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Technology and Development

AN EXPLORATION OF THE DATA

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KEYWORDS
Technology, Diffusion, Dataset

JEL CODES
O33 O47 F02

WORKING PAPER 617 · JUNE 2022

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The Center for Global Development is grateful for contributions from the Bill & Melinda Gates Foundation in support of this work.

Charles Kenny and George Yang. 2022. "Technology and Development: An Exploration of the Data." CGD Working Paper 617. Washington, DC: Center for Global Development. https://www.cgdev.org/publication/technology-and-development-exploration-data

Please download the full replication code here and download the spliced and un-spliced updated CHAT dataset in .csv and STATA .data here.

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May 19, 2022

Abstract

We present data on the global diffusion of technologies over time, updating and adding to Comin and Mestieri's 'CHAT' database. We analyze usage primarily based on per capita measures and divide technologies into the two broad categories of production and consumption. We conclude that there has been strong convergence in use of consumption technologies with somewhat slower and more partial convergence in production technologies. This reflects considerably stronger global convergence in quality of life than in income, but we note that universal convergence in use of production technologies is not required for income convergence (only that countries are approaching the technology frontier in the goods and services that they produce).

1 Introduction

The recent Covid-19 crisis has demonstrated negative global spillovers from infectious disease but also the considerable positive spillovers from technology development: every country has benefited from Covid-19 RNA sequencing, the development of tests, vaccines and treatments, and research on the efficacy of public health interventions. Meanwhile, the distribution of vaccine production technologies and barriers to greater diversification has been a matter of heated debate alongside the availability of vaccines themselves. The

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distribution of benefits from technological progress that vaccines embody was markedly unequal throughout the first eighteen months of their availability. Technological progress and its distribution are an underlying force behind both global development and its unequal reach, and the debates that emerged during the Covid pandemic reflect similar discussions around the levels and distribution of technologies across countries more broadly.

When looking at technology diffusion, it is worth differentiating technology creation, technologies of production and technologies of consumption. Technology creation involves the research and development process. 'Production technologies' make goods and services that consumers buy (robots in a car plant, water wheels grinding corn). By making better products or by making those products more efficiently, production technologies benefit consumers.

'Consumption technologies' are technologies that directly increase the consumer's utility (washing machines, vaccines). Whereas production technologies increase output for cost, consumption technologies increase utility for cost. Note that there are many technologies that contribute both to production and consumption: engines, mobile phones, and Internet search engines, for example.

As production technologies are associated with higher productivity, they are a force behind national income growth. There is considerable controversy over calculating 'total factor productivity' (TFP)—how effectively physical and human capital are combined with labor to produce output. Jesus Felipe (1997) noted that different assumptions produced radically different productivity numbers, and smacked of trying to divide up credit for the tastiness of a cake between the flour, sugar and eggs.[1] Nonetheless, it is abundantly clear that TFP is a vital part of the story of global economic growth.[2] And in turn, while there is a lot more to TFP than the use of technologies, including both labor and capital misallocation driven by poor policy, weak institutions or other factors, technology use is undeniably an important force behind TFP growth —the *Lever of Riches* in Joel Mokyr's elegant phrase.[3]

[1]If technological change is embodied in new types of capital goods, then 'technological change' would be responsible for both TFP and part of 'capital-deepening' and the TFP growth prevented declining profitability and lower rates of investment (though even allowing for that, capital probably had a larger role than in Western European catch-up) (Crafts and Woltjer (2021)).

[2] See also Jones (2015), who has suggested total factor productivity accounts for 80 percent of US growth since 1948 and that levels of TFP plotted against GDP per worker for 128 countries in 2010 are highly correlated at 0.96.

[3]See Jones (ibid.) on these other factors but note Restuccia and Rogerson (2013) argue that"the literature

Comin and Mestieri (2018) have demonstrated the tight correlation between the spread of technologies of production and levels of GDP per capita. They argue that differing adoption of technologies including artificial fertilizer, trucks and electricity across countries over the last century and a half can account for as much as 82 percent of the variation in incomes between Western and non-Western countries. For ten 'production technologies' Comin and Mestieri find that technology usage lags are large, often comparable to lags in real GDP per capita (so that, as it might be, electricity use per capita in Venezuela is equivalent to the level in the US in 1950, which is similar to the lag behind the US in GDP per capita). These usage lags are highly correlated across technologies.[4] While this is correlation rather than evidence of ultimate causation, it is clear that rich countries use more technologies that boost productivity—from combine harvesters over hand harvesting and threshing through factories over artisanal production.

Turning to consumption technologies, many have spread widely even in the poorest developing countries. Such technologies include matches, soap, plastic sheeting, corrugated iron, LED lighting, mobile phones, radios and televisions, vaccines, antibiotics, cars and financial services. The utility associated with new consumption technologies is often poorly measured in price data so that they often have little impact on measures of real income. Instead, the increased utility for cost they provide helps to account for the fact that the quality of life at a given real income is improving over time. For example, countries with a GDP per capita of $300 in 1999 have approximately the same life expectancy (46 years) as a country with an income of $3,000 in 1870. In 1975, predicted child mortality per thousand live births for a country with an income of $1,000 was 224. By 2005 it had dropped to 163.[5]

This paper will present data and evidence on the concentration and diffusion of research and technologies over time. It builds on the database and analysis of Comin and Mestieri (ibid.), updating data on existing variables in their 'CHAT' database as well as adding some new variables largely on the consumption side. As opposed to their focus on per GDP usage levels, we analyze usage primarily based on per capita measures (total population or target population for vaccines) with the exception of agricultural variables

features many studies that seek to explore the extent to which specific policies, institutional factors and market imperfections can generate effects on aggregate TFP via misallocation. While many studies indicate that TFP losses on the order of several percentage points are possible from individual factors [such as a law or a policy], with the exception of a few studies that have found relatively large effects from credit market imperfections, the effects from any one particular factor are very small relative to the scale of differences found across rich and poor economies."

[4] Comin, Hobijn, and Rovito (2008)

[5] Casabonne and Kenny (2012)

where we use per area measures. We divide technologies into the two broad categories of production and consumption and conclude that there has been strong convergence in consumption technologies with somewhat slower and more partial convergence in production technologies. This reflects considerably stronger global convergence in quality of life than in income,[6] but it should be noted that universal convergence in use of production technologies is not required for income convergence (which only requires that countries are approaching the technology frontier in the goods and services they produce). The next sections describe and explore an expanded dataset of technology availability to examine diffusion and its relationship to income.

2 Extending the CHAT Dataset

This dataset is designed to extend the Cross-country Historical Adoption of Technology (CHAT) dataset,[7] both in number of available technologies and in coverage across time. To the best of our ability, when adding data on variables included in the CHAT database, we sourced variables from the same sources as original CHAT data. This includes, for example, the Maddison historical GDP datasets, FAO, and OECD. In both using the underlying sources used by CHAT and different sources, there were sometimes differences between CHAT data and (new) source data regarding particular country-year datapoints, potentially connected to updates in the case of the same source or slight differences in definitions or raw data. To overcome these issues, we spliced data using the methods described in Section 2.2 (in general, using a weighted mean on overlapping years or forecasting forward from the CHAT data using percent growth from the new source variable).

