# Your money or your life? The carbon-development paradox

## Supplementary materials

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# 1 Table S1: List of the 70 countries included in the analysis

| | | |
|---|---|---|
| Algeria | Ghana | Pakistan |
| Argentina | Greece | Panama |
| Australia | Guatemala | Paraguay |
| Austria | Honduras | Peru |
| Bangladesh | Iceland | Portugal |
| Benin | India | Republic of Korea |
| Bolivia | Indonesia | Senegal |
| Brazil | Iran | South Africa |
| Cameroon | Iraq | Spain |
| Canada | Ireland | Sri Lanka |
| Chile | Israel | Sweden |
| China | Italy | Thailand |
| Colombia | Jamaica | Togo |
| Congo | Japan | Trinidad and Tobago |
| Costa Rica | Kenya | Tunisia |
| Côte d'Ivoire | Mexico | Turkey |
| Dominican Republic | Morocco | United Kingdom |
| Ecuador | Myanmar | United States of America |
| Egypt | Nepal | Uruguay |
| El Salvador | Netherlands | Venezuela |
| Finland | New Zealand | Zambia |
| France | Nicaragua | Zimbabwe |
| Gabon | Nigeria | |
| Germany | Norway | |

# 2 Correlation tables of variables considered in the analysis

These tables correspond to the data used in the paper, for the countries listed in Table S1.

**Table S3**: correlation coefficients for the variables in 1971

| **Variable** | **Carbon emissions** | **Primary energy** | **Income MER** | **Income PPP** | **Food supply** | **Residential electricity** | **Life expectancy** |
|---|---|---|---|---|---|---|---|
| Units | t CO2 per cap | GJ per cap | $ per cap | $ per cap | kCals per cap per day | kWh per cap | years |
| | *log* | *log* | *log* | *log* | *log* | *log* | *linear* |
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 1 | 1.000 | 0.884 | 0.901 | 0.887 | 0.744 | 0.890 | 0.791 |
| 2 | 0.884 | 1.000 | 0.883 | 0.879 | 0.737 | 0.877 | 0.777 |
| 3 | 0.901 | 0.883 | 1.000 | 0.937 | 0.795 | 0.913 | 0.794 |
| 4 | 0.887 | 0.879 | 0.937 | 1.000 | 0.789 | 0.883 | 0.800 |
| 5 | 0.744 | 0.737 | 0.795 | 0.789 | 1.000 | 0.760 | 0.762 |
| 6 | 0.890 | 0.877 | 0.913 | 0.883 | 0.760 | 1.000 | 0.840 |
| 7 | 0.791 | 0.777 | 0.794 | 0.800 | 0.762 | 0.840 | 1.000 |

**Table S4**: correlation coefficients for the variables in 2014

| Variable | Carbon emissions | Primary energy | Income MER | Income PPP | Food supply | Residential electricity | Life expectancy |
|---|---|---|---|---|---|---|---|
| Units | t CO2 per cap | GJ per cap | $ per cap | $ per cap | kCals per cap per day | kWh per cap | years |
| | *log* | *log* | *log* | *log* | *log* | *log* | *linear* |
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 1 | 1.000 | 0.916 | 0.878 | 0.898 | 0.720 | 0.896 | 0.729 |
| 2 | 0.916 | 1.000 | 0.890 | 0.883 | 0.670 | 0.901 | 0.654 |
| 3 | 0.878 | 0.890 | 1.000 | 0.979 | 0.749 | 0.940 | 0.812 |
| 4 | 0.898 | 0.883 | 0.979 | 1.000 | 0.769 | 0.944 | 0.833 |
| 5 | 0.720 | 0.670 | 0.749 | 0.769 | 1.000 | 0.722 | 0.647 |
| 6 | 0.896 | 0.901 | 0.940 | 0.944 | 0.722 | 1.000 | 0.808 |
| 7 | 0.729 | 0.654 | 0.812 | 0.833 | 0.647 | 0.808 | 1.000 |

# 3 Relation of Functional Dynamic Decomposition (FDD) to other methods

In this section, we relate the FDD method to other related or similar methods which others may have used or choose to use in the future.

## 3.1 Time derivative

If we can generally write:

Equ S7. $y_i(\mathrm{t}) = a(t) + b(t) \cdot x_i(t) + e_i(t)$

Then we can express the change in y as a time derivative:

Equ S8. $\dot{y_\iota}(\mathrm{t}) = \dot{a}(t) + \dot{b}(t) \cdot x_i(t) + b(t) \cdot \dot{x_\iota}(t) + \dot{e_\iota}(t)$

This approach would work for small (infinitesimal) and smooth changes in *y*. Unlike the FDD approach, it is not an exact decomposition, and does not express the full change in *y* for larger shifts in *a*, *b*, *x* and *e*.

