking feature of Table 7 is the relatively small share of high-skilled workers and the relatively high of share medium-skilled workers in the HCI sectors. The observation is valid in relation to the USA economy as a whole, and relative to the LCI sectors regardless of whether REST is included in the averages.

Table 8 extends the analysis to the full sample of 39 advanced and developing countries. It reports the correlation of $\ln(ci_{ci})$ and variables above using different samples in 2007. The first column uses a sample which includes all sectors in HCI_c and LCI_c and reports results for advanced and developing countries separately. In light of the influence REST sector can have on results, the second column of the table drops REST from the sample if it happens to be an LCI sector. The log transformation of carbon intensity is to minimize the influence of the outliers and the results are similar, albeit more noisy, without it. Moreover, data from 2007, rather than 2009, are used to maximize the geographic coverage of the sample because capital stock data is missing for several countries in 2008-9. The resulting cross-section patterns reported below are not sensitive to the choice of the year.

The table makes it clear that the negative relationship between a sector's carbon intensity and its share in aggregate employment is statistically significant regardless of the sample. Sectors with high carbon intensity tend to account for a smaller share of employment in a country. The correlation is somewhat stronger, i.e. more negative, when REST is excluded. In other words, the exclusion of REST does have some quantitative but no qualitative implications for the correlation coefficient between $ln(ci_{ci})$ and $emp_{ci}/\sum_i emp_{ci}$.

Whether or not one uses the restricted samples has quantitative *and* qualitative implications for the correlation statistics involving the capital stock and labor productivity. This is to be expected given the evidence from the USA discussed above. REST is an LCI sector in a majority of countries

[10] Below I take account of the special status of REST by reporting statistics with and without this sector.

and a country's housing stock as well as the income derived from it appears in this sector.[11] Once this sector is excluded, the negative and significant correlation coefficient between sectors' carbon intensity and their share of capital stock weakens in advanced countries and becomes insignificant in developing countries. In other words, a larger share of an advanced country's non-housing capital stock tend to be in LCI than HCI sectors, whereas a similar relationship is not observed in developing countries.

At the same time, the relationship between carbon intensity and capital intensity is positive and significant, and much more so when REST is excluded.[12] This suggests that workers in HCI sectors have much more capital to work with relative to their counterparts in LCI sectors. This positive correlation may appear inconsistent with the observed relationship between labor productivity and carbon intensity. After all, one would expect the more capital a worker has to work with the more output s/he can generate but the insignificant and negative correlation coefficients in the advanced and developing countries suggest otherwise.

This is due to determinants of labour productivity other than capital per worker, e.g. multifactor productivity and human capital per worker. Calculating internationally comparable multifactor productivity *levels* of sectors is beyond the scope of this paper.[13] However, the dataset contains indicators for human capital deployed in each sector, namely the number of hours supplied by skill level.

Table 8 shows that there is a negative correlation between carbon intensity and share of hours provided by high-skilled workers. In other words, relatively more hours are provided by high-skilled workers in the LCI sectors in both advanced and developing countries. Conversely, a grater share of the hours are provided by low-skilled workers in HCI sectors of advanced countries. These patterns are consistent with the average skill level of the workforce being greater in the LCI sectors, particularly in advanced countries. Fact 3 summarizes the preceding discussion.

Fact 3. *HCI sectors in advanced and developing countries tend to (i) account for a smaller share of employment; (ii) be more capital intensive; and (iii) employ a workforce with a lower average skill level.*

Next I focus on the long run changes in HCI and LCI sectors. Specifically, I calculate growth rates of employment, total number of hours supplied at each skill level for each sector, capital and capital per worker. To capture long term productivity trends, I report average growth rates of output per worker and multifactor productivity. The latter indicator, denoted mfp_{cit}, is computed based on gross value-added using to the procedure outlined in OECD (2001).

[11]Italy has exceptionally high (low) share of the capital stock in COMMser (REST) relative to other countries in the sample suggesting its housing stock is included in COMMser. A similar but less extreme case is Korea. Excluding these country-sectors does not alter the results.

[12]The same relationship is documented by Cole and Elliott (2003) using country-level data for four pollutants including CO2.

[13]Rate of change of multifactor productivity is much easier to incorporate into the analysis. See below for details.

The growth rate of these variables are computed over several years using all available data. In majority of the countries and sectors this corresponds to 1995-2009. Specifically, for variable

$$x_t \in \left\{ emp, hrs, hrs^{HS}, hrs^{MS}, hrs^{LS}, cap, \frac{cap}{emp}, mfp, \frac{va}{emp} \right\}$$

where $t = 1, 2, ..., \bar{t}$ the following simple specification is estimated

$$log(x_{cit}) = \theta_{ci} + g(x_{ci})t + \varepsilon_{cit}$$

I interpret the point estimate of $g(x_{ci})$ as the average growth rate per year.

Table 9 reports the unweighted mean $g(x_{ci})$ in HCI and LCI sectors as well as the t-test results of the null hypothesis that the two growth rates are equal against the two-sided alternative that they are not. The economy-wide growth rate of each variable is also provided for reference.

The table shows that on average HCI sector employment (hours) in the 39 countries of the sample declined at 0.6% (0.8%) per year, which contrasts with the 1.7% (1.6%) growth in the LCI sectors. The share of high-skilled workers in both HCI and LCI sectors rose over time since $g(hrs^{HS})$ is greater than $g(hrs^{MS})$ and $g(hrs^{LS})$ in each case. Against the backdrop of declining employment and total hours in HCI sectors, this implies that the increase in hours supplied by high skilled workers did not match the decline in the hours supplied by low-skilled workers.

In contrast, LCI sector hours supplied by high- and medium-skilled workers increased and those by low-skilled workers declined. In addition, the table also shows that $g(cap)$ was positive in both HCI and LCI sectors and greater in the latter. Taken together, these trends imply that capital per worker increased at a faster rate in HCI sectors and in the economy as a whole.

One might expect the faster growth in capital intensity to be reflected in higher labour productivity growth in HCI sectors but there is no evidence for this in the sample. This is likely due to significantly higher multifactor productivity growth in LCI sectors. As highlighted above, changes in labour productivity can be driven by changes in the composition of the workforce, capital intensity or multifactor productivity. In both HCI and LCI sectors the skill level of the average worker has increased. However, in HCI sectors growth in capital intensity was high and growth in the multifactor productivity was moderate. Conversely in LCI sectors, multifactor productivity growth was strong but capital intensity growth was moderate. These changes are consistent with output per worker growing at approximately the same rate in HCI and LCI sectors. Fact 6 summarizes these observations.