Please see Table A.1 for a comprehensive list of variables, their sources, and some summary statistics on available GDP per capita and country-availability. In this table, we use the term "mean/median of the annual average". To create this mean/median, GDP was first collapsed (across multiple countries) using a mean to the technology-year level. Then, the data was collapsed (across multiple years) using either a mean or a median to the technology level.

Much of the resulting data was not used in the final analysis for lack of representative

[6] Kenny (2005)
[7] Comin and Hobijn (2009)

country-coverage. They are nonetheless included for completeness—to extend the original CHAT dataset for those who are interested in using it. The narrower dataset which we use for analysis is shown in Table 3.5.

2.1 Raw data sources and cleaning choices:

We obtained data from the original CHAT dataset. We dropped North Vietnam, South Vietnam, South Yemen and Indochina from this dataset. To update and extend the CHAT dataset we used:

The Maddison dataset (2020),[8] which gives historical population and GDP per capita. We obtained GDP per capita PPP from the World Bank World Development Indicators (hereafter WB WDI) (NY.GDP.PCAP.PP.KD), and used growth from the WDI figures to project forwards the Maddison GDP per capita figures to 2020 where available. Note that there are some (mostly small) countries where we do not have GDP per capita estimates from Maddison but do have GDP per capita estimates from the WDI.[9] If Maddison did not have population values for a country-year (e.g., 2019 and 2020), we filled the missing values by using the percent growth in population from World Bank population values (SP.POP.TOTL). For income groupings, we constructed quintiles of real GDP figures based on the distributions of available real GDP figures in a specific year.

The WB WDI for data on aggregate metric tons of fertilizer consumed (fert_total, AG.CON.FERT.ZS); electric power consumption (KWH) (elec_cons, EG.USE.ELEC.KH.PC); ATMs (atm, FB.ATM.TOTL.P5); patent applications, residents (patents, IP.PAT.RESD); civil aviation ton-km of cargo carried (aviationtkm, IS.AIR.GOOD.MT.K1); air transport, passengers carried (aviation_pass, IS.AIR.PSGR); freight carried on railways (excluding livestock and passenger baggage) (ton-km) (railtkm, IS.RRS.GOOD.MT.K6); passenger journeys by railway (passenger-km) (railpkm, IS.RRS.PASG.KM); rail lines (total route-km) (railline_wdi, IS.RRS.TOTL.KM); cellular subscriptions (cell_subsc, IT.CEL.SETS.P2); personal computers (computer, IT.CMP.PCMP.P2); fixed telephone subscriptions (telephone_canning_wdi,

[8] Bolt and Zanden (2020)

[9] These include Aruba, Antigua & Barbuda, Bahamas, Belize, Bermuda, Brunei, Bhutan, Curacao, Cayman Islands, Fiji, Micronesia (Federated States of), Grenada, Guyana, Kiribati, St. Kitts & Nevis, Macao SAR China, Maldives, Marshall Islands, Nauru, Palau, Papua New Guinea, Solomon Islands, San Marino, Somalia, Suriname, Sint Maarten, Turks & Caicos Islands, Timor-Leste, Tonga, Tuvalu, St. Vincent & Grenadines, Vanuatu, and Samoa.

IT.MLT.MAIN); secure internet servers (servers, IT.NET.SECR); people with internet access (internetuser, IT.NET.USER.ZS); measles vaccination rates (pctimmunizmeas, SH.IMM.MEAS); and beds in hospitals and rehabilitation centers (bed_hosp, SH.MED.BEDS.ZS). Fertilizer was obtained by multiplying fertilizer per arable land by FAO's measure of arable land.[10]

Our World in Data for vaccination information (excluding measles). They obtain their data originally from the World Health Organization (WHO) and UNICEF. Here, the data come in per-child format. We do not convert vaccination data from per-child to absolute numbers in the analysis except for our HHI calculations.

UN World Population Prospects (WPP) for population figures separated by age group. We use this data only during our HHI calculations to convert percent vaccinations into an estimate of vaccinations delivered. Otherwise, for total population figures, we rely on the Maddison and the World Bank. Note, for all vaccines except the yellow fever vaccine, we take the population less than or equal to one years old as the target population; for yellow fever vaccines, we take the population less than 60 years old as the target population.

The OECD for data on computerized tomography (CT), magnetic resonance imaging (MRI), positron emission tomography (PET), and drug use.

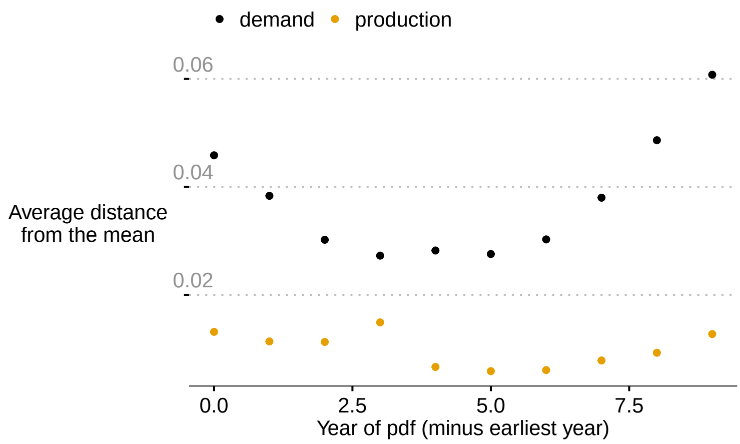
The WB Global Payment Systems Survey (GPSS) 2004-2015 for credit and debit cards. This data was manually obtained from pdf reports. Here, we gather data on transaction volume from debit cards and credit cards, as well as number of cards issued. Data from cheques did not have a unified definition, and so were excluded (i.e. sometimes, cheques included intrabank transfers, and sometimes did not include these numbers).

The World Steel Report's Steel Statistical Yearbook from 1967-2019 for data on steel consumption and production. Data was manually obtained from the annual pdf reports. We obtained the tables on 'absolute crude steel production' and 'apparent consumption of crude steel'. 'Apparent consumption of crude steel' is production plus net imports minus net exports and is an industry metric of steel demand. Depending on when the World Steel Association published the report, numbers differ. e.g., Argentina steel consumption in 2010 will be different in the 2011 report vs. 2015 report vs. the 2017 report. Often, the 2011 report and 2017 report will have bigger differences from the mean than the 2015 report (see Figure 1 below). We do not believe this to be a purely statistical anomaly. But, to reconcile these differences, we take the most recent estimate for each country-year (in the above example,

[10]Note that the World Bank has a measure of arable land, but the source is FAO.

we would have taken Argentina's 2010 steel consumption figure from the 2017 pdf). Since we only have 1 steel production variable (World Steel) in the new data, we calculate steel production from CHAT as a sum of steel from acid Bessemer, basic Bessemer, and basic oxygen furnace (BOF) processes.