## 3.2 Elasticity

The elasticity approach is used to characterise the connection between the change in two variables, like the time derivative approach above, when their functional relationship is well described by a log-log relation (as it is for the GDP-carbon part of our analysis, and the relationship between the variables is not expected to change over time.

Then we would be able to write:

Equ S1. $\log\left(\mathrm{y}_i(\mathrm{t})\right) = a + b \cdot \log\left(x_i(t)\right) + e_i(t)$

then

Equ S2. $\frac{\dot{y_\iota}(\mathrm{t})}{y_i(\mathrm{t})} = b \cdot \frac{\dot{x_\iota}(\mathrm{t})}{x_i(\mathrm{t})} + \dot{e_\iota}(t)$

If $e_i(t)$ is also expected not to change much or systematically over time, then the change in time of *y* is simply related to the change in *x* through *b*: a change in *x* of 1% will translate to a change in *y* of *b*% (b is the the time elasticity characterising the relation). This approach is commonly used, but deeply flawed in the case when in fact *a* and *b* themselves are time-varying parameters. If *a* and *b* change over time, the FDD gives a full accounting of the change in *y*, and even the time derivative approach above gives a more complete description of the change in time of *y*. In contrast, the elasticity approach is flawed because it attributes all change in *y* to changes in *x* through *b*: no changes in other parameters (such as the functional relation itself) are allowed to be considered in this formalism.

### 3.3 Easterlin Paradox

The Easterlin Paradox method, most recently published here (Easterlin, McVey et al. 2010), takes as its starting point the fact that a correlation in *x* and *y* at one point in time would lead to a correlation between changes in *x* and in *y* (according the difference & rates of change shown in Table S5). Easterlin uses this method to contrast international level changes ($\Delta$y) in life satisfaction with rates of change in income $\Delta$x/x, implicitly using a log-linear relationship between the two.

This method is also used in a slightly different form to test Okun's law, relating changes in unemployment to changes in economic output (Lee 2000), but in this case it is used for one country at annual intervals, rather than for an international sample at across a large time span.

We applied Easterlin's approach to our variables in Table 1, and found no significant correlation between changes in *x* and changes in *y*. This is similar to Easterlin's result, but unexpected in our case, since at least for Market Exchange Rate income and carbon emissions, for instance, we would expect to see a very significant correlation between $\Delta$x/x and $\Delta$y/y. Our own FDD results show that 90% of MER income growth can be statistically attributed to emissions growth. We investigated this result further, and showed by Monte Carlo simulations on a synthetic dataset that the Easterlin approach tends to produce null results when the stochastic change (residual change $\Delta e_i$ in Eq. 2) is on the same order of magnitude as the driver change ($\bar{b} \cdot \Delta x_i$ in Eq. 2). The Easterlin approach may thus mask systematic relations between international parameters when the stochastic change in individual countries is significant, as it can be expected to be over long time spans. It may be worth revisiting the Easterlin income-happiness paradox using a version of the FDD method to resolve this issue.

The application of this method to Okun's Law analysis, considering differences only within one country and over shorter (annual) timespans, would suffer much less from the issue of $\Delta e_i$ being as large as (or larger than) $\bar{b} \cdot \Delta x_i$, since the stochastic term is expected to vary much less at short time intervals and within one country.

## 3.4 Panel data analysis

Panel data analysis is an econometric technique that is used to quantify the relationship between different variables using data that involve spatial and temporal dimensions. In other words, the analysis involves data for several observational units at a specific moment in time, as well as time series for each single unit. This method is thus particularly helpful when we wish to statistically estimate relationships between variables that belong to more than one country over a certain period of time.

The objective of the analysis is to estimate the parameters of a linear regression equation that involves a dependent (y) and one or more independent variables (x, z, etc.). In the case of a bivariate regression, the general form of the equation can be expressed as:

$$y_{it} = a + b \cdot x_{it} + u_{it}$$

where the indices '*i*' and '*t*' stand for the individual observational units and time, respectively, while 'a' and 'b' are the parameters to be estimated. The term 'u' represents the stochastic error.