Fact 4. *Labour supply declined in HCI sectors and increased in LCI sectors with its composition shifting towards high-skilled workers in both. Capital intensity growth was faster in HCI sectors but their multifactor productivity growth was lower.*

Table 10 provides a breakdown of the results in Table 9 by level of development. Note that the table also provides t-test results for three distinct hypotheses. The results reported in column (I) are analogous to those in Table 9. They indicate whether the difference between the growth rates of a given variable across HCI and LCI sectors is significant in developing and advanced country subsamples. Column (II), on the other hand, tests if the difference between the growth rates of a variable across advanced and developing countries in the HCI sector subsample is significant. Column (III) does the same for LCI sector subsample. The alternative hypothesis in all cases is two sided and significance level of the test is 10%.

Table 10 conveys three messages. First, it shows that Fact 4 holds in the advanced and developing country subsamples. The only exception is capital intensity growth rates in advanced countries which are 3.3% in HCI sectors and 2.5% in the LCI sectors. However, this difference is not statistically significant at 10% with a two-sided test.[14]

Second, for all growing, as opposed to declining variables, in Table 10, the growth rates in developing countries is greater than or equal to those in advanced countries in the statistical sense. This observation is consistent with the notion that developing countries are catching up with, or at least not falling behind, advanced countries along these dimensions.

Third, for the declining variables in Table 10, the difference between advanced and developing countries is not statistically significant for $g(emp)$, $g(hrs)$, $g(hrs^{MS})$ and $g(hrs^{LS})$ suggesting they evolved similarly over time in the two subsamples. However, it is significant for hours supplied by low-skilled workers in LCI sectors which declined at 1.8% in advanced countries but was constant in developing countries. Given that the HCI and aggregate hours per worker at this skill level declined over the sample period, the LCI sectors likely acted as a cushion for low-skilled workers in developing countries. Such cushion may be particularly valuable because upgrading worker skills is costly and slow, and the social safety net providing for those who cannot do so is likely weak in developing countries. These observations are summarized in Fact 5.

Fact 5. *In developing countries the average growth rates of factor inputs and productivity indicators were greater than or equal to those in advanced countries. Moreover, the hours supplied by low-skilled workers in LCI sectors did not decline in developing countries.*

[14]The difference is significant at 10% with a one-sided test.

5 Conclusions and policy relevance

Emissions reductions consistent with the goals of the Paris Agreement (2015) can be achieved through reductions in economic activity, declines in its carbon intensity or changes in its its structure. The former is not a viable option in many, especially developing, countries. In fact, continued economic growth is essential to meet several key Sustainable Development Goals adopted by the UN in 2015, and implies that favorable changes due to *intensity* and *structure* of activity must be even larger.

Applying index decomposition analysis to cross-country data covering 1995-2009 and using relative cumulative emissions as a metric, Fact 1 of this paper documents that economic growth indeed pushed emissions up in all countries. At the same time, at least one, and often both, of the *intensity* and *structure* channels operated so as to constrain emissions in a vast majority of countries. This motivates the need for a better understanding of the characteristics of the sectors which are at the tails of the sector-level carbon intensity distribution.

Fact 2 demonstrates the enormous heterogeneity in the carbon intensity of HCI and LCI sectors, and the tendency that sector carbon intensities are higher in developing countries. This suggests there may be lessons to learn from high achievers. Some of the heterogeneity is clearly due to exogenous factors such as geography and resource endowments that may be beyond the reach of policy. However, differences in technology, regulation, market structure, international trade and industrial policies are also likely drivers of the heterogeneity and may offer insights regarding how carbon intensity of HCI sectors can be improved in the low achievers.

Adopting a factor input perspective, Fact 3 shows that HCI sectors tend to account for a relatively small share of employment, and are capital intensive. The skill level of an average HCI worker is lower than her/his LCI counterpart. Over the sample period, Fact 4 documents that employment in HCI sectors declined and the skill level of the average worker employed in this sector increased. This contrasts with LCI sectors where both employment and the skill level of the average worker have increased. In addition, as shown in Fact 5 LCI sectors, especially in developing countries, are the more dynamic sectors of the economy exhibiting greater multifactor productivity growth than both the HCI sectors and the aggregate economy.

In part, these changes are a reflection of the structural transformation away from agriculture and manufacturing, and towards services. It is therefore not surprising that the pace of change is greater in developing countries. Moreover, the coverage of the sample is such that climate change policies are unlikely to have been the main driver of the patterns documented in Facts 3-5 in all but a few northern European countries. This is good news in the sense that policy needs to augment rather than reverse the underlying fundamental transformation. However, it does make the attribution of any additional change to the effect of policies difficult, an issue which may prove tricky politically and economically when evaluating the effectiveness and unintended consequences of climate change policies.

Disentangling the effects of climate change policies and the underlying structural transformation will be all the more difficult as the transformation itself is often a target of government policy. As a consequence, climate change and, say, industrial policies can be coordinated to ensure they do not work at cross purposes. Poorly designed policies which aim to slow down or reverse deindustrialization may simultaneously undermine climate change policies. Conversely, improvements in labour market flexibility and increased opportunities for (re)training workers are likely to reduce the adverse impact of climate change policies which may be concentrated geographically and on workers in HCI sectors.

The appropriate balance between polices targeting the intensity and structure channels is another important consideration. Subsidies to R&D on carbon capture and storage technologies may be considered as an example of the former. Feed-in-tariff programs for renewable energy production or a ban on new coal-fired electricity generation aim to reduce emissions through the structure channel, albeit within the crucial PWR+ sector. Ultimately, the right balance for the portfolio of policies is likely to depend on a country's specific circumstances including its level of development, energy endowments, existing capital stock etc.

The adoption of a comprehensive carbon price is often advocated by economists as an effective climate change policy tool. This instrument has an impact on both the intensity and structure channels. By making it costly to emit carbon it compels emitters to find ways to substitute away from carbon in their production processes, and thereby reduce carbon intensity. By raising the relative price of goods and services produced by sectors with high carbon intensity, it can reduce the share of these sectors in GDP.