Figure 1: World Steel Annual Report Discrepancy



NOTE— Depending on when the World Steel Association published the report, numbers differ. e.g., Argentina steel consumption in 2010 will be different in the 2011 report vs. 2015 report vs. the 2017 report. Often, the 2011 report and 2017 report will have bigger differences from the mean than the 2015 report.

The FAO for data on fertilizer, pesticides, and arable land. Some historical countries and country groupings are excluded.[11] When reconciling the variables from FAO versus those from CHAT, note that CHAT has a variable called 'pctirrigated', which we equate to 'agriculture area actually irrigated' from FAO.[12]

The World Motor Vehicle Production (BTS) dataset from the US Department of Transportation, the *International Organization of Motor Vehicle Manufacturers (OICA) and the Organization for Economic Co-operation and Development (OECD)* for motor vehicle data. BTS data gives us passenger car amounts, commercial vehicles, and their totals (Yugoslavia was excluded). OICA provides data on commercial vehicles, passenger car vehicles, and total vehicles

[11]Belgium-Luxembourg, Channel Islands, Czechoslovakia, Netherlands Antilles (former), Pacific Islands Trust Territory, Serbia and Montenegro, Yugoslav SFR, Ethiopia PDR, USSR, Sudan (former), and FAO's China variable (an aggregate of Hong Kong, Taiwan, and mainland China—though note that FAO does provide individual levels for mainland China, which are included).

[12]This is because cropland has a narrower definition than agricultural land, in that cropland is used for cultivation of crops only, while agricultural land includes that used for both crops and husbandry. Thus, agricultural land includes permanent meadows and pastures, while cropland does not. Moreover, cropland includes arable land and permanent crops. The CHAT dataset for the variable 'pctirrigated' says, "Irrigated area (as defined above) as a share of cultivated land, which includes land used for permanent and temporary crops, pasture, land used for temporary crops, and land lying temporarily fallow". Thus, we take this to mean agricultural land actually irrigated.

from 2005 to 2015. OECD provides data on passenger cars from 2000 to 2019. Of note: the passenger cars variable from OECD is statistically significantly larger than that of OICA when using a linear fit. We combine the passenger car variables from OICA and OECD using an arithmetic mean first; later, we use a weighted mean on overlapping years (a process decribed below) to merge with the CHAT dataset.

The Canning Database of World Infrastructure Stocks, *Our World in Data (OWID)*, and *WB WDI* for infrastructure. Canning provides data on rail lines, telephones, and electricity generation capacity (not to be confused with electricity production).[13] Our World in Data provides electricity production (originally sourced from the BP Statistical Review of World Energy). To facilitate comparison with CHAT, we sum the OWID electricity generated from coal, gas, oil, nuclear, hydro, solar, wind, and other renewables, to get a total electricity production variable. We merge WDI and Canning datasets for telephones by taking an arithmetic mean between the two, as they have a near-perfect correlation on overlapping terms.

The Clio Infra project provides aluminum production data from 1850-2012. This data is compiled by Kees Klein Goldewijk and Jonathan Fink-Jensen at Utrecht University, who obtain their data originally from the British Geological Survey (BGS), U.S. Bureau of Mines, and U.S. Geological Survey (USGS).

Note that except for vaccines, where possible, we convert figures from per capita values to absolute numbers using population figures from Maddison and the World Bank (where, as stated above, we only use the World Bank's population figures to extrapolate Maddison figures to where they are not available). Again, see Table A.1 for a list of our variables and their original sources.

[13] Note the 'Database of World Infrastructure Stocks' has an easily resolved data-entry mistake. The dataset itself has two ways of identifying a country: the country name, and the variable id (which is numeric). Across technologies, the labels for ids 45 and 44 are mixed between the country names Congo Kinshasa and Brazzaville. To resolve this, we matched the country with higher GDP to the country with higher rail line values. Thus, the "correct" match turns out to be the one based on the *name* of country ("Zaire", "Congo"), not the *id* variable (44/45). A similar occurrence happens with Lithuania and Liechtenstein with id 119. Here, we simply delete the countries marked with id 119. This is because 1) the data is completely absent for the non-telephone variables, 2) unlike the previous case, there is only one id label for two countries, making it difficult to know which country it is.

2.2 Splicing with CHAT dataset

There are 5 approaches we took to combining (or leaving separate) the CHAT database and the new data: 1) replacing the CHAT variable entirely; 2) keeping CHAT's metric and deleting our metric (not updating); 3) simple combination 4) splicing using weighted mean; 4) splicing using growth; 5) keeping two separate series.

If our new data series had a longer time series and was more comprehensive than CHAT, we simply dropped the CHAT data. This included the following variables: aggregate metric tons of fertilizer consumed (fert_total), personal computers (computer), people with internet access (internetuser), beds in hospitals and rehabilitation centers (bed_hosp), agricultural harvesters (ag_harvester), milking units (ag_milkingmachine), agricultural tractors (ag_tractor), % children who received a DPT immunization (pctimmunizdpt), % children who received a measles immunization (pctimmunizmeas), metric tons of active ingredients in pesticides used in or sold to the agricultural sector (pest_total), steel production (steel_production),[14] and cellular subscriptions (cell_subsc).

If our new variable did not provide a meaningful extension to the CHAT dataset, we excluded it. This included only one variable: rail lines from Canning's World Infrastructure dataset, where the data ranged from 1950 to 2005, but CHAT (variable railline) ranged from 1825 to 2004. (We also find that there were many country-years where there were more than a 10% difference between Canning's rail-line data and that of CHAT.) Note that we also obtain a rail-line variable from the World Bank WDI, railline_wdi. However, as explained later, because the two series were quite different, we keep them as separate series.

We simply combine data sources for variables that had 0 years overlap but on visual inspection of the plotted data series looked very well-matched. This includes: ATMs (atm), passenger journeys by railway in passenger-km (railpkm), ton-km of freight carried on railway (railtkm), and commercial vehicles (vehicle_com).

A weighted mean was used to splice data that are in the same units but attempts to avoid sudden jumps between the CHAT dataset and our updated dataset due to (small) discrepancies between data sources. We use weighted means for the data series that describe the same variable as CHAT's data and where a) the new dataset comes from

[14]For crude steel production, CHAT's data set goes from 1960 to 1971, while our new series ranges from 1967 to 2019. However, since there were only 14 overlapping country-years and around a 47 percent difference between the two series within those years, we decided to exclude the CHAT data altogether.

the same source as the CHAT dataset but CHAT has a longer historical time series; and b) variables where a very tight linear fit (untransformed and un-logged) can be found between the overlapping years.[15] There is some discretion to this process, and readers are encouraged to go through the replication file for the un-spliced data for those who would like to explore further. This includes: non-commercial vehicles (vehicle_car); electricity production (elecprod); irrigated agricultural area (irrigatedarea); and irrigated agriculture area as a share of agricultural land (pctirrigated).