A common econometric procedure is to conduct regressions using variables expressed in first differences and logarithmic form, which is comparable to expressing the variables in terms of annual percentage changes. The estimated slope parameter thus represents an elasticity, which indicates the extent to which the dependent variable changes when the independent changes in 1%. Differencing the variables also allows controlling for omitted factors that are time invariant and prevents co-integration issues, given that the differenced variables are stationary. Applying first differences to a variable already expressed in log form denotes subtracting its value in time 't-1' from its value in 't', as shown below:

$$\Delta \log(y_i) = \log(y_{it}) - \log(y_{it-1})$$

Rearranging, the general form of a bivariate equation in differences can be expressed as:

$$\Delta\log(y_{it}) = b\Delta\log(x_{it}) + \Delta u_{it}$$

The parameters in the regression equation are then estimated taking into account any issues that affect the residuals, like as heteroskedasticity, serial correlation or cross-sectional correlation. If any such issues are present, ordinary least squares may yield statistically inefficient estimators and other techniques are thus more appropriate. In cases where heteroskedasticity and serial correlation are present, the method of feasible generalized least squares (FGLS) can produce more efficient estimators.

At the outset, panel data analysis seems to be an appropriate method to examine to what extent improvements in international life expectancy can be attributed to contemporaneous growth in carbon emissions, income or food supply over time. The same can be said in relation to the increase in income that can be attributed at an international scale to carbon emissions. In fact, regressions using cross-sectional data (i.e. at a moment in time) expressed in levels (non-differentiated) yield satisfactory goodness-of-fit values larger than 75% when examining life expectancy versus emissions, income and food. Similar results are obtained when using pooled data (i.e. all countries and all years). However, when we examined the same functional form over time and used data expressed as first differences, the goodness-of-fit values that we found were low. This is essentially analogous to Easterlin's result. However, we also found that the same variables had predictive power in this method and in FDD, showing consistency across analytic approaches. The difficulty in using traditional panel methods in the particular case of this paper is that these produce slope estimators (i.e. elasticities) for each independent variable, which characterise the behaviour of the different observational units (i.e. countries) during the whole time period. Nevertheless, as is illustrated in this article, the estimators or parameters do change over time, and these methods do not truly capture these dynamics.

### 3.5 Multilevel regression analysis

Multilevel regression analysis, also known as hierarchical or mixed-level analysis, is commonly used when observational units can be organised at more than one level or category. This technique thus allows determining how parameters, like the slope and intercept, in a regression vary at different levels (Hox, 2010). The multilevel method offers an advantage over the general pooled regression model, which ignores the variation between observational units. In this paper, multilevel regression analysis was used given that it is useful to assess how both intercepts and slopes vary over time. By considering time as the 'level' or 'grouping' criteria for a dataset comprised of 70 countries, this tool allows estimating the intercept and slope parameters for every year in the period under study. The annual variations, as well as the trend, of the estimated parameters can then be analysed. The case of a bivariate linear multilevel regression model can expressed as follows:

$$Y_{it} = \beta_{0t} + \beta_{1t} X_{it} + e_{it} \tag{1}$$

where *Y* and *X* are the dependent (e.g. life expectancy) and independent variables (e.g. $CO_2$ emissions per capita) expressed in logs, respectively; *e* stands for the residuals, subscript *i* refers to the units (or countries) and subscript *t* to individual years. In turn, the estimated intercept $\beta_0$ and slope $\beta_1$ parameters are assumed to present variations over time. If no additional level-specific predictors are used, then it can be said that the parameters are given by:

$$\beta_{0t} = \gamma_{00} + u_{0t} \tag{2}$$

$$\beta_{1t} = \gamma_{10} + u_{1t} \tag{3}$$

By substituting equations (2) and (3) back into (1), a general expression can be obtained:

$$Y_{it} = \gamma_{00} + \gamma_{10}X_{it} + u_{1t}X_{it} + u_{0t} + e_{it} \qquad (4)$$

The right-hand side of equation (4) can be divided into two portions. The first one, given by $\gamma_{00} + \gamma_{10}X_{it}$, represents the fixed or deterministic part of the model, while the second, given by $u_{1t}X_{it} + u_{0t} + e_{it}$, contains the random and stochastic elements.[1] It is worth noting that the terms $\gamma_{00}$ and $\gamma_{10}$ represent the mean of the yearly intercepts and slopes, respectively. The parameters in this last expression can then be estimated using maximum likelihood estimation. See Hox (2010) and Gelman and Hill (2007) for a more detailed description of estimation procedures used in multilevel regression analysis.

In order to compare the goodness of fit in this type of models, the traditional $R^2$ cannot be used due to the complex structure of the residuals, as can be implied from (4). Measures such as the Akaike Information Criteria (AIC) or the Bayesian Information Criteria (BIC) can be employed to check the quality of each specification, relative to others.

### 3.6 Comparison of Functional Dynamic Decomposition and Multilevel Regression

We conducted multilevel regression analysis on the same dataset as we used in the main paper. Two data issues had to be addressed, since Gabon and Iraq both had years missing for the residential electricity indicator (these countries were thus omitted for specific years for regressions involving that variable).