In this respect, the experiences of Finland and Sweden, which implemented explicit carbon prices prior to the period considered in this paper, are illustrative. In both countries, the structure of the economy shifted towards low carbon sectors and the carbon intensity of sectors declined, and did so more than the average observed in advanced countries. Simultaneously, these countries recorded robust economic growth. Although far from conclusive, the evidence from Finland and Sweden is encouraging.

Moreover, a carbon price is a technology-neutral instrument, and has the potential to raise revenue. The revenue can in principle be used to (re)train workers, particularly low-skilled workers, in HCI sectors which are likely to be disproportionately affected. Alternatively, it can fund subsidies designed to correct innovation and learning-by-doing externalities for low carbon technologies. That said, a few examples notwithstanding, a comprehensive and sufficiently high carbon price has proven politically difficult to implement. In addition, Coady et al (2015) and OECD (2015) show that many countries have a long way to go in removing fossil fuel subsidies first before imposing a price on carbon.

The choice of the policy instrument to achieve a given emissions reduction goal is a crucial dimension of the problem because instruments differ in their cost effectiveness. In addition, advanced and developing countries also need to decide the stringency of their climate policy interventions. Indeed, the ambitious goals of the Paris Agreement require that future policy is much more stringent than it has so far been. To optimize their net benefits, the choice and calibration of climate change policies should be informed by a clear understanding of the characteristics of, and the trends in, sectors with particularly high and low carbon intensity. In particular, the impacts on HCI sectors will be substantial because their carbon intensity and/or share in GDP must decline with ramifications for the factor inputs deployed there. The evidence presented here suggests that LCI sectors are more dynamic, particularly in developing countries, and have the potential to cushion the impact on HCI sectors.

Acknowledgements

This research was supported by the ESRC Centre for Climate Change Economics and Policy, which is funded by the UK Economic and Social Research Council. I am grateful for many helpful conversations with Alex Bowen. Kaboo Leung provided excellent assistance with compiling the data. The usual disclaimers apply.

References

Allen, Myles R. "Drivers of peak warming in a consumption-maximizing world." Nature Climate Change (2016).

Ang, Beng W. "Decomposition analysis for policymaking in energy: which is the preferred method?." Energy Policy 32.9 (2004): 1131-1139.

Ang, Beng W. "The LMDI approach to decomposition analysis: a practical guide." Energy policy 33.7 (2005): 867-871.

Coady, David, et al. "How large are global energy subsidies?", IMF Working Paper WP/15/105 (2015)

Cole, Matthew A., and Robert JR Elliott. "Determining the trade–environment composition effect: the role of capital, labor and environmental regulations." Journal of Environmental Economics and Management 46.3 (2003): 363-383.

Douglas, Stratford, and Shuichiro Nishioka. "International differences in emissions intensity and emissions content of global trade." Journal of Development Economics 99.2 (2012): 415-427.

Erumban, Abdul Azeez, et al. “WIOD Socio-Economic Accounts (SEA): Sources and methods.” WIOD Technical report (2012). Available here.

Ferrarini, Benno, and Gaaitzen J. De Vries. "What Accounts for the Growth of Carbon Dioxide Emissions in Advanced and Emerging Economies? The Role of Consumption, Technology, and Global Supply Chain Trade." Asian Development Bank Economics Working Paper Series 458 (2015).

Genty , Aurelien, et al. “Final database of environmental satellite accounts: Technical report on their compilation.” WIOD Technical report (2012). Available here.

Gouma, Reitze, et al. “Employment and compensation in the WIOD Socio-Economic Accounts (SEA): Revisions for 2008/2009 and new data for 2010/2011.” WIOD Technical report (2012). Available here.

Hübler, Michael, and Alexander Glas. “The Energy–Bias of North–South Technology Spillovers: A Global, Bilateral, Bisectoral Trade Analysis.” Environmental and Resource Economics 58.1 (2014): 59-89.

Hoekstra, Rutger, and Jeroen CJM Van den Bergh. “Comparing structural decomposition analysis and index.” Energy economics 25.1 (2003): 39-64.

Levinson, Arik. "A Direct Estimate of the Technique Effect: Changes in the Pollution Intensity of US Manufacturing, 1990–2008." Journal of the Association of Environmental and Resource Economists 2.1 (2015): 43-56.

OECD. “Measuring productivity: Measurement of aggregate and industry-level productivity growth.” OECD Publishing (2001).

OECD “OECD Companion to the Inventory of Support Measures for Fossil Fuels 2015.” OECD Publishing (2015). Available here.

Paris Agreement (2015). Available here.

Schymura, Michael and Voigt, Sebastian. “What Drives Changes in Carbon Emissions? An Index Decomposition Approach for 40 Countries.” ZEW - Centre for European Economic Research Discussion Paper No. 14-038 (2014). Available here.

Voigt, Sebastian, et al. "Energy intensity developments in 40 major economies: Structural change or technology improvement?." Energy Economics 41 (2014): 47-62.

Xu, X. Y., and Beng W. Ang. "Index decomposition analysis applied to CO2 emission studies." Ecological Economics 93 (2013): 313-329.

Xu, Yan, and Erik Dietzenbacher. “A structural decomposition analysis of the emissions embodied in trade.” Ecological Economics 101 (2014): 10-20.