The next method of splicing uses percentage growth. This simply extrapolates the existing CHAT dataset using variable growth reported in the new data. We proposed using this method when a linear fit between two variables had a large and significant intercept and a log-log fit between the overlapping years has a tighter, near-1 slope. The limitation of this method is that it can only produce a spliced dataset for variables that have overlapping years with CHAT. We reserve it only for the data that has more than 1000 overlapping country-year observations. This number is arbitrary, but it sits below the median and mean number of overlapping country-years for our variables. Only one variable passed this filter: civil aviation ton-km of cargo carried (aviationtkm).

Finally, for variables not covered in the previous lists, we keep the series as separate series. This most often occurred for variables where the CHAT variable is not closely matched by a counterpart variable with more recent data. There are also some variables that had significant percent differences between data sources even if they shared a similar definition. These un-spliced variables, kept as separate series, included computed tomography exams, total (ct_scans) vs. CT scanners (med_catscanner); magnetic resonance imaging exams, total (mri_scans) vs. MRI units (med_mriunit); air transport, passengers carried (aviation_pass) vs. civil aviation passenger-km traveled (aviationpkm); electricity generating capacity, 1000 kilowatts (electric_gen_capacity) vs. gross output of electric energy (TWH) (elecprod); rail lines (total route-km) (railline_wdi) vs. geographical/route lengths of line open at the end of the year (railline); fixed telephone subscriptions (telephone_canning_wdi) vs. fixed telephone subscriptions (telephone); and number of credit or debit card transactions (creditdebit_volume) vs. payments by credit and debit cards (creditdebit). Again, see Table A.1 for a list of our variables and the method with which we spliced them.

[15] If there are X years of overlap, each year we take a weighted average of the two sources, with the weights in year one being $\frac{X}{X+1}$ for the recent update and $\frac{1}{X+1}$ for CHAT, in year two $\frac{X-1}{X+1}$ for the update, $\frac{2}{X+1}$ for CHAT. For the i^{th} overlapping row, we put a weight on CHAT of $\frac{i}{X+1}$, and the complement of this value as the other weight. If there is only 1 year of overlap, then that year is equal weighted across the two datasets.

2.3 Technologies used

For our analysis, we restricted our variables to technologies that we deemed had adequate country and year coverage:

1. We restrict analysis of individual technological trends to those years in which the technology's start and end date has a sample of greater than or equal to 10 countries.
2. We delete technology-years where there is a rapid drop in the number of countries that have data available. We do this by calculating a 3 year moving average of the number of countries in the sample, taking a percentage difference between that 3 year moving average and the current-year number of countries in the sample and dropping years in the series from the analysis where there is a greater than 30% decline in the number of countries compared to this 3 year moving average.
3. We restrict analysis to years where there are more than 2 countries within each of the poorest 2 quintiles for the technology-year (four countries in total). We determine the poorest quintiles by looking at quintiles of GDP per capita in that year.
4. We require 10 percent of the values at the start and end dates to be nonzero.
5. For each technology we looked only at countries where there was at least one date that is prior to 1990 and that the duration of data from start to end is at least 20 years.
6. For the start-end analysis, we keep only the variables that have more than 20 countries (Tables 3.3 and 3.4). For the analysis where we look at the coefficient of variation across time (Figures A2, A3, A4, and A6), no restriction is made.

This gives us a set of technologies that spans across a range of sectors (shown in Table 3.5), although it does involve dropping much of the original, raw dataset. We divide these remaining technologies into sectoral categorizations (communications, vaccines, agriculture, energy, industry, transport) as well as 'production' and 'consumption.' Again, production technologies are those primarily used to increase output productivity. With regard to information and communications technologies, most telephone and internet use is part of consumption rather than production, even though these technologies have clear productivity effects. Meanwhile, most electricity is used in industry, agriculture and commercial services rather than at the residential level—even though electricity powering home lighting, heating, consumer durables, entertainment and communications obviously has considerable impact on reducing the cost of the quality of life. Transport was divided into passenger cars as consumption; flights carrying passengers (a measure of the ownership of plane capacity), air cargo capacity, and commercial vehicles were labeled as production technologies.

Table 3.5 shows the variables that were used in this analysis. We provide the earliest date with available data, whether the variable originally came as a percentage, how it was spliced with newer versions of the data, the source of the data, and metrics on contemporaneous GDP per capita. Table 3.5 is a subset of Table A.1. Note that while Table 3.5 shows that some variables did not originally come in percentage form, for the following analysis of coefficient of variation and adoption rates, we divide by either population (Maddison) or hectares of arable land (FAO) to create proportions.

3 Analysis

Table 3.1 and 3.2 give tables of different measures of means and distribution in start and end years. Column two gives the number of countries that are present in the fixed sample (with low coverage often associated with a greater skew toward richer countries). Subsequent columns provide the mean (weighted and unweighted), standard deviation (weighted and unweighted), and poor-rich ratio at start and end points. The poor-rich ratio gives the average adoption rate in the bottom quintile of the GDP per capita distribution in that year divided by the adoption rate of the top quintile GDP per capita distribution. From here on out, for non-agricultural variables, weights are total population, while for agricultural variables, weights are land area.

In Tables 3.1 and 3.4, we look at various convergence metrics and label them as TRUE or FALSE depending on whether each statistic was indicative of convergence. Here, the statistics are the coefficient of variation (weighted and unweighted), the poor-rich ratio, and the Preston curve slope. If the coefficient of variation in the end was smaller than the coefficient of variation at the start, then that would be indicated with a TRUE in the table. If a poor-rich ratio was higher in the end than at the start, then that would also be TRUE. For the Preston curve, we run a regression with log technology per capita (or land area) against log GDP per capita (or land area) at start and end periods and examine the coefficient on income. If the size of the coefficient on income has fallen, then we mark this as a sign of convergence. Two exceptions to this are that for vaccines and proportion of people with internet access, where use a levels-log regression as opposed to a log-log regression (i.e., technology per capita against log GDP per capita), since for these technologies, the maximum value is bounded at one per capita.

The communications category demonstrates signs of both growth and convergence, the starkest being cellular subscriptions. From 1980 to 2020 we moved from global rarity to global ubiquity of access. In 2020, the average adoption rate of the poorest quintile of countries was 0.638 of the richest quintile countries. The story is similarly positive for vaccination coverage. From 1980 to 2020, all countries with available data saw greater adoption of the vaccines listed in Table 3.1.

