Tales from the tails: Sector-level carbon intensity distribution

Baran Doda*

CCCEP & Grantham Research Institute

London School of Economics

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Abstract

The level of GDP, its sector composition and the carbon intensity of individual sectors together determine a country's emissions. To evaluate the contribution of changes in each determinant, I construct counterfactual emissions scenarios in a sample consisting of 34 sectors in 37 countries over 1995-2009. I compare these scenarios quantitatively using a novel metric, namely the relative cumulative emissions. I find that the composition of output and the carbon intensity of sectors individually or jointly constrained emissions in a large majority of countries. This motivates an analysis of high- and low-carbon intensity sectors, denoted HCI and LCI, where emissions and value-added tend to be concentrated, respectively. I document the cross-country variation in HCI sectors' carbon intensity and show it declines over time largely due to improvements in developing countries. HCI sectors tend to account for a smaller share of employment; be more capital intensive; and employ a workforce with a lower average skill level. 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.

Keywords: *sector-level analysis; index decomposition of carbon emissions; carbon intensity and primary inputs; carbon intensity and productivity; climate policy*

*Email: L.B.Doda@lse.ac.uk

1 Introduction

Reductions in carbon emissions are essential to slow down climate change. In an economy consisting of many sectors which differ in carbon intensity, i.e. the amount of carbon emitted per unit of value generated, these reductions can come from improvements in sectors' carbon intensity, *the intensity channel*, from a reallocation of production away from relatively carbon-intensive sectors, *the structure channel*, or from reductions in the level of GDP, *the activity channel*. The paper uses data from 34 sectors in 37 countries over 1995-2009 to provide empirical evidence on the historical importance of these channels and on the economic characteristics of the sectors which are at the tails of the carbon intensity distribution. The results are summarised in four descriptive stylised facts. Such facts are crucial for building a theory consistent with the real world which in turn provides the basis for designing effective climate policies.

I find that the observed changes in carbon intensity *and* the shifting composition of economic activity constrained emissions in 25 of the 37 countries in the sample. Conversely, in the absence of the changes in GDP, emissions would have been lower in all countries (fact 1). A key contribution is the systematic evaluation of the quantitative importance of intensity and structure channels using a novel metric, namely the relative cumulative emissions associated with a given counterfactual emissions scenario.

Using this metric the paper shows that in most countries, including the USA, both intensity and structure channels contribute to constraining emissions. However, there are examples, most prominently 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.

The dataset also allows a closer look at those sectors in the tails of the carbon intensity distribution, hereafter high-carbon intensity (HCI) and low-carbon intensity (LCI) sectors. I propose a rule to construct country-specific as well as global HCI and LCI sets, and populate them. I document the cross-country variation that exists in carbon intensity of important HCI sectors which typically account for a large share of a country's emissions. I show that carbon intensity declines over time primarily due to improvements in developing countries (fact 2). I find that HCI sectors tend to account for a smaller share of employment, be more capital intensive and employ workers with lower average skill level than LCI sectors (fact 3).

Adopting a longer term perspective, I show that employment and hours worked 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 find that the pace of change was typically greater in the former, especially in the LCI sectors. Put differently, the LCI sectors, particularly in developing countries, are among the most dynamic sectors of the economy.

Voigt et al. (2014), Schymura & Voigt (2014) and Di Cosmo & Hyland (2015) are recent studies which use the same dataset with a similar motivation.[1] 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. Using an approach that relies on energy use, rather than cumulative emissions which is behind the current paper's fact 1, Voigt et al. (2014) also find that changes in the composition of GDP and the energy intensity of sectors were important in driving aggregate intensity changes.[2]

Schymura & Voigt (2014) focus on *carbon intensity* and use a more detailed decomposition which also accounts for changes in emissions factors and fuel mix. They confirm that the main conclusions of Voigt et al. (2014) remain valid for carbon intensity. Di Cosmo & Hyland (2015) do not undertake a decomposition analysis but compare the *carbon intensity* of sectors regulated under the European Union's Emissions Trading System (EU-ETS) to those sectors not covered by the EU-ETS both in the EU and in China. Based on evidence from two years, i.e. 2005 and 2009, they argue the EU-ETS may have played a role in reducing emissions intensity.

Combining sector-level data from different sources Mulder & de Groot (2012) study the evolution of *energy intensity* in OECD countries using IDA and convergence analysis. The authors' IDA assigns an increasingly important role to the structure channel, while their convergence analysis concludes that after 1995 the cross-country variation in energy intensity levels has declined.

Against this backdrop, the current paper takes advantage of the WIOD database to focus on *emissions intensity*, much like Schymura & Voigt (2014). In addition, it proposes a new metric, the relative cumulative emissions, to compare structure, intensity and activity channels over time, extending the results in Voigt et al. (2014), Schymura & Voigt (2014) and Mulder & de Groot (2012). Moreover, it provides a method to identify high and low carbon intensity sectors. Finally, it makes an entirely new contribution to the literature by describing the economic characteristics of these sectors as well as their evolution over time in advanced and developing countries.

The rest of the paper is organised as follows. I describe the dataset in more detail in the next section. Section 3 presents the results of the IDA and introduces the metric for comparing them. In section 4, I propose a rule for defining HCI and LCI sectors, and review their key economic characteristics. Section 5 provides a brief discussion of the policy implications of these findings. Section 6 concludes. All numbered tables and figures can be found at the end.

[1] For the diverse literature using this database, see http://www.wiod.org/published

[2] Earlier papers including Miketa (2001) and Miketa & Mulder (2005) focus on the *energy intensities* of manufacturing sectors in advanced and developing countries using samples which just precede the current paper. See Mulder & de Groot (2012) for a succinct overview.

2 Data

The paper uses the Socioeconomic and Environmental Accounts of the World Input Output database (release 2013) described in Timmer et al. (2015) and Genty et al. (2012) respectively.[3] Data are available for the 35 sectors described in Table 1. The four columns in the table provide the intuitive sector code this paper uses, the code from the underlying WIOD database, 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 because it is available for only a few countries and, where available, tiny compared to the rest of the economy.

Table 2 lists the data in the Socioeconomic 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 as number of workers as well as number of hours. Moreover, hours worked are subdivided into hours worked by high-, medium- and low-skilled workers based on the education level of 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. 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*. 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 those used in WIOD database in constructing its world input-output tables. The key data from Environmental Accounts are the total carbon emissions (CO2) measured in kilotons.

There are 37 countries in the sample including most EU member states, several non-EU OECD countries and key emerging markets as indicated in Table 3.[4] The three smallest emitters of carbon in the WIOD database, namely Luxembourg, Malta and Cyprus, are excluded because their data are patchy, especially in sectors with high carbon intensity. Below I often distinguish between advanced and developing countries which are sorted into these groups based on the World Bank income group classification as it existed in 1995. This implies there are 20 advanced and 17 developing countries in the sample.

[3] The data can be downloaded from http://www.wiod.org/release13.

[4] Tables and Figures below identify countries by their ISO 3166-1 alpha-3 code.