Tables and Figures

Table 1: Sectors in WIOD database

This Paper	**WIOD**	**Sectors**	**NACE**
AGR+	AtB	Agriculture, Hunting, Forestry and Fishing	01, 02, 05
MIN+	C	Mining and Quarrying	10-14
FD+	15t16	Food, Beverages and Tobacco	15, 16
TEX	17t18	Textiles and Textile Products	17, 18
LEA	19	Leather, Leather and Footwear	19
WD+	20	Wood and Products of Wood and Cork	20
PPR+	21t22	Pulp, Paper, Paper , Printing and Publishing	21, 22
RFUEL	23	Coke, Refined Petroleum and Nuclear Fuel	23
CHEM	24	Chemicals and Chemical Products	24
PLAS	25	Rubber and Plastics	25
MINnm	26	Other Non-Metallic Mineral	26
MINm	27t28	Basic Metals and Fabricated Metal	27, 28
MCHnec	29	Machinery, Nec	29
EQPeo	30t33	Electrical and Optical Equipment	30-33
EQPtr	34t35	Transport Equipment	34, 35
MANnec	36t37	Manufacturing, Nec; Recyclin	36, 37
PWR+	E	Electricity, Gas and Water Supply	40, 41
CNS	F	Construction	45
VEHser	50	Sale, Maintenance and Repair of Motor Vehicles and Motorcycles; Retail Sale of Fuel	50
WHL	51	Wholesale Trade and Commission Trade, Except of Motor Vehicles and Motorcycles	51
RET	52	Retail Trade, Except of Motor Vehicles and Motorcycles; Repair of Household Goods	52
HOSP	H	Hotels and Restaurants	55
TRAinl	60	Other Inland Transport	60
TRAwat	61	Other Water Transport	61
TRAair	62	Other Air Transport	62
TRAoth	63	Other Supporting and Auxiliary Transport Activities; Activities of Travel Agencies	63
TCOM	64	Post and Telecommunications	64
FIN	J	Financial Intermediation	65-67
REST	70	Real Estate Activities	70
COMMser	71t74	Renting of Machinery and Equipment and Other Business Activities	71-74
PUB	L	Public Admin and Defence; Compulsory Social Security	75
EDU	M	Education	80
HLTH+	N	Health and Social Work	85
OTHser	O	Other Community, Social and Personal Services	90,-93
HH	P	Private Households with Employed Persons	95
TOT	TOT	Total Industries	

Table 2: Countries and variables in WIOD database

CONSOLIDATED WIOD DATA

Source: WIOD database, February 2012 release (socio economic data) and May 2012 release (energy and emissions data)

Countries

Acronym	***Name***
AUS	Australia
AUT	Austria
BEL	Belgium
BRA	Brazil
BGR	Bulgaria
CAN	Canada
CHN	China
CYP	Cyprus
CZE	Czech Republic
DNK	Denmark
EST	Estonia
FIN	Finland
FRA	France
DEU	Germany
GRC	Greece
HUN	Hungary
IND	India
IDN	Indonesia
IRL	Ireland
ITA	Italy
JPN	Japan
KOR	Korea, Republic of
LVA	Latvia
LTU	Lithuania
LUX	Luxembourg
MLT	Malta
MEX	Mexico
NLD	Netherlands
POL	Poland
PRT	Portugal
ROU	Romania
RUS	Russia
SVK	Slovak Republic
SVN	Slovenia
ESP	Spain
SWE	Sweden
TWN	Taiwan
TUR	Turkey
GBR	United Kingdom
USA	United States

Variables

Values	***Description***
GO	Gross output by industry at current basic prices (in millions of national currency)
II	Intermediate inputs at current purchasers' prices (in millions of national currency)
VA	Gross value added at current basic prices (in millions of national currency)
COMP	Compensation of employees (in millions of national currency)
LAB	Labour compensation (in millions of national currency)
CAP	Capital compensation (in millions of national currency)
GFCF	Nominal gross fixed capital formation (in millions of national currency)
EMP	Number of persons engaged (thousands)
EMPE	Number of employees (thousands)
H_EMP	Total hours worked by persons engaged (millions)
H_EMPE	Total hours worked by employees (millions)
Prices	
GO_P	Price levels gross output, 1995=100
II_P	Price levels of intermediate inputs, 1995=100
VA_P	Price levels of gross value added, 1995=100
GFCF_P	Price levels of gross fixed capital formation, 1995=100
Volumes	
GO_QI	Gross output, volume indices, 1995 = 100
II_QI	Intermediate inputs, volume indices, 1995 = 100
VA_QI	Gross value added, volume indices, 1995 = 100
K_GFCF	Real fixed capital stock, 1995 prices
Additional variables	
LABHS	High-skilled labour compensation (share in total labour compensation)
LABMS	Medium-skilled labour compensation (share in total labour compensation)
LABLS	Low-skilled labour compensation (share in total labour compensation)
H_HS	Hours worked by high-skilled persons engaged (share in total hours)
H_MS	Hours worked by medium-skilled persons engaged (share in total hours)
H_LS	Hours worked by low-skilled persons engaged (share in total hours)
Energy and Emissions related variables	
EM	Emission relevant energy use in TJ (all fuels)
CO2	CO2 emissions in Gg (kt) (all fuels)

Notes

Currency unit: Local currency

Acknowledgements and disclaimer

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WIOD project is funded by the European Commission, Research Directorate General as part
of the 7th Framework Programme, Theme 8: Socio-Economic Sciences and Humanities. Grant Agreement no: 225 281
Any errors or omissions are entirely the responsibility of the GGDC (Groningen Growth and Development Centre).
For comments and suggestions please send an email to: wiod@rug.nl.

Table 3: Relative cumulative emissions under NIC, NSC and NAC scenarios

Country	rce_c^{NIC}	rce_c^{NSC}	$rcae_c^{NAC}$
TWN	**-0.324**	0.271	**-0.242**
IDN*	**-0.103**	**-0.061**	**-0.163**
CZE*	**-0.076**	0.278	**-0.186**
CYP*	**-0.062**	0.043	**-0.261**
AUS	**-0.059**	0.119	**-0.241**
RUS*	**-0.033**	0.203	**-0.168**
BRA*	**-0.032**	**-0.013**	**-0.181**
HUN*	**-0.021**	0.341	**-0.297**
ITA	**-0.018**	0.081	**-0.089**
JPN	0.008	0.052	**-0.081**
TUR*	0.030	0.022	**-0.324**
MEX*	0.033	0.040	**-0.270**
EST*	0.036	0.531	**-0.475**
AUT	0.037	0.007	**-0.166**
ESP	0.042	0.018	**-0.225**
GRC	0.050	0.036	**-0.229**
USA	0.054	0.148	**-0.258**
NLD	0.071	0.074	**-0.203**
IND*	0.071	0.056	**-0.412**
SVN*	0.085	0.083	**-0.271**
CAN	0.090	0.042	**-0.233**
DNK	0.092	**-0.094**	**-0.131**
ROU*	0.100	0.254	**-0.105**
FIN	0.104	0.071	**-0.273**
FRA	0.110	0.051	**-0.170**
BEL	0.116	0.047	**-0.152**
SWE	0.116	0.105	**-0.263**
MLT*	0.142	**-0.061**	**-0.198**
GBR	0.148	0.051	**-0.207**
PRT*	0.149	**-0.117**	**-0.176**
DEU	0.150	0.002	**-0.117**
SVK*	0.152	0.236	**-0.313**
KOR	0.155	0.009	**-0.342**
IRL	0.245	0.073	**-0.439**
POL*	0.293	0.106	**-0.324**
LTU*	0.323	0.105	**-0.383**
CHN*	0.338	**-0.101**	**-0.534**
LVA*	0.430	0.091	**-0.383**
BGR*	0.652	**-0.372**	**-0.106**
$mean_{full}$	0.095	0.072	-0.246
$mean_{adv}$	0.062	0.061	-0.214
$mean_{dev}$	0.125	0.083	-0.277

* indicates developing countries as defined in Section 2.