The transport category spans both production technologies (Table 3.2) and consumption technologies (Table 3.1). We see a considerable rise in aviation from 1970 to 2020, where number of passengers on airplanes per capita rising from 0.155 to 0.464. However, for air transport in particular, the standard deviation also rises, and across 102 countries, the poor-rich ratio drops, indicative of divergence in airline carrying capacity. On the other hand, for passenger cars, in 1930, there were only 1.6 passenger cars for 100 people. In 2020, this number increased to 42. Moreover, the poor-rich ratio of adoption increased from 0.03 to 0.33.

Within the agriculture category, we see a massive increase in fertilizer use, from an adoption rate of 59 kilograms of fertilizer per hectare of arable land in 1960 to 177 kilograms in 2020. Not only this, but poor-rich adoption ratios are higher in 2020 compared to 1960, going from 0.0179 to 0.0705. This same story is seen for agricultural harvesters, milking units, and general pesticide use.

Within energy, gross output of electric energy and electric power consumption has increased on average across-the-board. However, looking at the rich poor ratio for electric power consumption in 1970 compared to 2010 across 109 countries, we see moderate divergence (for gross output of electric energy over the longer term from 1930 to 2020, we have a smaller sample of 30 countries, but we see convergence in the poor-rich ratio and the weighted standard deviation). Turning to industry, looking at steel from 1980 to 2020, on an unweighted average, countries see lower per capita steel production and demand, but a population weighted average shows the reverse, suggesting a concentration of production in large countries (particularly China). All measures suggest convergence.

Table 3.4 suggests a mixed but mostly positive story with regard to convergence. Exceptions include agricultural harvesters and milking units, air transport and hydroelectric energy, which have not declined in coefficient of variation. Meanwhile, the slope of the Preston curve for insecticides, wind energy, and measures of aviation has increased.

Across all of our included consumption technologies, the coefficient of variation has decreased. The poor-rich ratio across all consumption technologies has also improved. The only exception to this is BCG immunization rates. For BCG, the situation in the past was that poor countries had on average a *higher* adoption rate compared to rich countries. Historically, BCG was infrequently recommended by public health authorities in (richer) countries with a low TB burden, and our measure of divergence reflects those countries slowly adopting BCG despite that.

Next, we move on to Figures A1 - A6. Figure A1 plots the Herfindahl-Hirschman Index (HHI) for each variable in particular countries over time within a fixed sample of countries. The HHI is a measure of concentration which takes a high value if or a few one countries account for most of the most stock of a technology and a low value if it is more equally diffused. It is computed at the country level for total volumes of technologies (not per capita). We compute our market share measure for the HHI using the country-level adoption rates (e.g., Tanzania's number of cell phones) divided by the total global adoption (e.g., global number of cell phones).[16] A declining HHI indicates that (absolute) stocks of a technology are more equally spread across countries.

For all consumption technologies, except BCG, we see a decrease in concentration. The same story does *not* hold for production technologies, although solar and wind energy became considerably less concentrated. While steel demand has become more diffuse, steel production has become more concentrated in a few countries.

Figures A2 and A3 show the weighted and unweighted coefficient of variation across 5-year intervals for various technologies. We maintain a fixed sample; though here, we do not restrict our sample to have greater than 20 observations throughout the entire period. A lower coefficient of variation across time indicates greater cross-country convergence. Within the weighted graphs (Figure A3), for agricultural technologies, values are weighted by arable land. Otherwise, values are weighted by population.

Communications technologies and vaccines once again show rapid convergence, especially in the 1985-1990 time frame. This monotonic drop in the coefficient of variation is not as apparent in agriculture, energy, and transport technologies. There, we see high volatility in fertilizer coefficient of variation in the unweighted series, but low volatility in the weighted series; this indicates that the main driver for such volatility is likely to be smaller countries with small land area). Confirming what we have seen in the earlier tables and the HHI plot, wind and solar electricity use has converged since 2000. However, other electric power consumption and electricity consumption metrics have not. As in agriculture, many metrics of electricity generation have remained flat in coefficient of variation across time. Passenger cars do see convergence, while air transport does not. For industrial technologies, we see a relatively flat coefficient of variation for aluminum technologies, but steel has seen convergence in coefficient of variation since the 1980s.

Figure A4 graphs the mean adoption rates across 5-year periods for consumption and production technologies. Shaded areas indicate plus or minus one standard deviation. Samples across the entire dataset are fixed. Figure A5 plots scatter plots of adoption rates

[16]Because we are using adoption rates, some metrics are flows, while other measures are stocks. For example, vaccine measures are derived by multiplying the annual vaccination rate by the target population (most commonly population $\leq$ 1 years old), and therefore represent a flow of vaccinations, rather than a stock of vaccines.

(Y) to GDP per capita (X) for the start and end periods of each technology. As in the previous tables with Preston curves, a log-log curve is fit to each date and technology: here, we primarily fit the log of adoption rate to the log of GDP per capita. However, for the vaccines and internet access variables with a maximum value of 100upwards in the intercept and a flattening of the line of best fit indicates convergence.

Our last plot, Figure A6 summarizes our previous findings. Here, we plot an index of the coefficient of variation across time within a fixed sample of countries across five-year periods for a specific set of technologies. For production technologies the variables are gross output of electric energy (TWH) per capita, commercial vehicles (bus, taxi) per capita, thousand metric tons of steel produced, and aggregate kg of fertilizer consumed per hectare of arable land. For consumption technologies, fixed telephone subscriptions per capita, % children who received a DPT immunization, and passenger car vehicles per capita were included. The index is calculated by first computing an unweighted average of the coefficient of variation for each technology-year. Then, we divide each of those values by the initial coefficient of variation in 1960 (less 1). Finally, we average across technologies in the two bundles of consumption and production. A lower coefficient of variation index across time indicates convergence. We see a smooth decline in the indexed average coefficient of variation for the selected consumption variables. Production variables do not see such a rapid or monotonic decline—though they do decline from 1960 to 1980, and then again from 1995 to 2005.