We then used the slope and intercept coefficients resulting from the multilevel analysis in the FDD decomposition (Eqs. 2 & 3 in the main text).

These results are summarized in Table S1. Unlike FDD, the multilevel regression does not result in an exact decomposition, and thus the remaining fraction of $\Delta y$ is shown as a residual term.

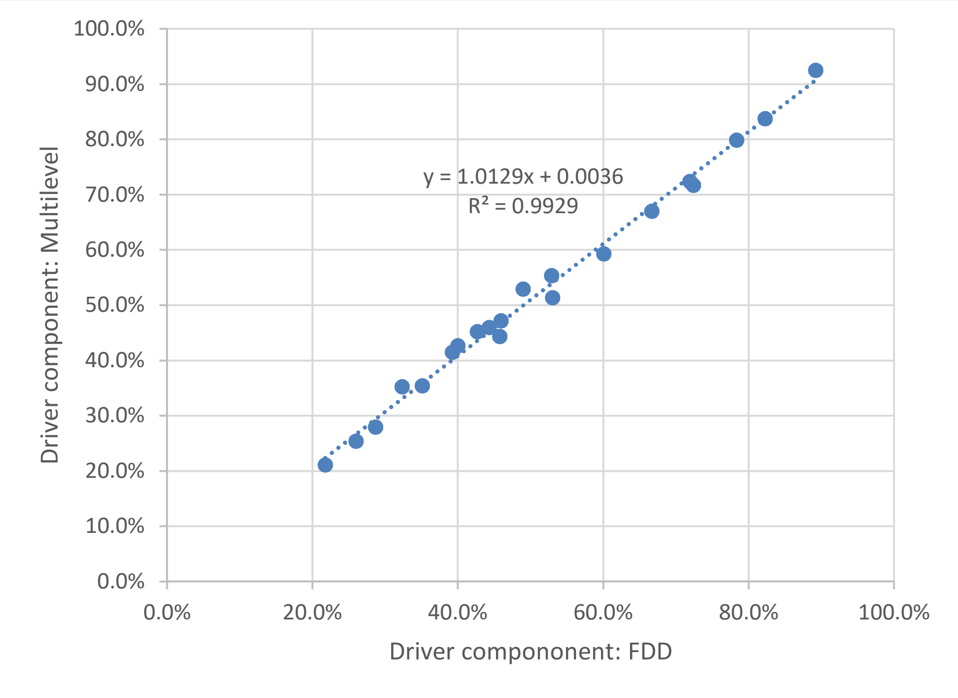
The result we report in the article is the "driver", or $\Delta x$ related fraction of $\Delta y$. We compare these specifically in Figure S1. The correspondence is extremely good, and means that we are effectively measuring the same quantity with both methods. As a consequence, we only display the results for FDD in the paper itself, since it is the simpler method.

[1] It is important not confuse this terminology with that used in panel data regression analysis, where 'fixed' and 'random' effects are related to completely different models (see: Wooldridge, 2002).

**Table S1:** Comparison of multilevel and FDD results.

| Dependent variable | Independent variable | Multilevel $\frac{\Delta Driver}{\Delta y}$ | Multilevel $\frac{\Delta Func.}{\Delta y}$ | Multilevel Residual | Multilevel AIC | FDD $\frac{\Delta Driver}{\Delta y}$ | FDD $\frac{\Delta Func.}{\Delta y}$ |
|---|---|---|---|---|---|---|---|
| Primary Energy | Carbon emissions | 71.7% | 18.0% | 10.3% | 3324 | 72.4% | 27.6% |
| MER income | Carbon emissions | 72.4% | 9.8% | 17.8% | 5783 | 71.9% | 28.1% |
| MER income | Primary energy | 92.6% | 6.8% | 0.7% | 5909 | 89.2% | 10.8% |
| PPP income | Carbon emissions | 42.7% | 53.2% | 4.1% | 3837 | 40.0% | 60.0% |
| PPP income | Primary energy | 53.0% | 39.9% | 7.2% | 4190 | 48.9% | 51.1% |
| PPP income | MER income | 55.4% | 41.5% | 3.1% | 1462 | 52.9% | 47.1% |
| Food supply | Carbon emissions | 35.3% | 51.3% | 13.4% | -4297 | 32.3% | 67.7% |
| Food supply | Primary energy | 41.5% | 43.7% | 14.8% | -3751 | 39.2% | 60.8% |
| Food supply | MER income | 45.3% | 43.6% | 11.2% | -4554 | 42.7% | 57.3% |
| Food supply | PPP income | 79.9% | 10.3% | 9.8% | -4512 | 78.4% | 21.6% |
| Residential electricity | Carbon emissions | 35.4% | 60.0% | 4.6% | 6564 | 35.1% | 64.9% |
| Residential electricity | Primary energy | 46.0% | 51.1% | 3.0% | 6247 | 44.3% | 55.7% |
| Residential electricity | MER income | 47.2% | 53.8% | -1.0% | 5166 | 45.9% | 54.1% |
| Residential electricity | PPP income | 83.8% | 19.8% | -3.6% | 6037 | 82.3% | 17.7% |
| Residential electricity | Food supply | 67.0% | 19.1% | 13.9% | 8907 | 66.7% | 33.3% |
| Life expectancy | Carbon emissions | 21.2% | 73.8% | 5.0% | 19814 | 21.7% | 78.3% |
| Life expectancy | Primary energy | 25.4% | 74.3% | 0.3% | 20518 | 26.0% | 74.0% |
| Life expectancy | MER income | 28.0% | 68.0% | 4.0% | 19378 | 28.7% | 71.3% |
| Life expectancy | PPP income | 51.4% | 44.4% | 4.2% | 18950 | 53.0% | 47.0% |
| Life expectancy | Food supply | 44.4% | 48.4% | 7.2% | 20234 | 45.7% | 54.3% |
| Life expectancy | Residential electricity | 59.3% | 31.4% | 9.3% | 19058 | 60.0% | 40.0% |