3 Sector-level carbon intensity and composition of GDP

Carbon intensity of production is defined as

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

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

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

where $Y_{jt} = \sum_i va_{jit}$ is the sum of value-added across sectors (i.e. the country's GDP) and s_{jit} is sector i's share in Y_{jt}. I use index decomposition analysis (IDA) to compute the contribution of changes in each component to changes in observed aggregate emissions. 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.[5]

Dropping the country subscript for brevity and letting $\Delta E_t = E_t - E_{t-1}$, I have

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

where subscripts *int*, *str* and *act* identify the contribution of intensity, structure and activity changes. I adopt the additive log-mean divisia index (LMDI) method to calculate each component. The desirable properties of this decomposition method are well-established and described in Ang (2004). Its implementation is straightforward so I omit the formulae 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, I set $\Delta E_{int,t} = 0$ in each t but allow the changes in the structure of the economy (i.e. structure channel) and in the level of economic activity (i.e. activity channel)

[5] In recent years, the aggregate variable of choice has often been greenhouse gas emissions. The surveys by Schipper et al. (2001) and more recently Xu & Ang (2013) provides a rich overview of the studies using this method which focus on carbon emissions. Hoekstra & van den Bergh (2003) compares the pros and cons of IDA relative to its main alternative, namely structural decomposition analysis.

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 USA 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 preclude similarly unambiguous statements regarding the contribution of the intensity channel. Over this period the NIC series deviate 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.

For China, changes in the level of the economic activity also constituted the dominant channel for the observed increase 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 35 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 USA 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 is extremely persistent in the atmosphere. In other words, if a particular channel adds a million tonne of carbon in a given year and reduces them by the same amount in the following year, its climate change impact over the two years is negligible. Put differently, it is the the cumulative emissions of carbon that determine the climate change impact (Allen, 2016).

In order to implement this idea in the current context, I define the *relative* cumulative emissions in scenario $S \in \{NIC, NSC, NAC\}$ as

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

When $rce^S > 0$, the cumulative emissions under S are greater than those observed, implying greater climate change impacts as well. Note also that it is possible to interpret the magnitude of rce_j^S across scenarios.

Using USA as an example once again, I compute $rce_{USA}^{NAC} = -0.26$, meaning cumulative emissions would have been almost 26% lower under the NAC scenario. The shift towards less carbon-intensive sectors implied that $rce_{USA}^{NSC} = 0.15$, i.e. shutting down the structure channel would have implied 15% higher cumulative emissions. Similarly, $rce_{USA}^{NIC} = 0.05$ so that the intensity channel also constrained cumulative emissions over the sample period.

For China, $rce_{CHN}^{NAC} = -0.53$, $rce_{CHN}^{NSC} = -0.10$ and $rce_{CHN}^{NIC} = 0.34$ 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_j^S for all countries, with advanced countries in the left panel of the table. The cross-country mean and standard deviation of rce_j^S are given at the bottom of the table for subsamples by level of development. The table ranks countries in increasing order of rce_j^{NIC}. There are several noteworthy patterns.

To start, rce_j^{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 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 Russia and a number of Eastern European countries which experienced economic upheaval following the collapse of the Soviet Union. Comparing the sample means for rce_j^{NAC} by level of development, one can conclude that the activity channel increased the developing country emissions by more.[6]

For a large majority of countries – 25 out of 37 – both the intensity and structure channels constrained the emissions increases implied by the activity channel. Moreover, in all advanced countries except Portugal the structure channel contributed to decreasing cumulative emissions. These patterns are apparent in Figure 2 which provides a visual summary of the information in Table 3 by plotting rce_j^{NIC} versus rce_j^{NSC}. Not surprisingly, several Eastern European countries feature the largest $rce_j^{NIC} > 0$ and/or $rce_j^{NSC} > 0$ due to the economic transition they experienced over the sample period. 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_j^{NIC}, rce_j^{NSC} and $|rce_j^{NAC}|$ 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 suggestive to note, but not read too much into, the fact that Finland and Sweden are among the first countries to introduce an explicit carbon tax.

There are important exceptions to the broad pattern of positive rce_j^{NIC} and rce_j^{NSC}. For example in Figure 2, the pattern $rce_j^{NIC} < 0$ and $rce_j^{NSC} > 0$ is observed (i.e. the bottom right quadrant) for seven countries including Russia, and the opposite pattern $rce_j^{NIC} > 0$ and $rce_j^{NSC} < 0$ prevailed in three 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 broad features of the preceding observations are summarised in the first stylised fact of this paper.

Fact 1. *Intensity and structure channels constrained emissions in 25 of the 37 countries in the sample. In contrast, the activity channel increased emissions for all countries and by a greater margin in developing countries.*

In passing, note that the figure also highlights advanced (blue) and developing (red) countries in the sample. The observation from Taiwan and Portugal notwithstanding, developing countries tend to be over-represented in the tails of rce_j^{NIC} and rce_j^{NSC} distributions. This suggests structural and technological channels had a more varied quantitative and qualitative impact in developing countries relative to advanced countries, increasing emissions in some while constraining them in others. The cross-country standard deviation statistics in Table 3 confirm this visual impression.[7]

[6] The p-value of the t-test for the equality of means in advanced and developing country samples assuming unequal variances is 0.045 for rce^{NAC}. The difference is not significant at 5% level for rce^{NIC} and rce^{NSC}.

[7] The p-values of the F-tests for the equality of variances against the alternative that the variances were greater

Fact 1 uses rce^S as a novel metric to compare the contribution of changes in intensity, structure and activity channels. It identifies economically interesting regularities in the sign, magnitude and distribution of the intensity and structure channels in the sample. Crucially, in a large majority of countries both intensity and structure channels have helped constrain cumulative emissions. This motivates a closer look at the HCI and LCI sectors of the economy where the emissions and value-added tend to be concentrated, respectively. Analysing the patterns in these sectors in an era predating stringent climate policies can be instrumental for insights regarding the data generating process and for designing effective climate policies based on theories leveraging these insights.

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

To that end, I start by describing the rule I use to identify the HCI and LCI sectors. For each country and year in the sample

1. Order sectors in decreasing order of ci_{jit}, 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 highest (lowest) ranking five sectors as the HCI_j (LCI_j) set.

A number of points are worth highlighting. First, the sets HCI_j and LCI_j 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. Second, HCI_j and LCI_j 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_j and LCI_j in at least k countries.[8]

Table 4 lists the sectors in HCI_j and LCI_j for selected countries, i.e. two advanced European, two advanced non-European and two large developing countries. The mean carbon intensity levels and total share of emissions and value added for these sectors 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_j and LCI_j. 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 developing country sample are 0.008 for rce^{NIC}; 0.000 for rce^{NSC}; and 0.054 for rce^{NAC}. Excluding TWN as an outlier does not alter these results.

[8] Observe that as k becomes larger, HCI_G and LCI_G shrink.

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 37 countries in the sample as demonstrated by the nine HCI_G sectors. 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_G sectors and there are eleven sectors in LCI_G. These suggest LCI_G sectors are somewhat more diverse.

In the 2009 data the unweighted mean carbon intensity levels in HCI_j and LCI_j show much variation across countries despite the fact that the members of these sets are very 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_j. 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. The differences are reflected in the total share of emissions from a country's HCI sectors, which ranges from 39% in France to 78% in China. Observe that the contribution a country's HCI sectors make to its GDP is about an order magnitude smaller. The converse is true for LCI sectors. That is, their contribution to GDP is about an order of magnitude greater than their contribution to emissions.