Table 3.1: Table of Measures of Convergence: **Consumption**

Label	Num. Countries in Fixed Sample	Year	Mean	Standard Deviation	Weighted Mean	Weighted Standard Deviation	Poor/Rich Mean
Communications							
Cellular subscriptions per capita	123	1980	0.000465	0.0022	9.92e-05	0.000859	0
	123	2020	1.12	0.343	1.07	0.264	0.638
Fixed telephone subscriptions per capita	84	1960	0.0371	0.063	0.0491	0.0849	0.0054
	84	2020	0.179	0.163	0.126	0.156	0.0267
Newspaper copies circulated daily per capita	46	1950	0.145	0.152	0.118	0.167	0.0932
	46	2000	0.158	0.124	0.101	0.0796	0.198
People with internet access per capita	126	1990	0.000353	0.0013	0.000512	0.00179	0
	126	2020	0.636	0.266	0.566	0.23	0.257
Radios per capita	33	1940	0.0681	0.0759	0.119	0.113	0.0638
	33	2000	0.699	0.47	0.974	0.664	0.209
Television sets per capita	57	1960	0.0346	0.0622	0.0428	0.0883	0.00944
	57	2000	0.334	0.214	0.307	0.221	0.191
Transport							
Passenger car vehicles per capita	25	1930	0.0159	0.0351	0.0389	0.0642	0.0312
	25	2020	0.417	0.165	0.338	0.193	0.334
Vaccines							
% children who received a BCG immunization	49	1980	57.4	31	49.4	27.2	1.42
	49	2020	87.6	15.6	85.3	11.3	1.06
% children who received a DPT immunization	61	1980	51	29	53.9	32.1	0.638
	61	2020	90	10.9	87.1	10.3	0.882
% children who received a MCV1 immunization	63	1980	43.7	26.7	50.7	29.5	0.613
	63	2020	89.3	12.2	86.6	11	0.854
% children who received a measles immunization	63	1980	43.7	26.7	50.7	29.5	0.613
	63	2020	89.3	12.2	86.6	11	0.854
% children who received a Pol3 immunization	62	1980	52.2	31.8	62.8	33.2	0.521
	62	2020	88.7	12.6	86.5	10.9	0.852

NOTE— This is a table of measures of means and distribution in start and end years. Column two gives the number of countries that are present in the fixed sample (with low coverage often associated with a greater skew toward richer countries). Subsequent columns provide the mean (weighted and unweighted), standard deviation (weighted and unweighted), and poor-rich ratio at start and end points. The poor-rich ratio gives the average adoption rate in the bottom quintile of the GDP per capita distribution in that year divided by the adoption rate of the top quintile GDP per capita distribution. For non-agricultural variables, weights are total population, while for agricultural variables, weights are land area.

Table 3.2: Table of Measures of Convergence: **Production**

Label	Num. Countries in Fixed Sample	Year	Mean	Standard Deviation	Weighted Mean	Weighted Standard Deviation	Poor/Rich Mean
Agriculture							
Aggregate kg of fertilizer consumed per ha arable land	110	1960	59.2	133	27.6	83.2	0.0179
	110	2020	177	308	162	195	0.0705
Agricultural tractors in use per ha arable land	42	1960	0.00979	0.022	0.0113	0.0125	0.046
	42	2010	0.0385	0.0518	0.0245	0.0293	0.0253
Combine harvesters - threshers in use per ha arable land	22	1960	0.00154	0.0019	0.00308	0.00248	0.166
	22	2010	0.00472	0.0111	0.00312	0.00751	0.51
Milking machines in use per ha arable land	25	1960	0.00924	0.0146	0.00669	0.0134	0.00896
	25	1990	0.021	0.0362	0.0176	0.0318	0.0251
Pesticide fungicides and bactericides agricultural use tonnes per ha arable land	137	1990	0.00176	0.00617	0.000393	0.00192	0.0214
	137	2020	0.00176	0.0037	0.000505	0.00191	0.0621
Pesticide herbicides agricultural use tonnes per ha arable land	134	1990	0.00218	0.0108	0.000602	0.00246	0.0243
	134	2020	0.00275	0.00701	0.00123	0.00383	0.0346
Pesticide insecticides agricultural use tonnes per ha arable land	139	1990	0.00271	0.0154	0.000394	0.0014	0.0338
	139	2020	0.00331	0.0129	0.000401	0.00136	0.0668
Energy							
Electric power consumption (KWH) per capita	109	1970	1470	2400	1200	2170	0.0274
	109	2010	4530	6640	3060	3430	0.0252
Electricity from hydro (TWH) per capita	75	1980	1.3e-06	3.71e-06	4.44e-07	1.34e-06	0.0279
	75	2020	1.59e-06	5.13e-06	6.39e-07	1.19e-06	0.161
Electricity from nuclear (TWH) per capita	75	1980	5.39e-07	1.23e-06	3.5e-07	7.97e-07	0.000391
	75	2020	6.55e-07	1.37e-06	4.39e-07	9.48e-07	0.349
Electricity from other renewables (TWH) per capita	75	1980	3.09e-08	1.04e-07	1.82e-08	4.42e-08	0.0757
	75	2020	4.47e-07	1.91e-06	1.07e-07	2.06e-07	0.0873
Electricity from solar (TWH) per capita	78	1990	2.58e-11	1.69e-10	8.64e-11	3.39e-10	0.00108
	78	2020	1.12e-07	1.47e-07	1.13e-07	1.34e-07	0.127
Electricity from wind (TWH) per capita	75	1990	4.74e-10	3.91e-09	4.57e-11	1.17e-09	0
	75	2020	3.39e-07	5.37e-07	2.28e-07	3.24e-07	0.0499
Electricity Generating Capacity, 1000 kilowatts per capita	90	1950	0.000119	0.000185	0.000149	0.000183	0.0314
	90	2000	0.000978	0.00116	0.000793	0.00101	0.0214
Gross output of electric energy (TWH) per capita	30	1930	3.8e-07	6.2e-07	2.12e-07	3.38e-07	0.0607
	30	2020	7.45e-06	4.99e-06	6.35e-06	3.29e-06	0.333
Industry							
Aluminum primary production, in metric tons per capita	44	1910	0.000126	0.000431	4.73e-05	0.000172	0
	44	2010	0.0201	0.0629	0.00785	0.0166	0.00742
Steel demand in thousand metric tons per capita	56	1980	0.000246	0.000247	0.00037	3e-04	0.073
	56	2020	0.000216	0.00016	0.000216	0.000159	0.142
Steel production in thousand metric tons per capita	54	1980	0.000485	0.00175	0.00019	0.000327	0.00776
	54	2020	0.000315	0.000513	0.00031	3e-04	0.0654

Table 3.2: Table of Measures of Convergence: **Production** *(continued)*

Label	Num. Countries in Fixed Sample	Year	Mean	Standard Deviation	Weighted Mean	Weighted Standard Deviation	Poor/Rich Mean
Transport							
Air transport, passengers carried per capita	102	1970	0.155	0.284	0.127	0.226	0.0357
	102	2020	0.464	1.18	0.229	0.46	0.011
Civil aviation passenger-KM traveled per capita	21	1930	0.306	0.363	0.101	0.238	0.0913
	21	1990	857	765	218	453	0.0477
Civil aviation ton-KM of cargo carried per capita	25	1950	0.762	1.09	0.172	0.51	0.0753
	25	2020	53.2	66.7	12.2	26.1	0.0597
Commercial vehicles (bus, taxi) per capita	25	1930	0.00306	0.00505	0.00665	0.00949	0.0422
	25	2020	0.0836	0.0822	0.146	0.158	0.3

NOTE— This is a table of measures of means and distribution in start and end years. Column two gives the number of countries that are present in the fixed sample (with low coverage often associated with a greater skew toward richer countries). Subsequent columns provide the mean (weighted and unweighted), standard deviation (weighted and unweighted), and poor-rich ratio at start and end points. The poor-rich ratio gives the average adoption rate in the bottom quintile of the GDP per capita distribution in that year divided by the adoption rate of the top quintile GDP per capita distribution. For non-agricultural variables, weights are total population, while for agricultural variables, weights are land area.