**Figure S1:** comparison of $\frac{\Delta Driver}{\Delta y}$ in multilevel and FDD methods.




# 4 Summary of additional single and multi-variate analysis

This section presents additional material and explains the detailed rationale for our specific variable choices.

We present results including different energy indicators (section 4.1), multi-variable cases (section 4.2) and considerations of changes within the time interval of 1971-2014 (section 4.3). We also present more recent time interval results (1990-2014), during which both consumption-based and territorial emissions accounts are available (Le Quéré et al 2018, Peters & Hertwich 2008) (section 4.4). Finally, we show an extreme example of reverse paradoxical behaviour (low correlation but high dynamic coupling) for electricity and education (section 4.5).

All the analyses in the main text were conducted for the countries listed in Table S1. This is not the case for the analysis covered in this section: instead the number of countries covered is documented in each case. Restricting the analysis to the same countries involving so many variables & time intervals would result in a much smaller country sample, and hence internationally less representative results.

## 4.1 Comparing types of final energy use (as dynamic drivers of life expectancy)

The International Energy Agency provides final energy use for several aggregate sectors: industrial, commercial, residential and transport. We can test these separately in terms of their dynamic coupling with life expectancy.

**Table S5:** Comparing final energy types as dynamic drivers of life expectancy improvements, 1971-2014 (pairwise analysis)

| | Industrial Final Energy | Commercial Final Energy | Residential Final Energy | Transport Final Energy | Total Final Energy |
|---|---|---|---|---|---|
| ∆Driver | 15% | 44% | 8% | 37% | 22% |
| $R^2$ | 0.57 | 0.44 | 0.09 | 0.62 | 0.48 |
| Number of countries | 108 | 88 | 109 | 108 | 109 |

Commercial and transport final energy are clearly much more dynamically coupled to life expectancy improvements than industrial or residential. The reason residential final energy is so very different from residential electricity is because it is dominated by diverse heating and cooking fuels, which depend on locally available fuels, as well as geography and climate.

We repeat the same exercise for electricity use categories (Table S6).

**Table S6:** Comparing electricity categories as dynamic drivers of life expectancy improvements, 1971-2014 (pairwise analysis)

| | Industrial Electricity | Commercial Electricity | Residential Electricity | Transport Electricity | Total Electricity |
|---|---|---|---|---|---|
| ∆Driver | 33% | 64% | 61% | 17% | 52% |
| $R^2$ | 0.61 | 0.65 | 0.66 | 0.34 | 0.68 |
| Number of countries | 100 | 80 | 96 | 36 | 109 |

Residential and commercial electricity stand out as the most dynamically coupled to life expectancy. The reason we chose to use residential electricity in our analysis (rather than commercial electricity) is simply due to data availability: commercial electricity is available for far fewer countries than residential. As indicators, they are extremely tightly coupled internationally, and effectively express the same information: availability of electricity services in buildings, both public and private, for heating, cooling, cooking, food & medicine storage, communication, lighting, and many more.

### 4.2 Multi-variable results

Equations 1-3 can be trivially adapted to the case of multi-variable regressions (as long . as no non-linear interaction terms are included). Since this paper represents the first time this method is applied, we prefer to keep the analysis in the main text to simple bivariate cases. However, we have applied multi-variate analyses to our dataset, and some of the results are interesting enough to share here.