Table 4 is organised around the ranking of sectors by ci_{jit}. Accordingly, it does not provide information on the magnitude of an individual sector's carbon intensity on average or in a given country, or how it is distributed across countries. From an emissions abatement perspective this information is important for HCI sectors, particularly for those sectors which are in HCI_G with a high frequency. To explore this further, Table 5 and Figures 3-4 focus on PWR+, MINnm, RFUEL, TRAair and TRAwat, the top five sectors in HCI_G for a restricted sample which excludes a number of outlying country-sector-year observations to improve clarity of exposition.[9]

Specifically, Table 5 uses summary statistics for ci_{jit} to show a snapshot in 2009 based on the subsamples by level of development. The clear message is one of enormous heterogeneity in carbon intensity within and across HCI_G sectors as well as by level of development. For example, the most carbon-intensive PWR+ sector is in Russia and the least intensive one in Brazil, both developing countries. The ratio between the two is about 85. It is difficult to interpret the magnitude of this figure. Russia is 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 natural gas and coal for generating a large share of its power. Conversely in Brazil, which has substantial hydroelectric potential, only about 20% of power is generated using fossil fuels with natural gas most significant in the mix (IEA, 2017). Indeed, in Table 4 PWR+ is not even an HCI sector in Brazil.

[9]See the discussion in Appendix A for the exclusion criteria and results with the unrestricted sample.

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 (approximately 12.4 ktCO2/million 1995 US$) is about three times greater than 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% (IEA, 2017). 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+.[10]

In addition to within-sector heterogeneity, there are also large differences across sectors and by development level in Table 5. For example, the unweighted mean ci_{jit} of the HCI sectors falls in the range 1-23 ktCO2/million 1995 US$ in developing countries and 0.2-12 ktCO2/million 1995 US$ in advanced countries.

The snapshot in Table 5 is useful but it only provides a static and partial picture in 2009. Figures 3 and 4 graph the evolution of the mean and the cross-country standard deviation of ci_{jit} over the sample period. Two broad patterns can be observed regarding the mean carbon intensity of the HCI_G sectors in Figure 3. First, sector-level carbon intensities were typically higher in developing countries over the sample period. Second, the sector-level carbon intensity in developing countries declined substantially over the sample period. The domestic water transport sector TRAwat and manufacture of refined fuels RFUEL are partial exceptions to these broad patterns. In the case of the former the roles of advanced and developing countries are reversed. Note, however, the fact that the difference between the groups is relatively small compared to the other sectors included in the figure. Regarding RFUEL, there is a rapid increase in the mean carbon intensity of the sector in developing countries during the early years of the sample. Moreover, this sector exhibits cyclical fluctuations in intensity, likely driven by the fluctuations in the price of oil.

The evolution of the standard deviation of sector-level carbon intensity for the same sectors is provided in Figure 4. The trend has been flat or downward over the sample period with the exception of TRAair in the latter years of the sample. Combining this with evidence above, the convergence in sector-level carbon intensity levels in key HCI_G sectors have largely been driven by carbon intensity improvements in developing countries. The paper's second stylised fact summarises these observations.

[10]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.

Fact 2. *For global HCI sectors the sector-level carbon intensity exhibits substantial variation across countries. The mean of carbon intensity in these sectors tended to be lower in advanced countries and its standard deviation declined driven largely by changes in developing countries.*

Against this backdrop, next I focus on the systematic differences that may exist in other important economic characteristics of the sectors which differ in carbon intensity. In particular, I ask whether there is a relationship between the share of a country's productive inputs, namely its workers, physical and human capital used in a given sector and the sector's carbon intensity. If so, one is most likely to find evidence of this in the HCI and LCI sectors.

To answer this question, Table 6 reports the correlation of the log of carbon intensity with a number of key variables in 2007. The unit of observation is country-sector and the variables of interest include the sector's share in country's aggregate employment and capital stock; capital per worker; and share of hours provided by high-, medium- and low-skilled workers. The log transformation of carbon intensity is to minimise the influence of the outliers and the results are similar, albeit more noisy, without it. The data from 2007, rather than 2009, are used to maximise the geographic coverage of the sample because capital stock data are missing for several countries in 2008-9. The cross-section patterns below are not sensitive to the choice of the year.

The results are reported for three different samples. Column I uses a sample which includes all sectors in HCI_j and LCI_j and reports results for advanced and developing countries separately. In this sample real estate activities sector, REST, is included in LCI_j for 29 countries. This turns out to have important implications for the results for certain variables because a country's typically large stock of housing capital and imputed rental income from it is reported in REST as an accounting convention.[11] As a consequence, column II of the table drops REST from the sample if it happens to be in LCI_j in country j. Finally, the sample behind column III includes all sectors of the economy except REST. That is, it also includes non-HCI and non-LCI sectors.

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 exclusion of REST does have some quantitative but no qualitative implications for the correlation coefficient between $ln(ci_{ji})$ and $emp_{ji}/\sum_i emp_{ji}$.

Whether or not one excludes REST from the sample has quantitative *and* qualitative implications for the correlation statistics involving the capital stock. Once this sector is excluded, the negative and significant correlation coefficient between sectors' carbon intensities 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

[11] See Appendix B for a for a stark exposition of this using the USA as an example.

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 more capital to work with relative to their counterparts in LCI sectors.

Finally, Table 6 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 greater share of the hours are provided by low-skilled workers in HCI sectors. These patterns are consistent with the average skill level of the workforce being greater in the LCI sectors. Fact 3 summarises the preceding discussion.

Fact 3. *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.*

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_{jit}, is computed based on gross value-added using to the procedure outlined in OECD (2001).

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

$$x \in \left\{ci, emp, hrs, hrs^{HS}, hrs^{MS}, hrs^{LS}, cap, cap/emp, va/emp, mfp\right\}$$

the following simple specification is estimated

$$log(x_{jit}) = \theta_{ji} + g(x_{ji})t + \varepsilon_{jit}$$

where $t = 1, 2, ..., \bar{t}$. The point estimate of $g(x_{ji})$ can be interpreted as the annual growth rate of variable x in country j's sector i over the sample period. Table 7 reports the unweighted mean of $g(x_{ji})$ in HCI and LCI sectors for advanced and developing countries separately. It also provides several t-test results of the null hypothesis that the mean growth rates in different samples are equal against alternative that they are not. More specifically, the results reported in column I 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, the test assumes unequal variances

[12] Cole & Elliott (2003) also document this relationship using country-level data for CO2 among other pollutants.

and its significance level is 10%. Finally, the growth rate of each variable in the non-HCI sectors of the economy is also provided for reference in the last column of the table.

To build intuition and set the stage, I discuss the top panel of the table for mean growth rate of carbon intensity $g(ci)$ in detail. The top row is the advanced country mean. Observe that in advanced countries and on average, the carbon intensity of HCI sectors declined at a rate of -0.50% per annum versus -4.36% in LCI sectors. Column I indicates that the difference between the two means is statistically significant. In developing countries, the corresponding figures are -1.82% and -3.01% however the difference is not statistically significant. Similarly, the t-test results in columns II and III show that one cannot reject the hypothesis that the two rates are equal for the HCI and LCI sectors, respectively, across country groups by development levels.

The next panel focuses on labor supply and its composition by skill level. It shows that on average HCI sector employment and hours declined while LCI sector employment and hours increased. Moreover, the share of high-skilled workers in both HCI and LCI sectors rose over time because $g(hrs^{HS})$ is greater than $g(hrs^{MS})$ and $g(hrs^{LS})$ in each case. This implies that the average skill level of the workforce in HCI and LCI sectors increased over time.

The mean growth rates of capital and capital per worker are shown in the next panel of the table. Both $g(cap)$ and $g(cap/emp)$ were positive in HCI and LCI sectors. Taken together with the decline in the HCI sector employment, this implies $g(cap/emp) > g(cap)$ with the opposite result obtaining in LCI sectors. In other words the capital intensity grew faster in HCI sectors.[13]

One might expect the faster growth in capital intensity of HCI sectors to be reflected in higher labour productivity growth in these sectors. There is little evidence for this in the sample. This is shown in the final panel of the table where the differences between $g(va/emp)$ in HCI and LCI sectors is not statistically significant.