Table 3.3: Summary of Measures of Convergence: **Consumption**

Category	Label	Coefficient of Variation	Weighted Coefficient of Variation	Poor/Rich Mean	Preston Curve Slope
Communications	Cellular subscriptions per capita	TRUE	TRUE	TRUE	TRUE
	Fixed telephone subscriptions per capita	TRUE	TRUE	TRUE	TRUE
	Newspaper copies circulated daily per capita	TRUE	TRUE	TRUE	TRUE
	People with internet access per capita	TRUE	TRUE	TRUE	FALSE
	Radios per capita	TRUE	TRUE	TRUE	TRUE
	Television sets per capita	TRUE	TRUE	TRUE	TRUE
Transport	Passenger car vehicles per capita	TRUE	TRUE	TRUE	TRUE
Vaccines	% children who received a BCG immunization	TRUE	TRUE	FALSE	FALSE
	% children who received a DPT immunization	TRUE	TRUE	TRUE	TRUE
	% children who received a MCV1 immunization	TRUE	TRUE	TRUE	TRUE
	% children who received a measles immunization	TRUE	TRUE	TRUE	TRUE
	% children who received a Pol3 immunization	TRUE	TRUE	TRUE	TRUE

NOTE— This table gives various convergence metrics and labels them as TRUE or FALSE depending on whether each statistic was indicative of convergence. Here, the statistics are the coefficient of variation (weighted and unweighted), the poor-rich ratio, and the Preston curve slope. If the coefficient of variation in the end was smaller than the coefficient of variation at the start, then that would be indicated with a TRUE in the table. If a poor-rich ratio was higher in the end than at the start, then that would also be TRUE. For the Preston curve, we run a regression with log technology per capita (or land area) against log GDP per capita (or land area) at start and end periods and examine the coefficient on income. If the size of the coefficient on income has fallen, then we mark this as a sign of convergence. Two exceptions to this are that for vaccines and people with internet access, we use a levels-log regression as opposed to a log-log regression (i.e., technology per capita against log GDP per capita), since for these technologies, the maximum value is bounded at one per capita.

Table 3.4: Summary of Measures of Convergence: **Production**

Category	Label	Coefficient of Variation	Weighted Coefficient of Variation	Poor/Rich Mean	Preston Curve Slope
Agriculture	Aggregate kg of fertilizer consumed per ha arable land	TRUE	TRUE	TRUE	TRUE
	Agricultural tractors in use per ha arable land	TRUE	TRUE	FALSE	TRUE
	Combine harvesters - threshers in use per ha arable land	FALSE	FALSE	TRUE	TRUE
	Milking machines in use per ha arable land	FALSE	TRUE	TRUE	TRUE
	Pesticide fungicides and bactericides agricultural use tonnes per ha arable land	TRUE	TRUE	TRUE	TRUE
	Pesticide herbicides agricultural use tonnes per ha arable land	TRUE	TRUE	TRUE	TRUE
	Pesticide insecticides agricultural use tonnes per ha arable land	TRUE	FALSE	TRUE	FALSE
Energy	Electric power consumption (KWH) per capita	TRUE	TRUE	FALSE	TRUE
	Electricity from hydro (TWH) per capita	FALSE	TRUE	TRUE	TRUE
	Electricity from nuclear (TWH) per capita	TRUE	TRUE	TRUE	TRUE
	Electricity from other renewables (TWH) per capita	FALSE	TRUE	TRUE	FALSE
	Electricity from solar (TWH) per capita	TRUE	TRUE	TRUE	TRUE
	Electricity from wind (TWH) per capita	TRUE	TRUE	TRUE	FALSE
	Electricity Generating Capacity, 1000 kilowatts per capita	TRUE	FALSE	FALSE	TRUE
	Gross output of electric energy (TWH) per capita	TRUE	TRUE	TRUE	TRUE
Industry	Aluminum primary production, in metric tons per capita	TRUE	TRUE	TRUE	TRUE
	Steel demand in thousand metric tons per capita	TRUE	TRUE	TRUE	TRUE
	Steel production in thousand metric tons per capita	TRUE	TRUE	TRUE	TRUE
Transport	Air transport, passengers carried per capita	FALSE	FALSE	FALSE	FALSE
	Civil aviation passenger-KM traveled per capita	TRUE	TRUE	FALSE	TRUE
	Civil aviation ton-KM of cargo carried per capita	TRUE	TRUE	FALSE	FALSE
	Commercial vehicles (bus, taxi) per capita	TRUE	TRUE	TRUE	TRUE

NOTE— This table gives various convergence metrics and labels them as TRUE or FALSE depending on whether each statistic was indicative of convergence. Here, the statistics are the coefficient of variation (weighted and unweighted), the poor-rich ratio, and the Preston curve slope. If the coefficient of variation in the end was smaller than the coefficient of variation at the start, then that would be indicated with a TRUE in the table. If a poor-rich ratio was higher in the end than at the start, then that would also be TRUE. For the Preston curve, we run a regression with log technology per capita (or land area) against log GDP per capita (or land area) at start and end periods and examine the coefficient on income. If the size of the coefficient on income has fallen, then we mark this as a sign of convergence.

Table 3.5: Table of Variable Origins: Used Variables

Group	Category	Variable	Variable Label	Is this a percentage?	Mean of the annual average GDP per capita (2011 dollars)	Median of the annual average GDP per capita (2011 dollars)	Mean of the annual average number of countries in sample	Median of the annual average number of countries in sample	Earliest date with available data	Most recent date with available data	How spliced	Source
Consumption	Communications	cell_subsc	Cellular subscriptions	No	11866	10122	160	161	1960	2020	replaced CHAT variable with our variable	WDI
Consumption	Communications	internetuser	People with internet access	No	10694	11204	100	156	1960	2020	replaced CHAT variable with our variable	WDI
Consumption	Communications	newspaper	Newspaper copies circulated daily	No	7102	7134	80	104	1919	1999		CHAT
Consumption	Communications	radio	Radios	No	4560	3761	59	46	1820	2000		CHAT
Consumption	Communications	telephone_canning_wdi	Fixed telephone subscriptions	No	10369	8900	157	191	1950	2020	arithmetic mean	Canning; WDI
Consumption	Communications	tv	Television sets	No	9440	8875	88	98	1946	2002		CHAT
Consumption	Transport	vehicle_car	Passenger car vehicles	No	9330	6434	69	65	1895	2019	arithmetic mean of OECD and OICA data. then, weighted arithmetic mean of the most recent band of overlapping years with CHAT	OICA/OECD; CHAT
Consumption	Vaccines	BCG	% children who received a BCG immunization	Yes	9115	8069	140	152	1980	2019		OWID
Consumption	Vaccines	DPT	% children who received a DPT immunization	Yes	12514	11419	171	187	1980	2019	replaced CHAT variable with our variable	OWID
Consumption	Vaccines	MCV1	% children who received a MCV1 immunization	Yes	12510	11419	171	187	1980	2019		OWID
Consumption	Vaccines	pctimmunizmeas	% children who received a measles immunization	Yes	12510	11419	171	187	1980	2019	replaced CHAT variable with our variable	WDI
Consumption	Vaccines	Pol3	% children who received a Pol3 immunization	Yes	12497	11419	171	187	1980	2019		OWID
Production	Agriculture	ag_harvester	Combine harvesters - threshers in use	No	11352	11022	76	77	1961	2009	replaced CHAT variable with our variable	FAO
Production	Agriculture	ag_milkingmachine	Milking machines in use	No	14947	14091	39	40	1961	2009	replaced CHAT variable with our variable	FAO
Production	Agriculture	ag_tractor	Agricultural tractors in use	No	10023	8842	138	147	1961	2009	replaced CHAT variable with our variable	FAO
Production	Agriculture	fert_total	Aggregate kg of fertilizer consumed	No	11034	9209	139	131	1961	2018	replaced CHAT variable with our variable	WDI