First, we combine the final energy categories in Table S5 (except residential final energy, which does not warrant inclusion, due to its low dynamic explanatory power).

**Table S7:** Multi-variable results for final energy categories as dynamic drivers of life expectancy improvements, 1971-2014

| ∆Driver | |
|---|---|
| Industrial Final Energy | 7% |
| Commercial Final Energy | 10% |
| Transport Final Energy | 17% |
| Sum of all | 34% |
| $R^2$ | 0.69 |
| Number of countries | 88 |

Transport final energy stands out as the strongest contribution, much stronger here than commercial final energy (the reverse was true in Table S5 where single variable contributions were compared).

It is worth noting here that, because FDD is a 2-step process, where the first step consists in a linear regression, an explanatory variable that is more highly correlated to the dependent variable (as is the case with transport vs. commercial final energy and life dependency) will tend to have “stronger” (steeper) coefficients and dominate in the second stage of the method.

We then can conduct a multi-variable FDD on the different categories of electricity use (except transport, due to lack of significance and data in Table S6).

**Table S8:** Multi-variable results for electricity categories as dynamic drivers of life expectancy improvements, 1971-2014

| ΔDriver | |
|---|---|
| Industrial Electricity | 3% |
| Commercial Electricity | 19% |
| Residential Electricity | 40% |
| Sum of all | 62% |
| $R^2$ | 0.74 |
| Number of countries | 77 |

In the multi-variate case, industrial electricity fades to insignificance, whereas residential electricity dominates over commercial.

We now turn to combinations of transport final energy, residential electricity, food supply and PPP income, since these are the most important variables which qualify as “satisfiers” of life expectancy in our dataset (Table S9).

None of the variables in Table S9 fades to complete insignificance when considered alongside the others (as industrial electricity does in Table S8, for instance). However, every time transport is considered in the same models as residential electricity, its dynamic contribution to life expectancy improvements drops to 13% or less (from 37% when considered alone). This is the reason why we did not include it in the analyses presented in the main paper. In contrast, food supply maintains itself at a higher level, no matter which other indicators are included in the models.

In terms of the models shown in Table S9, we don’t consider that one multi-variable model is ultimately superior to the other, either through its dynamic explanatory power (higher sum of ΔDriver contributions) or goodness-of-fit ($R^2$). As shown in Table S10, this is a system with a lot of cross-correlation. Contributions from one variable in FDD could be easily attributed to another with similar statistical behaviour, so we do not venture any interpretation beyond the pair-wise analysis shown in the main text. However, in the next section, we will see that trends in the multi-variable results can be observed and do warrant interpretation.

**Table S9:** Multi-variable results for residential electricity, transport energy, food supply and PPP income as dynamic drivers of life expectancy improvements, 1971-2014

| *Model number*<br>∆Driver from: | *1* | *2* | *3* | *4* | *5* | *6* | *7* | *8* | *9* | *10* | *11* | *12* | *13* | *14* | *15* |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Residential Electricity | 61% | | | | 43% | 43% | 32% | | | | 31.5% | 22% | 22% | | 16% |
| Final Energy Transport | | 37% | | | 13% | | | 25% | 24% | | 9.5% | 10% | | 15% | 9% |
| Food Supply | | | 44% | | | 18% | | 22% | | 20% | 15.6% | | 14% | 18% | 12% |
| PPP income | | | | 42% | | | 22% | | 17% | 30% | | 18% | 18% | 14% | 15% |
| Sum of all | 61% | 37% | 44% | 42% | 56% | 61% | 54% | 47% | 41% | 50% | 56.7% | 50% | 54% | 47% | 51% |
| $R^2$ | 0.66 | 0.62 | 0.49 | 0.61 | 0.69 | 0.69 | 0.70 | 0.67 | 0.68 | 0.67 | 0.71 | 0.72 | 0.71 | 0.70 | 0.73 |
| Number of countries | 96 | 108 | 138 | 144 | 95 | 85 | 92 | 94 | 103 | 127 | 84 | 91 | 84 | 92 | 83 |

**Table S10**: correlation coefficients of variables in Table S9 (83 countries), all variables logged except life expectancy.