Technological advances driving higher multifactor productivity growth in LCI sectors could be one reason for this. Indeed, the growth of multifactor productivity was significantly greater in LCI sectors. In interpreting these $g(mfp)$ figures, it is important to keep in mind that the multifactor productivity measure employed here captures technological advances as well as all other changes that are not captured by the observed changes in capital and labour inputs used in production. These include the higher skill level of the average worker in both HCI and LCI workers already discussed above and the changes in other distortions that may be important for the functioning of markets. Fact 4 summarises these observations.

Fact 4. *Labour supply declined in HCI sectors and increased in LCI sectors with its composition shifting towards higher-skilled workers in both. Relative to LCI sectors capital intensity growth was faster but multifactor productivity growth was slower in HCI sectors.*

[13] The statement is true when *both* advanced and developing countries are included in the sample for the test. That said, the difference between capital intensity growth rates of advanced country HCI and LCI sectors, 3.3% and 2.6% respectively, is not significant with a two-sided test but significant with a one-sided test.

5 Implications of the findings for policy

Emissions reductions to meet the Paris Agreement goals can be achieved through reductions in economic activity, declines in its carbon intensity or changes in its composition. The former is not viable in many developing countries since poverty reduction requires economic growth, making favourable changes in carbon intensity and the composition of output all the more important.

Fact 1 shows that in a large majority of countries these two channels did indeed constrain emissions. Notwithstanding a potential announcement effect due to the adoption of the Kyoto Protocol, it is unlikely that climate policies, and any associated carbon leakage, were main drivers of these facts. Only a few European countries implemented stringent policies before and during the sample period. This suggests climate policy needs to enhance rather than reverse the underlying transformation induced by the powerful forces of globalisation and economic development. These forces operate through access to more efficient technologies and superior inputs, and the rationalisation of production structures they imply. While this is welcome, it also makes the ex post evaluation of climate policy effectiveness difficult.

What policy instruments are available to target the intensity and structure channels? Take PWR+, a prominent HCI sector, as an example. Government support to low-carbon electricity generation, transmission and storage can help overcome the innovation and network externalities rampant in this sector. In turn, this substitutes thermal generation reducing the carbon intensity of PWR+ (Doda & Fankhauser, 2017). Alternatively, the government can stop or reduce existing production and consumption subsidies to fossil fuels (Coady et al., 2017). Doing so could have a negative impact on the value-added share of prominent HCI sectors such as RFUEL+ and MINnm.

The government could go further and impose a carbon price, simultaneously impacting the intensity and structure channels. This has indeed been a popular policy in recent years. It is implemented through emissions trading in the EU, South Korea and more recently China, among others. Carbon taxes have also been used, for example in Sweden, Finland and the province of British Columbia in Canada. By making emissions costly, a carbon price compels emitters to find ways to substitute carbon with other inputs in their production reducing 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.[14] Ultimately, the right balance for the portfolio of policies is likely to depend on a country's specific circumstances including its level of development, resource endowments and existing human and physical capital stock.

Facts 2-4 suggest that the costs of these policies can be limited if they are designed and targeted well. The variation and trends in Fact 2 is a starting point for constructing detailed case studies

[14] In this context, the carbon prices introduced in Finland and Sweden before 1995 are suggestive and encouraging. In Table 3 both countries' rce_j^{NIC} and rce_j^{NIC} were positive and more so than the advanced country average. Simultaneously, large and negative rce_j^{NAC} indicates robust economic growth.

of country-sectors where carbon intensity declined rapidly. Facts 3 and 4 suggest, employment share of HCI sectors is relatively small and declining. They also identify a concentration of low-skilled workers in these sectors, which will bear the brunt of these costs (Walker, 2013). Targeted compensation and retraining programs would therefore be important as these workers move to more dynamic and less carbon-intensive sectors with higher multifactor productivity growth.

6 Conclusions

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 changes in both the sector-level carbon intensity and the composition of economic activity contributed to constrain emissions in a large 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 because these sectors are responsible for a large share of emissions or value added. Fact 2 demonstrates the enormous variation in the carbon intensity of HCI sectors and the tendency that carbon intensities are higher but declining in developing countries. Adopting a factor input perspective, Fact 3 highlights 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 or in the rest of the economy. Fact 4 documents that employment in HCI sectors declined and the skill level of the average worker employed in these sectors increased. This contrasts with LCI sectors where both employment and the skill level of the average worker have increased. In addition, 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.

To be cost-effective in reducing carbon emissions, the choice of climate policy instruments as well as their design and stringency must be informed by evidence, most importantly on the characteristics of, and the trends in, sectors from the tails of the carbon-intensity distribution. The current paper's value-added is the contribution it makes to this evidence base.

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References

Allen, M. R. (2016). Drivers of peak warming in a consumption-maximizing world. *Nature Climate Change*, **6**(7), 684–686.

Ang, B. (2004). Decomposition analysis for policymaking in energy:. *Energy Policy*, **32**(9), 1131–1139.

Ang, B. (2005). The LMDI approach to decomposition analysis: a practical guide. *Energy Policy*, **33**(7), 867–871.

Coady, D., Parry, I., Sears, L. & Shang, B. (2017). How large are global fossil fuel subsidies? *World development*, **91**, 11–27.

Cole, M. A. & Elliott, R. J. (2003). Determining the trade-environment composition effect: the role of capital, labor and environmental regulations. *Journal of Environmental Economics and Management*, **46**(3), 363–383.

Di Cosmo, V. & Hyland, M. (2015). Decomposing patterns of emission intensity in the EU and China: how much does trade matter? *Journal of Environmental Planning and Management*, **58**(12), 2176–2192.

Doda, B. & Fankhauser, S. (2017). Energy policy and the power sector in the long run. *GRI Working Paper*, (276).

Erumban, A., Gouma, R. & Vries, G. D. (2012). WIOD Socio-Economic Accounts (SEA): Sources and Methods. *WIOD Background Document*, 1–35.

Genty, A., Arto, I. & Neuwahl, F. (2012). *Final Database of Environmental Satellite Accounts: Technical Report on Their Compilation*. Technical report.

Hoekstra, R. & van den Bergh, J. C. (2003). Comparing structural decomposition analysis and index. *Energy Economics*, **25**(1), 39–64.

IEA (2017). *Electricity Information 2017*. OECD.

Miketa, A. (2001). Analysis of energy intensity developments in manufacturing sectors in industrialized and developing countries. *Energy Policy*, **29**(10), 769–775.

Miketa, A. & Mulder, P. (2005). Energy productivity across developed and developing countries in 10 manufacturing sectors: Patterns of growth and convergence. *Energy Economics*, **27**(3), 429–453.

Mulder, P. & de Groot, H. L. (2012). Structural change and convergence of energy intensity across OECD countries, 1970-2005. *Energy Economics*, **34**(6), 1910–1921.

OECD (2001). Measuring Productivity - OECD Manual. *International Productivity Monitor*, **2**(2), 1–154.

Schipper, L., Unander, F., Murtishaw, S. & Ting, M. (2001). Indicators of Energy Use and

Carbon Emissions: Explaining the Energy Economy Link. *Annual Review of Energy and the Environment*, **26**(1), 49–81.

Schymura, M. & Voigt, S. (2014). What Drives Changes in Carbon Emissions? An Index Decomposition Approach for 40 Countries. *SSRN Electronic Journal*, (14), 1–21.