Table 4: Members of HCI_c and LCI_c sets in select countries and globally

	GBR	FRA	USA	JPN	CHN	BRA
HCI ***Sectors***[†]	TRAwat PWR+ RFUEL TRAair MINnm	RFUEL TRAwat MINnm TRAair PWR+	PWR+ TRAwat MINnm TRAair RFUEL	TRAwat MINnm PWR+ TRAair MIN+	PWR+ MINnm TRAair MINm TRAwat	TRAwat MINnm RFUEL MIN+ TRAinl
Average Carbon Intensity	4.252	2.587	4.642	2.686	13.732	3.294
HCI_G ***Sectors***[††]	PWR+ (38), MINnm (36), RFUEL (31), TRAair (25), TRAwat (23), TRAinl (10), MINm (12), CHEM (9), MIN+ (6)					

	GBR	FRA	USA	JPN	CHN	BRA
LCI ***Sectors***[†]	TRAoth TCOM COMMser FIN REST	COMMser FIN TRAoth TCOM REST	VEHser FIN EQPeo WHL REST	VEHser EQPeo TCOM FIN REST	EQPeo WHL TCOM REST FIN	EDU HLTH+ WHL FIN REST
Average Carbon Intensity	0.019	0.011	0.023	0.015	0.064	0.029
LCI_G ***Sectors***[††]	REST (31), FIN (31), TCOM(22), EQPeo (16), WHL (13), COMMser(12), EDU (11), RET (11), PUB (8) , HLTH+ (7), HOSP (6)					

[†] In increasing order of average rank within country.
[††] For $k = 5$ and in decreasing order of the number of times with which the sector is in HCI_c or LCI_c in the 39 country sample.

Table 5: Carbon intensity of top three sectors in HCI_G and LCI_G

	mean	**std dev**	**min**	**max**	**N**
PWR+	16.257	19.622	0.643	104.347	39
MINnm	4.677	3.401	0.261	16.400	39
RFUEL	12.220	20.949	0.014	117.426	37
REST	0.035	0.056	0.000	0.292	38
FIN	0.041	0.091	0.001	0.530	38
TCOM	0.061	0.068	0.003	0.295	37

Table 6: Carbon intensity and factor inputs in HCI_{USA} and LCI_{USA} (2009)

	Sector (i)	ci_{cit}	$\frac{emp_i}{\sum_i emp_i}$	$\frac{cap_i}{cap_i}$	$\frac{cap_i}{emp_i}$	$\frac{va_i}{emp_i}$
	PWR+	12.385	0.004	0.036	1993.729	293.615
	TRAwat	2.790	0.000	0.001	619.690	301.499
HCI	MINnm	3.744	0.003	0.002	142.493	71.852
	TRAair	2.576	0.003	0.005	350.421	129.968
	RFUEL	1.719	0.001	0.003	880.336	926.184
HCI **Average**		**4.643**	**0.002**	**0.009**	**797.334**	**344.624**
	VEHser	0.031	0.008	0.009	263.386	176.004
	FIN	0.033	0.042	0.041	212.829	153.753
LCI	EQPeo	0.016	0.012	0.011	191.753	381.876
	WHL	0.026	0.041	0.019	99.011	204.439
	REST	0.008	0.012	0.450	7795.900	628.385
LCI **Average**		**0.023**	**0.023**	**0.106**	**1712.576**	**308.891**
(excl.REST)		**0.026**	**0.026**	**0.020**	**191.745**	**229.018**
USA Average					**215.852**	**74.104**

Table 7: Carbon intensity and skill composition in HCI_{USA} and LCI_{USA} (2009)

	Sector (i)	ci_{cit}	$\frac{hrs_i}{\sum_i hrs_i}$	$\frac{hrs_i^{HS}}{hrs_i}$	$\frac{hrs_i^{MS}}{hrs_i}$	$\frac{hrs_i^{LS}}{hrs_i}$
	PWR+	12.385	0.005	0.285	0.679	0.036
	TRAwat	2.790	0.001	0.152	0.747	0.101
HCI	MINnm	3.744	0.003	0.180	0.689	0.131
	TRAair	2.576	0.003	0.152	0.747	0.101
	RFUEL	1.719	0.001	0.329	0.609	0.062
HCI **Average**		**4.643**	**0.003**	**0.220**	**0.694**	**0.086**
	VEHser	0.031	0.008	0.323	0.605	0.072
	FIN	0.033	0.043	0.511	0.478	0.011
LCI	EQPeo	0.016	0.015	0.454	0.488	0.057
	WHL	0.026	0.046	0.135	0.772	0.093
	REST	0.008	0.012	0.412	0.534	0.054
LCI **Average**		**0.023**	**0.025**	**0.367**	**0.575**	**0.057**
(excl.REST)		**0.026**	**0.028**	**0.356**	**0.586**	**0.058**
USA Average				**0.345**	**0.569**	**0.085**

Table 8: Correlation between $\ln(ci_{ic})$ and key variables (2007)

		All HCI and LCI	**excl. REST**
$\frac{emp_{ic}}{\sum_i emp_{ic}}$	adv	-0.509^{***}	-0.591^{***}
	dev	-0.367^{***}	-0.419^{***}
$\frac{cap_{ic}}{\sum_i cap_{ic}}$	adv	-0.374^{***}	-0.216^{***}
	dev	-0.227^{***}	-0.094
$\ln\left(\frac{cap_{ic}}{emp_{ic}}\right)$	adv	0.125^{*}	0.513^{***}
	dev	0.130^{*}	0.335^{***}
$\ln\left(\frac{va_{ic}}{emp_{ic}}\right)$	adv	-0.126^{*}	0.050
	dev	-0.210^{***}	-0.125^{*}
$\frac{hrs_{ic}^{HS}}{hrs_{ic}}$	adv	-0.425^{***}	-0.367^{***}
	dev	-0.321^{***}	-0.276^{***}
$\frac{hrs_{ic}^{MS}}{hrs_{ic}}$	adv	0.177^{**}	0.112
	dev	0.119	0.101
$\frac{hrs_{ic}^{LS}}{hrs_{ic}}$	adv	0.296^{***}	0.281^{***}
	dev	0.071	0.053

Note: *, ** and *** indicate significance at 10%, 5% and 1%, respectively.