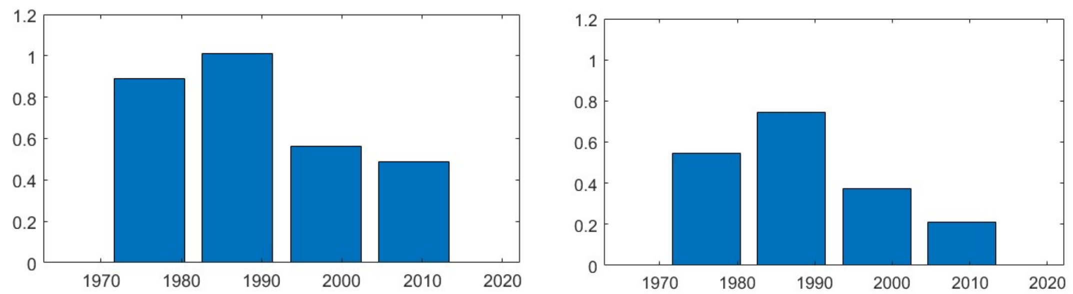
| | Final Energy Transport | Food Supply | PPP income | Life Expectancy |
|---|---|---|---|---|
| Residential Electricity | 0.926 | 0.750 | 0.887 | 0.816 |
| Final Energy Transport | | 0.755 | 0.879 | 0.811 |
| Food Supply | | | 0.729 | 0.730 |
| PPP income | | | | 0.773 |

### 4.3 Changes within the time interval 1971-2014

It is possible to apply the FDD method to different time intervals during the 43 years covered by the dataset: we show some of these results here.

Figure S2 shows the fraction of income growth which can be explained by increases in territorial per capita carbon emissions over time, for both MER and PPP income. The pattern is similar, showing first high and increasing dynamic coupling in the 1970s & 1980s, then decreasing in the 1990s & 2000s, although the level is always much higher for MER income than for PPP. The decline of territorial carbon emissions in statistically accounting for growth in income is quite dramatic, and we believe to be robust.

**Figure S2:** FDD analysis of dynamic coupling between per capita territorial carbon emissions and MER income (left) and PPP income (right) ( 1= 100%) over time. Each bar corresponds to a decade interval.




This trend is reversed, and dramatically so, when we consider consumption-based emissions rather than territorial emissions and their ability to account for growth in income (Figure S3). Consumption-based carbon emissions, sometimes known as carbon footprints, take into account the carbon embodied in traded goods and services (Le Quéré et al 2016, Peters & Hertwich 2008).

**Figure S3:** FDD analysis of dynamic coupling between per capita territorial (blue) and consumption-based (red) carbon emissions and MER income (2 plots on left) and PPP income (2 plots on right) ( 1= 100%) over time. Each bar corresponds to a decade interval.

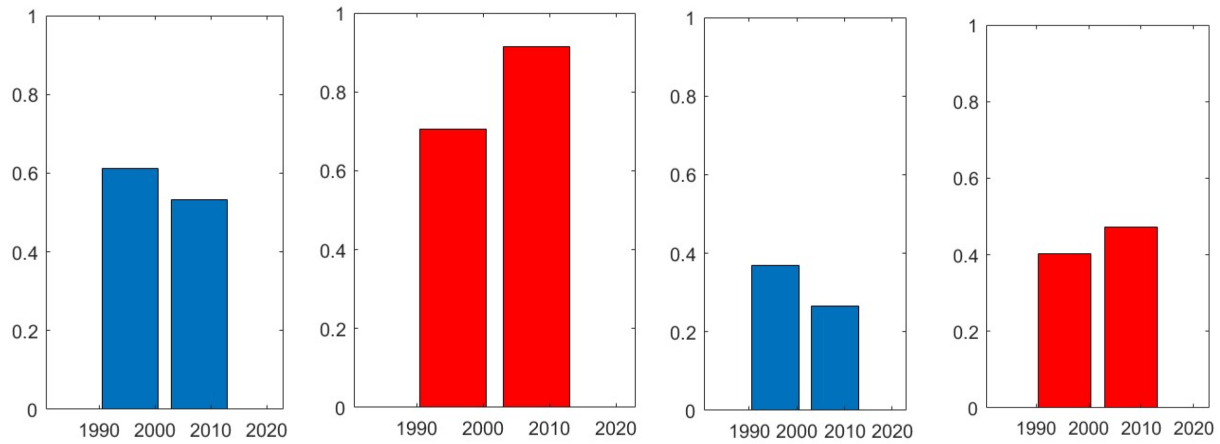
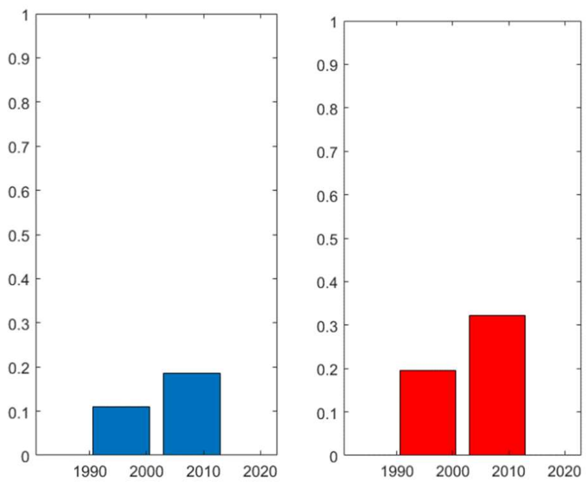