Timmer, M. P., Dietzenbacher, E., Los, B., Stehrer, R. & de Vries, G. J. (2015). An Illustrated User Guide to the World Input-Output Database: the Case of Global Automotive Production. *Review of International Economics*, **23**(3), 575–605.

Voigt, S., De Cian, E., Schymura, M. & Verdolini, E. (2014). Energy intensity developments in 40 major economies: Structural change or technology improvement? *Energy Economics*, **41**, 47–62.

Walker, W. (2013). The transitional costs of sectoral reallocation: Evidence from the clean air act and the workforce. *Quarterly Journal of Economics*, **128**(4), 1787–1835.

Xu, X. & Ang, B. (2013). Index decomposition analysis applied to CO2 emission studies. *Ecological Economics*, **93**, 313–329.

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: Variables in the WIOD database

Variable	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)
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
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
LABHS	High-skilled labour compensation (share in LAB)
LABMS	Medium-skilled labour compensation (share inLAB)
LABLS	Low-skilled labour compensation (share in LAB)
H_HS	Hours worked by high-skilled persons (share in H_EMP)
H_MS	Hours worked by medium-skilled persons (share in H_EMP)
H_LS	Hours worked by low-skilled persons (share in H_EMP)
EM	Emission relevant energy use in TJ (all fuels)
CO2	CO2 emissions in Gg (kt) (all fuels)

Table 3: Scenario-specific relative cumulative emissions by country, rce_j^S

	Advanced[1]			Developing[1]			
	rce^{NIC}	rce^{NSC}	rce^{NAC}		rce^{NIC}	rce^{NSC}	rce^{NAC}
TWN	-0.32	0.27	-0.24	**IDN**	-0.10	-0.06	-0.16
DNK	-0.06	0.05	-0.14	**CZE**	-0.08	0.28	-0.19
AUS	-0.06	0.12	-0.24	**RUS**	-0.03	0.20	-0.17
ITA	-0.02	0.08	-0.09	**BRA**	-0.03	-0.01	-0.18
JPN	0.01	0.05	-0.08	**HUN**	-0.02	0.34	-0.30
AUT	0.04	0.01	-0.17	**TUR**	0.03	0.02	-0.32
ESP	0.04	0.02	-0.22	**MEX**	0.03	0.04	-0.27
GRC	0.05	0.04	-0.23	**EST**	0.04	0.53	-0.47
USA	0.05	0.15	-0.26	**IND**	0.07	0.06	-0.41
NLD	0.07	0.07	-0.20	**SVN**	0.09	0.08	-0.27
CAN	0.09	0.04	-0.23	**ROU**	0.10	0.25	-0.10
FIN	0.10	0.07	-0.27	**SVK**	0.15	0.24	-0.31
FRA	0.11	0.05	-0.17	**POL**	0.29	0.11	-0.32
BEL	0.12	0.05	-0.15	**LTU**	0.32	0.10	-0.38
SWE	0.12	0.10	-0.26	**CHN**	0.34	-0.10	-0.53
GBR	0.15	0.05	-0.21	**LVA**	0.43	0.09	-0.38
PRT	0.15	-0.12	-0.18	**BGR**	0.65	-0.37	-0.11
DEU	0.15	0.00	-0.12				
KOR	0.16	0.01	-0.34				
IRL	0.20	0.09	-0.44				
Mean	0.06	0.06	-0.21	**Mean**	0.13	0.11	-0.29
StdDev	0.11	0.07	0.09	**StdDev**	0.21	0.20	0.13

[1] Countries are sorted into advanced and developing country groups based on World Bank classification as it existed in 1995.

Table 4: HCI and LCI sets in select countries and globally

	GBR	**FRA**	**USA**	**JPN**	**CHN**	**BRA**
***HCI_j Sectors*[1]**	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 TRAinl MIN+
***Mean* ci_{jit}**	4.25	2.59	4.64	2.69	13.73	3.29
$\sum_{HCI_j} e_{jit} / \sum_i e_{jit}$	0.62	0.39	0.61	0.53	0.78	0.40
$\sum_{HCI_j} va_{jit} / \sum_i va_{jit}$	0.04	0.03	0.04	0.04	0.11	0.07
***LCI Sectors*[1]**	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
***Mean* ci_{jit}**	0.02	0.01	0.02	0.02	0.06	0.03
$\sum_{LCI_j} e_{jit} / \sum_i e_{jit}$	0.02	0.03	0.02	0.02	0.01	0.03
$\sum_{LCI_j} va_{jit} / \sum_i va_{jit}$	0.39	0.37	0.30	0.24	0.25	0.29

Global HCI and HCI sectors[2]

HCI_G	PWR+ (36), MINnm (35), RFUEL (28), TRAair (25), TRAwat (23), MINm (11), TRAinl (9), CHEM (9), MIN+ (5)
LCI_G	FIN (30), REST (29), TCOM(21), EQPeo (15), WHL (13), COMMser(11), EDU (11), RET (11), PUB (8) , HLTH+ (7), HOSP (5)

[1] In increasing order of average rank within country.
[2] For $k = 5$ and in decreasing order of frequency with which the sector is in HCI_j or LCI_j.

Table 5: Carbon intensity of top five sectors in HCI_G (2009)

	Advanced					**Developing**				
	N	Mean	StdDev	Min	Max	N	Mean	StdDev	Min	Max
PWR+	20	7.07	7.44	1.02	32.54	16	22.64	15.13	0.64	54.93
MINnm	20	2.95	2.22	0.81	11.42	16	6.11	2.57	2.11	10.94
RFUEL	20	8.62	11.69	0.65	47.78	15	10.18	11.48	0.01	34.98
TRAair	20	5.15	2.33	0.17	8.69	16	5.58	5.87	0.04	17.18
TRAwat	20	0.35	0.17	0.15	0.72	17	1.32	0.78	0.25	2.94

Table 6: Correlation between $\ln(ci_{ji})$ and key variables (2007)

		(I)	**(II)**	**(III)**
$\frac{emp_{ji}}{\sum_i emp_{ji}}$	adv	-0.50^{***}	-0.57^{***}	-0.40^{***}
	dev	-0.39^{***}	-0.45^{***}	-0.16^{***}
$\frac{cap_{ji}}{\sum_i cap_{ji}}$	adv	-0.36^{***}	-0.22^{***}	-0.12^{***}
	dev	-0.24^{***}	0.11	0.05
$\ln\left(\frac{cap_{ji}}{emp_{ji}}\right)$	adv	0.18^{**}	0.58^{***}	0.42^{***}
	dev	0.16^{**}	0.40^{***}	0.23^{***}
$\frac{hrs_{ji}^{HS}}{\sum_i hrs_{ji}}$	adv	-0.38^{***}	-0.33^{***}	-0.22^{***}
	dev	-0.41^{***}	-0.37^{***}	-0.24^{***}
$\frac{hrs_{ji}^{MS}}{\sum_i hrs_{ji}}$	adv	0.13^{*}	0.09	0.06
	dev	0.09	0.06	-0.01
$\frac{hrs_{ji}^{LS}}{\sum_i hrs_{ji}}$	adv	0.23^{***}	0.21^{***}	0.12^{***}
	dev	0.16^{**}	0.16^{**}	0.13^{***}

Note: Column (I) reports results for all HCI and LCI sectors; column (II) excludes REST if it happens to be an LCI sector; column (III) reports results from all sectors except REST. *, ** and *** indicate significance at 10%, 5% and 1%, respectively.