Table 9: Mean growth rates for key variables: HCI and LCI sectors

	HCI **Sectors**	LCI **Sectors**	**Δ significant?**	**Aggregate**
$g(emp)$	-0.006	0.017	Y	0.010
$g(hrs)$	-0.008	0.016	Y	0.007
$g(hrs^{HS})$	0.028	0.046	Y	0.039
$g(hrs^{MS})$	-0.001	0.016	Y	0.016
$g(hrs^{LS})$	-0.036	-0.009	Y	-0.020
$g(cap)$	0.036	0.044	Y	0.036
$g(\frac{cap}{emp})$	0.043	0.025	Y	0.025
$g(mfp)$	0.033	0.052	Y	0.042
$g(\frac{va}{emp})$	0.029	0.029	N	0.025

Note: The t-test results reported are for the null hypothesis that the mean growth rates of a given variable are equal in HCI and LCI sectors against the two-sided alternative that they are not. The significance level for the test is 10%.

Table 10: Mean growth rates for select variables: HCI and LCI sectors

		HCI **Sectors**	LCI **Sectors**	**(I)**	**Δ significant?** **(II)**	**(III)**	**Aggregate**
$g(emp)$	adv	-0.004	0.013	Y	N	Y	0.011
	dev	-0.009	0.022	Y			0.008
$g(hrs)$	adv	-0.007	0.012	Y	N	Y	0.008
	dev	-0.010	0.021	Y			0.007
$g(hrs^{HS})$	adv	0.027	0.043	Y	N	N	0.038
	dev	0.029	0.048	Y			0.040
$g(hrs^{MS})$	adv	-0.002	0.008	Y	N	Y	0.013
	dev	0.001	0.024	Y			0.019
$g(hrs^{LS})$	adv	-0.037	-0.018	Y	N	Y	-0.022
	dev	-0.036	0.000	Y			-0.019
$g(cap)$	adv	0.028	0.041	Y	Y	N	0.033
	dev	0.044	0.047	N			0.038
$g(\frac{cap}{emp})$	adv	0.033	0.025	N	Y	N	0.020
	dev	0.054	0.025	Y			0.030
$g(mfp)$	adv	0.025	0.046	Y	Y	Y	0.034
	dev	0.041	0.059	Y			0.050
$g(\frac{va}{emp})$	adv	0.021	0.026	N	Y	N	0.015
	dev	0.035	0.031	N			0.035

Note: The t-test results reported are for the null hypothesis that the mean growth rates of a given variable are equal across the specified groups against a two-sided alternative. The significance level for the test is 10%. In column (I), the difference between the mean growth rates of HCI and LCI sectors across advanced and developing countries is tested. In column (II), the difference between advanced and developing country mean growth rates in HCI sectors is tested. In the final column, the same difference in LCI sectors is tested.