Figure S3 shows two striking facts: first that trade-adjusted carbon emissions are much more highly dynamically coupled than territorial emissions to income, especially for MER income, and second that this coupling is increasing over time. In the years between 2002 & 2014, territorial emissions increases could only explain 53% of MER income growth – but consumption-based emissions could account for a whopping 91%. It would thus be incorrect to state that economic growth is in any way decoupled or decoupling from emissions growth. Trade-corrected metrics are clearly increasingly important to understand the resource dependency of societies. However, since they are unavailable for most countries before 1990, we did not use them in the main article, which focused on the longer timespan 1971-2014.

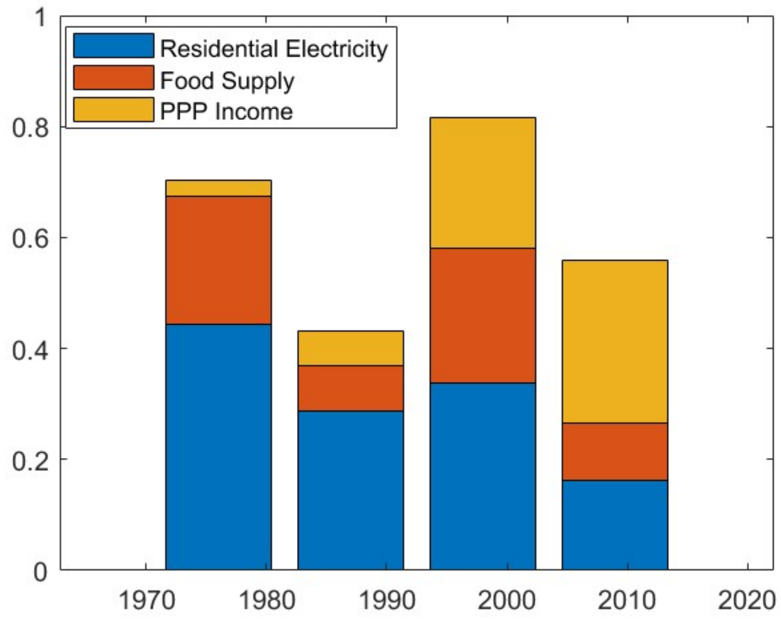
In terms of dynamic coupling with life expectancy, both consumption-based and territorial emissions show an increased coupling over time (Figure S4). Again, consumption-based emissions are markedly more highly dynamically coupled to life expectancy than territorial emissions, but remain at an overall low level (below one third).

**Figure S4:** FDD analysis of dynamic coupling between per capita territorial (blue) and consumption-based (red) carbon emissions life expectancy ( 1= 100%) over time. Each bar corresponds to a decade interval.




We now turn to the changes in FDD contributions to life expectancy, considering the multi-variable case of model 13 in Table S9: residential electricity, food supply and PPP income (Figure S5).

**Figure S5:** changing multivariate contributions of residential electricity, food supply and PPP income to improvements in life expectancy (1 = 100%). Each bar corresponds to a decade interval.




The total level of improvement in life expectancy which can be accounted for by these indicators is highly variable and shows no clear trend. However, there is a clear trend in the increasing proportion of life expectancy improvements which can be accounted for by PPP income. The proportion accounted for by food supply is variable, but relatively stable, and the proportion accounted for by residential electricity is decreasing. Without more information, it is difficult to interpret these results, but it may be that adequate food supply and electricity access are becoming more widespread, and hence contribute less to relative improvements in life expectancy over time. PPP income can be understood here as a proxy for diverse forms of consumption and access not covered by either food or electricity, but without more detail on which types of expenditure or investment are most important it is not possible to make clear statements of priorities. Again this points to the importance of identifying and measuring specific satisfiers of human needs, rather than blanket economic or resource use metrics.

### 4.4 Reverse paradox: education and electricity

One of the most curious and interesting cases in our dataset was that of education, measured by the World Bank indicator of "School enrollment, primary (% gross)". Despite being very weakly correlated to residential electricity use (goodness-of-fit $R^2$ of 0.22), the growth in electricity use between 1971 and 2014 can account for 49% of the improvement in school enrolment. This is an extreme example of reverse paradoxal behaviour: low correlation at each point in time, but relatively high dynamic coupling. The reason we did not include this indicator and result in our main paper is due to lack of data: if we had included it, the number of countries in our dataset would have decreased to 56, representing only 70% of global population.

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