Table 7: Mean growth rates for select variables: HCI and LCI sectors

		HCI **Sectors** %	LCI **Sectors** %	**Δ significant? (I)**	**(II)**	**(III)**	**Non-HCI Sectors** %
$g(ci)$	adv	−0.50	−4.36	Y	N	N	−2.29
	dev	−1.82	−3.01	N			−3.47
$g(emp)$	adv	−0.51	1.37	Y	N	Y	0.25
	dev	−0.67	2.57	Y			1.34
$g(hrs)$	adv	−0.83	1.13	Y	N	Y	−0.00
	dev	−0.75	2.50	Y			1.14
$g(hrs^{HS})$	adv	2.69	4.30	Y	N	N	3.52
	dev	3.07	5.04	Y			4.37
$g(hrs^{MS})$	adv	−0.24	0.80	Y	N	Y	0.51
	dev	0.21	2.55	Y			1.94
$g(hrs^{LS})$	adv	−3.71	−2.03	Y	N	Y	−2.94
	dev	−3.40	0.29	Y			−1.20
$g(cap)$	adv	2.83	4.26	Y	Y	N	3.55
	dev	4.64	4.80	N			5.43
$g(\frac{cap}{emp})$	adv	3.36	2.80	N	Y	N	3.21
	dev	5.34	2.24	Y			4.11
$g(\frac{va}{emp})$	adv	2.34	2.78	N	N	N	1.72
	dev	3.35	3.00	N			3.43
$g(mfp)$	adv	2.55	4.55	Y	Y	Y	2.64
	dev	4.05	6.04	Y			5.47

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 and assuming unequal variances. The significance level for the test is 10%. In column (I), the difference between the mean growth rates of HCI and LCI sectors in advanced and developing countries is tested. In column (II), the difference between advanced and developing country mean growth rates in HCI sectors is tested. Finally, in column (III) the same difference in LCI sectors is tested.