Figure 1: Observed vs Counterfactual Emissions in the USA and China

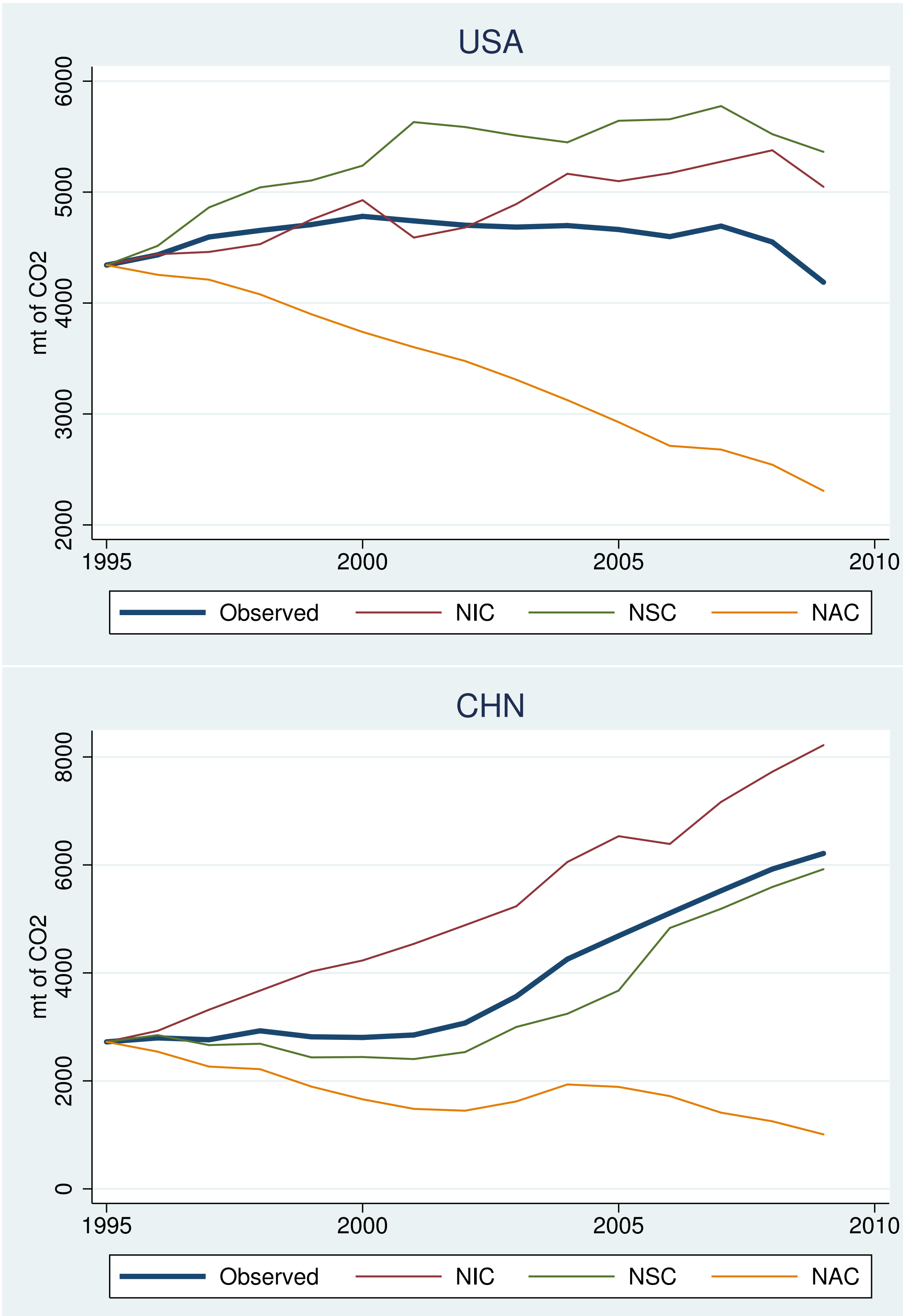


Figure 2: Relative cumulative emissions under NSC and NIC

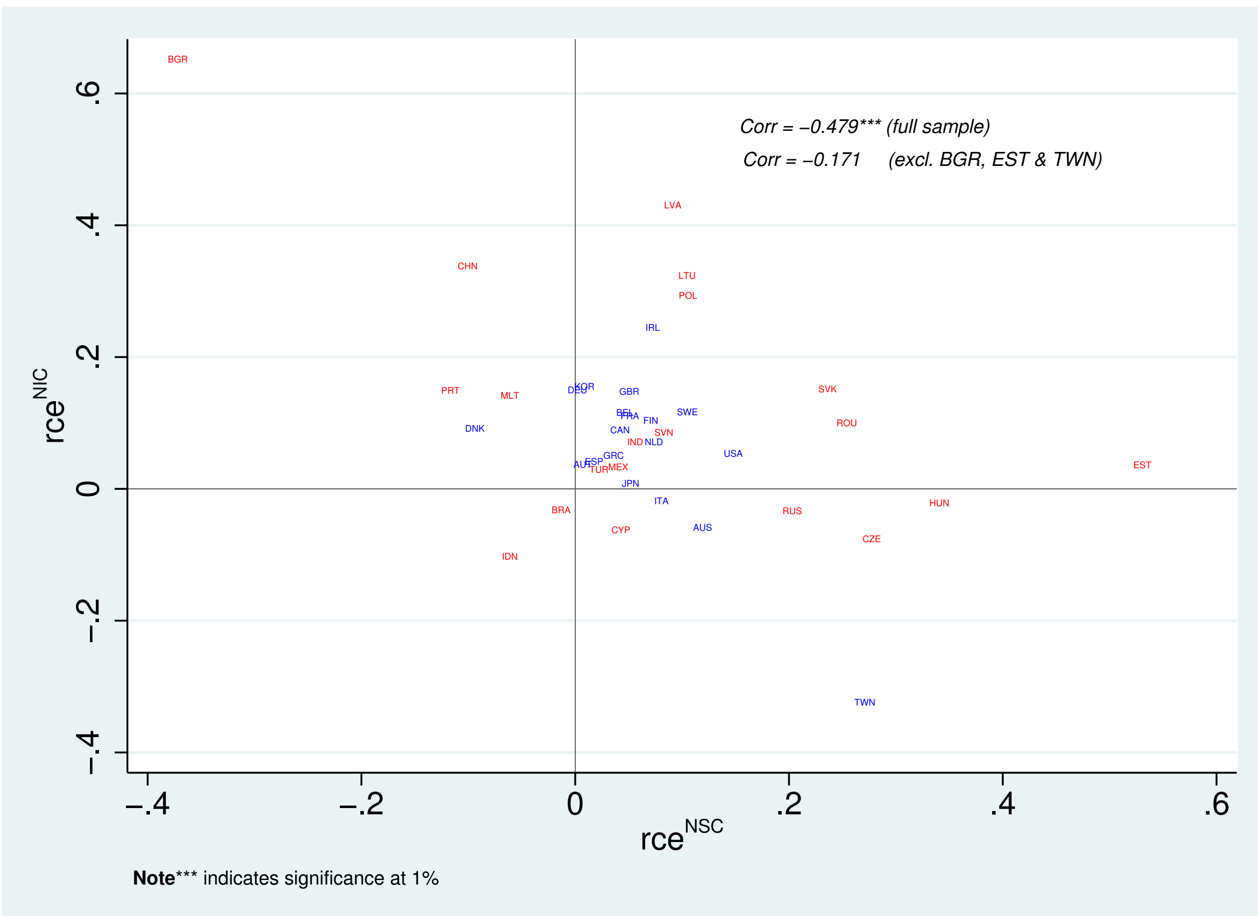
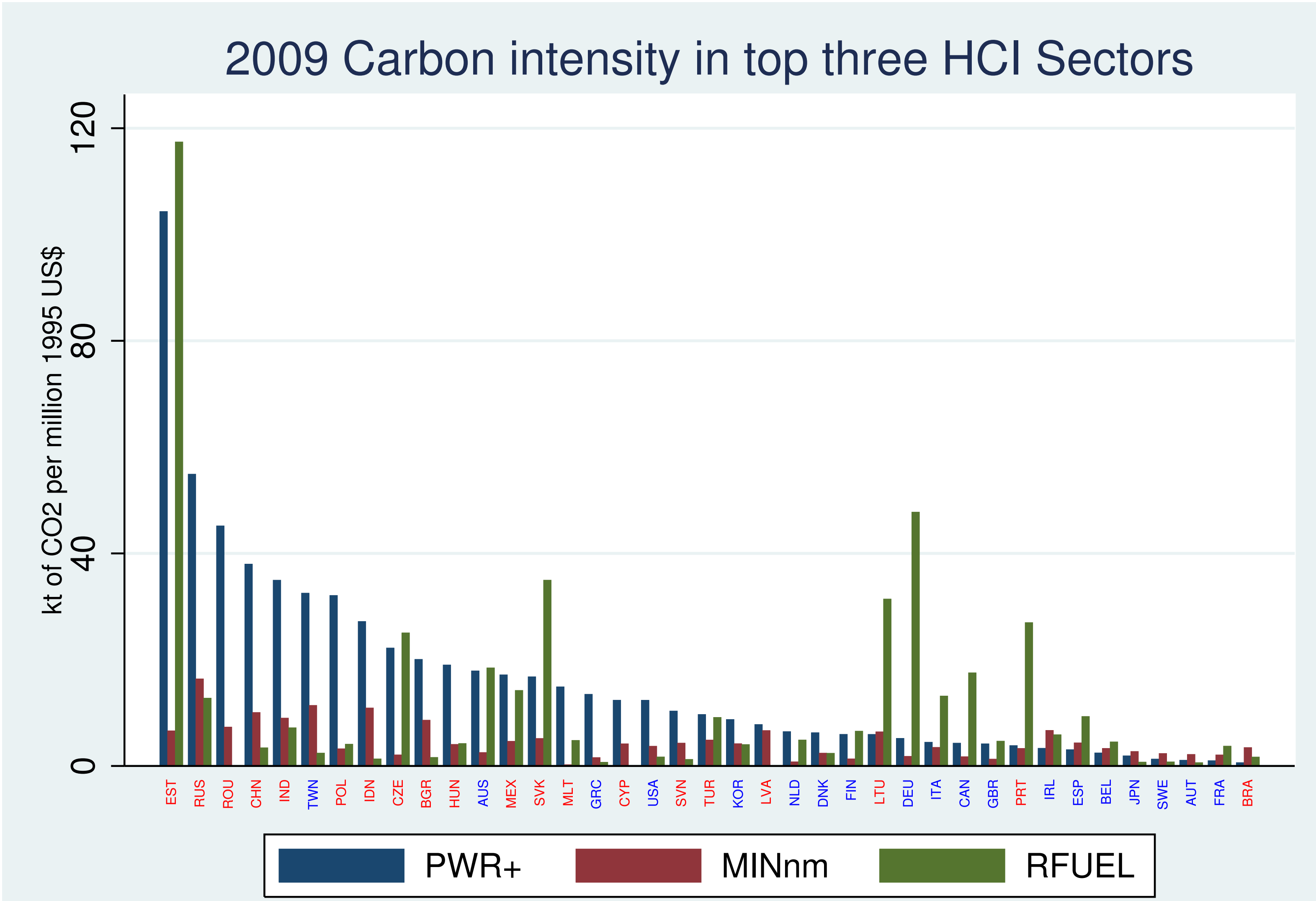
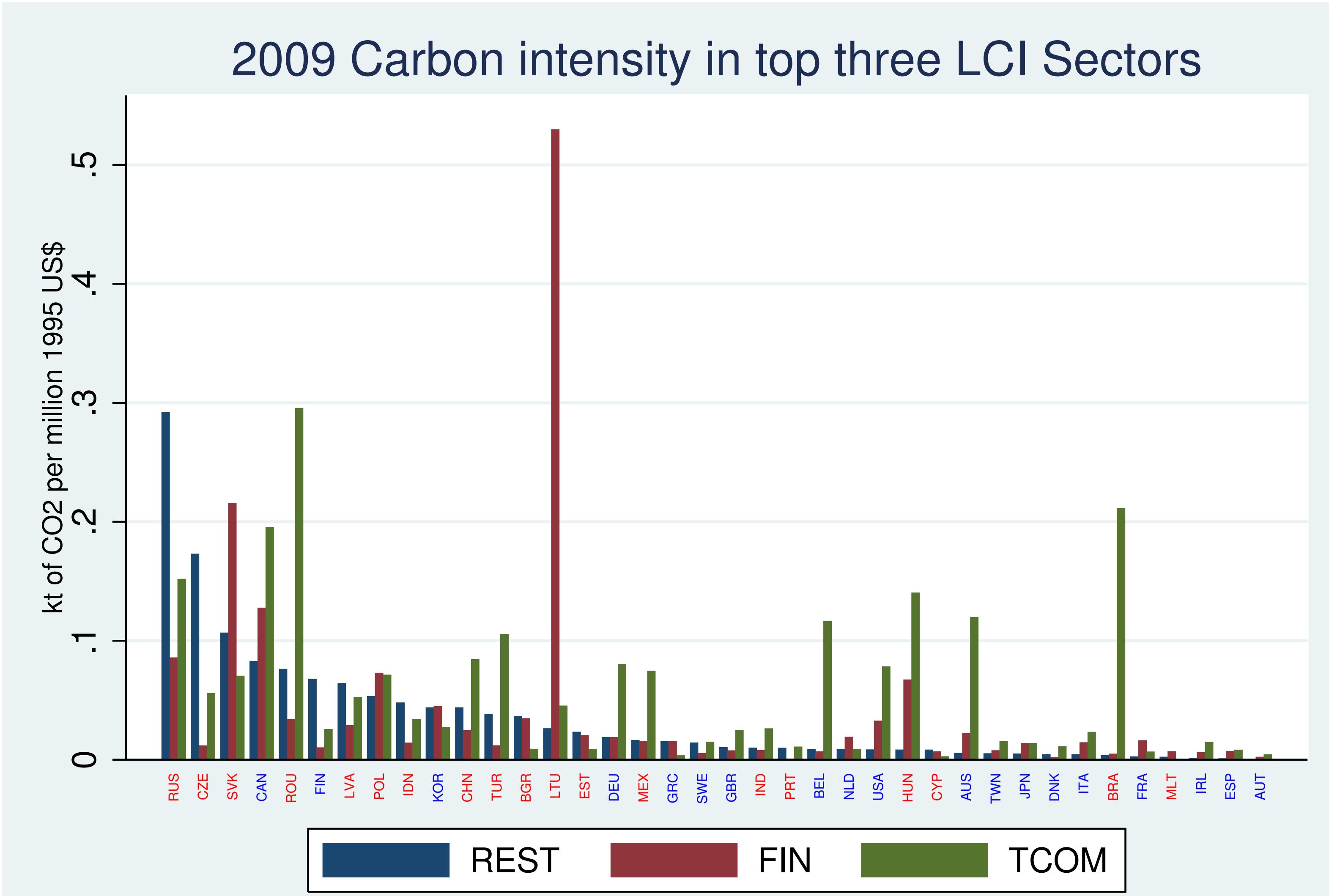


Figure 3: Distribution of High Carbon Intensity (HCI) Sectors



Note: Countries ordered in decreasing order of carbon intensity in PWR+ in 2009. Advanced and developing countries based on the paper's definition are indicated in blue and red, respectively.

Figure 4: Distribution of Low Carbon Intensity (LCI) Sectors



Note: Countries ordered in decreasing order of carbon intensity in PWR+ in 2009. Advanced and developing countries based on the paper's definition are indicated in blue and red, respectively. SVN excluded due to missing data in 2009.