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

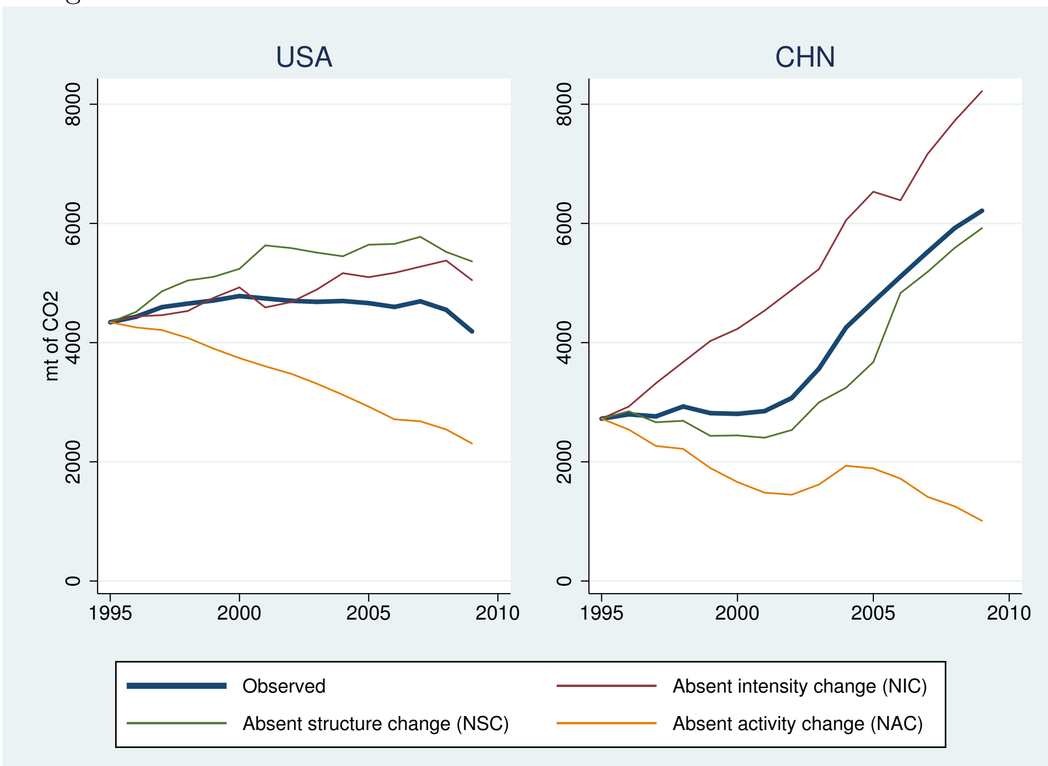


Figure 2: Relative cumulative emissions under NSC and NIC

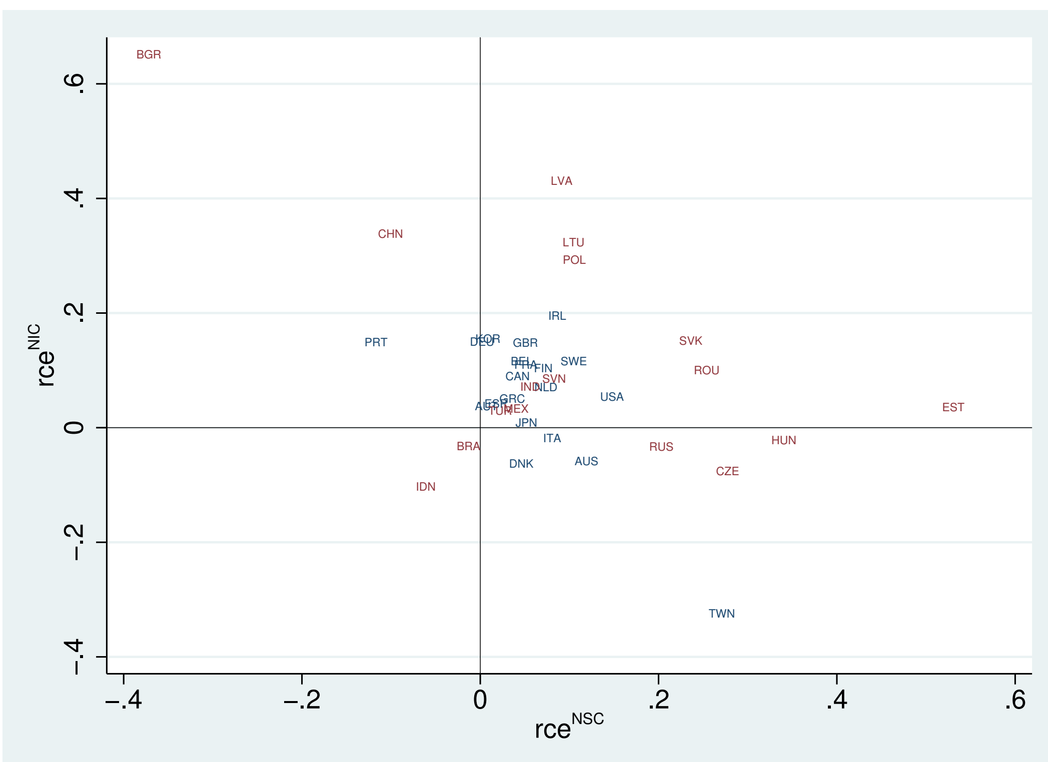


Figure 3: Mean carbon intensity of top five sectors in HCI_G over time

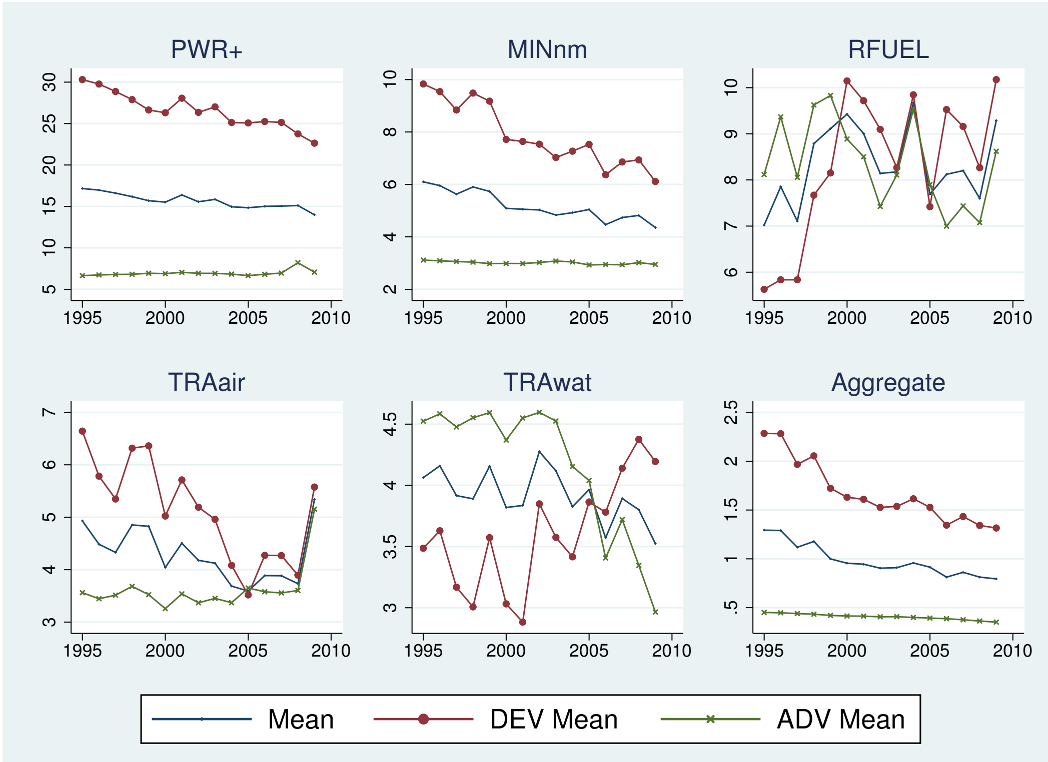
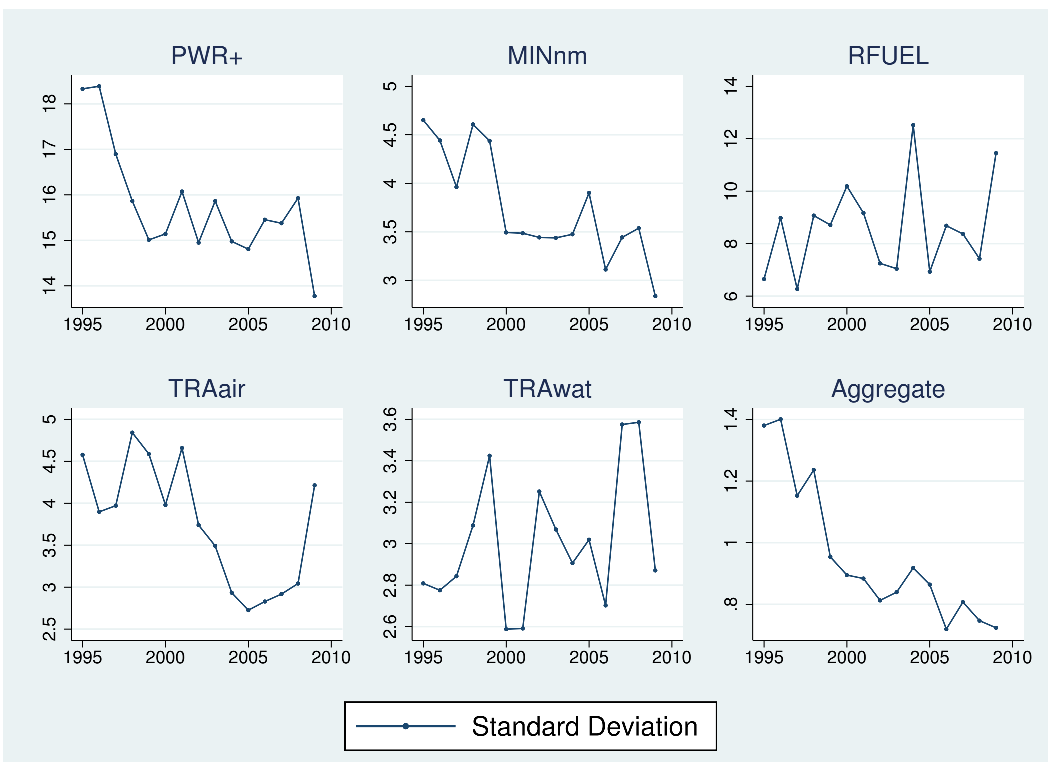


Figure 4: Standard deviation of carbon intensity of top five sectors in HCI_G over time



Appendix

A Fact 2 with full sample

This section describes the criterion used in restricting the sample behind Table 5 and Figures 3 and 4 in the main text and lists all the observations excluded. The figures based on the full sample are provided at the end to emphasise that the restrictions adopted in the main text are for clarity and does not affect Fact 2. Specifically, an observation is not in the restricted sample if ci_{jit} is more than three standard deviations away from the cross-country mean for that sector-year, which implies that following observations are excluded:

- **PWR+**: Estonia 1995-2009
- **MINnm**: Bulgaria 1995-2004
- **RFUEL**: Estonia 1995-2009; Czech Republic 2005-2008; Germany 2008; Portugal 1995
- **TRAair**: Hungary 2000,2002-2006,2008,2009; Latvia 1995-1998; Poland 2001
- **TRAwat**: Denmark 2008, 2009; Latvia 2002; Mexico 2000, 2001; Romania 1997-2000; Slovakia 2007; Taiwan 2006, 2009
- **Aggregate**: none

Note that all observations from Estonia's PWR+ and RFUEL sectors are excluded. For PWR+, observations from Estonia are between 6.1-7.5 times greater than the year-specific 37-country mean depending on the year. For RFUEL, they are 5.1-24.2 times greater. Similarly, observations from Bulgaria's MINnm sector between 1995-2004 sector are atypical in that they are 3.9-9.1 times greater than the full sample mean. The other excluded country-sector-year observations are idiosyncratic and suggest measurement problems. In all cases, the differences are large enough to influence the sample-mean for the year.

Figures A.1 and A.2 are analogous to Figures 3 and 4 but use the entire sample. I highlight two main differences. First, the scales of the vertical axes are greater in Figures A.1 and A.2, particularly in the panels for RFUEL, TRAair and TRAwat. Second, there is much more noise in Figures A.1 and A.2 obscuring, but not altering, the patterns highlighted in Fact 2.

Figure A.1: Mean carbon intensity of top five sectors in HCI_G over time

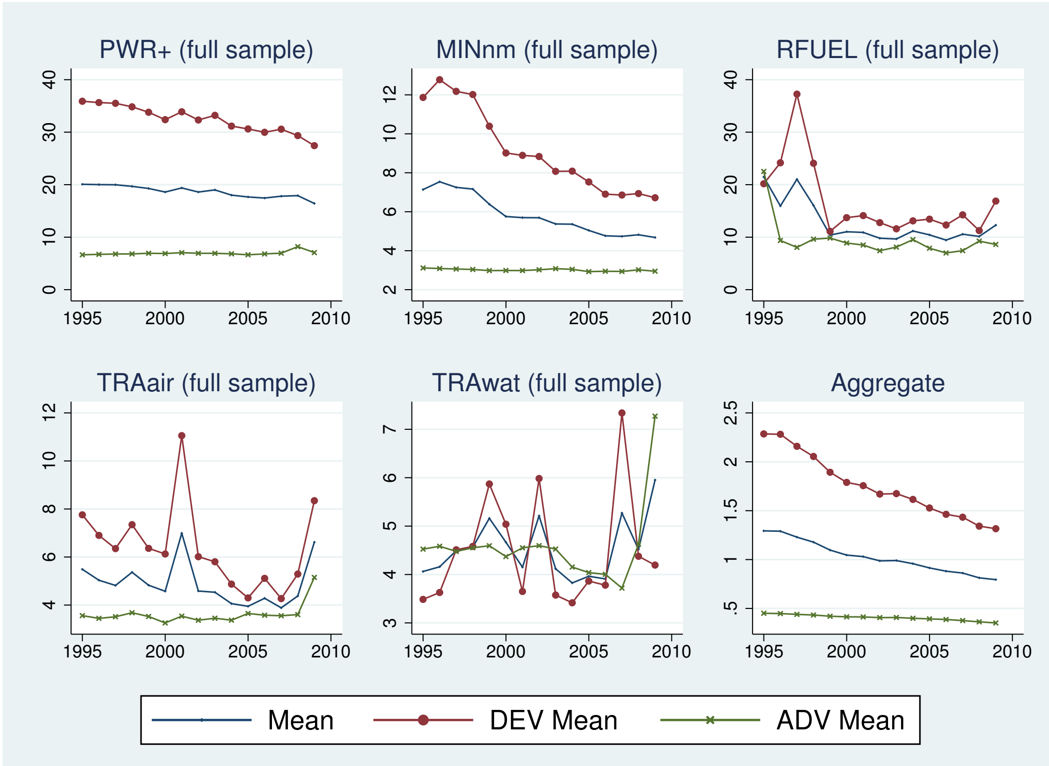
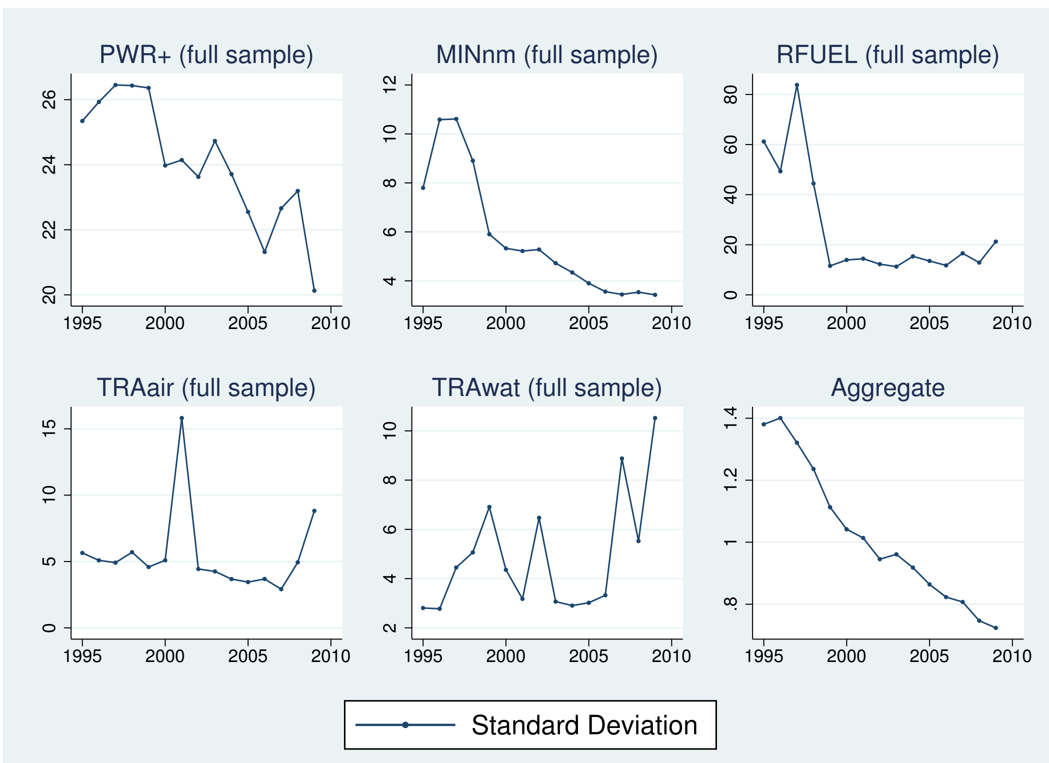


Figure A.2: Standard deviation of carbon intensity of top five sectors in HCI_G over time



B Carbon intensity and factor inputs in the USA

Tables B.1 and B.2 use the USA as an example to illustrate the sector level variables studied in Table 6 for an individual country. In 2009, HCI sectors of the USA 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.

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. Indeed, the sector is such an outlier that excluding REST from LCI_j average renders the group much less capital intensive.[15]

Table B.1 shows that HCI sectors employ a smaller share of the US workers and use more capital intensive technologies. Table B.2 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 B.2 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 relative to the USA economy as a whole, and relative to the LCI sectors regardless of whether REST is included in the averages.

[15] 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 South Korea. Excluding these country-sectors does not alter the results in the main text.

Table B.1: Carbon intensity and factor inputs in HCI_{USA} and LCI_{USA} (2009)

	Sector (i)	ci_{jit}	$\frac{emp_i}{\sum_i emp_i}$	$\frac{cap_i}{\sum_i cap_i}$	$\frac{cap_i}{emp_i}$
HCI	PWR+	12.385	0.004	0.036	1993.729
	TRAwat	2.790	0.000	0.001	619.690
	MINnm	3.744	0.003	0.002	142.493
	TRAair	2.576	0.003	0.005	350.421
	RFUEL	1.719	0.001	0.003	880.336
***HCI* mean**		**4.643**	**0.002**	**0.009**	**797.334**
LCI	VEHser	0.031	0.008	0.009	263.386
	FIN	0.033	0.042	0.041	212.829
	EQPeo	0.016	0.012	0.011	191.753
	WHL	0.026	0.041	0.019	99.011
	REST	0.008	0.012	0.450	7795.900
***LCI* mean**		**0.023**	**0.023**	**0.106**	**1712.576**
(excl.REST)		**0.026**	**0.026**	**0.020**	**191.745**
USA mean					**215.852**

Table B.2: Carbon intensity and skill composition in HCI_{USA} and LCI_{USA} (2009)

	Sector (i)	ci_{jit}	$\frac{hrs_i}{\sum_i hrs_i}$	$\frac{hrs_i^{HS}}{hrs_i}$	$\frac{hrs_i^{MS}}{hrs_i}$	$\frac{hrs_i^{LS}}{hrs_i}$
HCI	PWR+	12.385	0.005	0.285	0.679	0.036
	TRAwat	2.790	0.001	0.152	0.747	0.101
	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**
LCI	VEHser	0.031	0.008	0.323	0.605	0.072
	FIN	0.033	0.043	0.511	0.478	0.011
	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**