Table 3.5: Table of Variable Origins: Used Variables *(continued)*

Group	Category	Variable	Variable Label	Is this a percentage?	Mean of the annual average GDP per capita (2011 dollars)	Median of the annual average GDP per capita (2011 dollars)	Mean of the annual average number of countries in sample	Median of the annual average number of countries in sample	Earliest date with available data	Most recent date with available data	How spliced	Source
Production	Agriculture	pest_fund_bact	Pesticide fungicides and bactericides agricultural use tonnes	No	14526	14604	159	161	1990	2018		FAO
Production	Agriculture	pest_herb	Pesticide herbicides agricultural use tonnes	No	14806	14885	156	157	1990	2018		FAO
Production	Agriculture	pest_insect	Pesticide insecticides agricultural use tonnes	No	14347	14423	161	163	1990	2018		FAO
Production	Energy	elec_cons	Electric power consumption (KWH)	No	12667	11511	95	110	1960	2019		WDI
Production	Energy	elec_hydro	Electricity from hydro (TWH)	No	16381	16305	150	209	1985	2020		OWID
Production	Energy	elec_nuc	Electricity from nuclear (TWH)	No	16381	16305	150	209	1985	2020		OWID
Production	Energy	elec_renew_other	Electricity from other renewables (TWH)	No	16381	16305	150	209	1985	2020		OWID
Production	Energy	elec_solar	Electricity from solar (TWH)	No	16381	16305	150	209	1985	2020		OWID
Production	Energy	elec_wind	Electricity from wind (TWH)	No	16381	16305	150	209	1985	2020		OWID
Production	Energy	elecprod	Gross output of electric energy (TWH)	No	7923	5392	96	111	1895	2020	weighted arithmetic mean of the most recent band of overlapping years	CHAT; OWID
Production	Energy	electric_gen_capacity	Electricity Generating Capacity, 1000 kilowatts	No	7731	8114	147	125	1950	2002		Canning
Production	Industry	aluminum	Aluminum primary production, in metric tons	No	6971	4553	72	72	1850	2012		CLIO
Production	Industry	steel_demand	Steel demand in thousand metric tons	No	15119	13831	93	110	1967	2019		World Steel
Production	Industry	steel_production	Steel production in thousand metric tons	No	16560	14165	74	88	1967	2019	replaced CHAT variable with our variable	World Steel
Production	Transport	aviation_pass	Air transport, passengers carried	No	12463	10231	146	148	1970	2020		WDI
Production	Transport	aviationpkm	Civil aviation passenger-KM traveled	No	6845	6322	59	58	1920	1993		CHAT
Production	Transport	aviationtkm	Civil aviation ton-KM of cargo carried	No	9628	8410	95	125	1929	2020	growth	WDI; CHAT
Production	Transport	vehicle_com	Commercial vehicles (bus, taxi)	No	8444	6732	71	82	1904	2015	simple combine	OICA; CHAT

4 Conclusions/Policy

There is a growing literature suggesting good ideas are becoming harder to find.[17] That would be a force for convergence from above, fostered by slower TFP growth in the richest countries. But there is also some hope for convergence from below, due to faster technological catch up.

The technology diffusion that 'matters' is access to the productivity, cost and quality gains associated with technology advance. For consumption technologies embedded in tradeable goods, this does not require local production. Similarly, in competitive, traded markets, much of benefit of improved production technologies will be global because consumers everywhere will see lower prices and more goods—see, for example, the global benefit of the availability and declining cost-for-quality of mobile phones produced in only a few countries. Diffusion of individual production technologies for traded goods is (only) important to ensure that countries are near the technological frontier for the technologies related to those traded products they make.

But for technologies of both production and consumption embedded in non-tradeable equipment or services, diffusion is obviously important. The data presented in this paper is insufficient to allow strong statements as to whether this is occurring (for that data on a wider range of technologies would have to be matched with data on current and potential production and consumption of related products), but there are hopeful signs with regard to strong convergence in some recent 'dual (production and consumption) use' technologies including information and communication technologies.

On the production side, if an appropriate capital-labor ratio remains crucial to technology adoption, then subsidized capital to industry might be a necessary part of technological catch-up.[18] Again, there may be a role for investment in research and development to adapt technologies for use in local institutional or physical environments (pest-resistant varieties of local crops, for example). Governments may also need to intervene to ensure the supportive infrastructure is in place to allow utilization of new technologies (as it might be, access to electricity to enable steel production, communications, lighting, air conditioning and so on). Especially regarding consumer technologies that are networked or have other spillover effects, there is a role to spread those technologies in areas such as health.

[17] Bloom et al. (2020)

[18] Daruich, Easterly, and Reshef (2019)

Additional methods to ease technology transfer internationally might include adoption of international standards including ISOs. Certainly in the case of the Covid-19 vaccines, the speed of international diffusion was increased thanks to the use of WHO authorizations in place of national regulatory approaches to licensing. Similarly, the GSM standard for mobile phones allowed rapid adoption of the same equipment worldwide. Global agreement on standards, as well as limits to intellectual property rights in cases where they are likely to be a significant barrier to the diffusion of the gains from technology advance, could both help increase global welfare.

Overall, the analysis in this paper suggests a broadly positive story with regard to technology diffusion. Looking at consumer technologies, recent convergence appears to have been dramatic. With production technologies, while not every country needs to be a major steel producer or own a globe-spanning airline in order to ensure its citizens a high quality of life, convergence has been slower and more partial. There are still considerable income gains to be made from the wider adoption of existing productivity-enhancing technologies, but the rapid spread of 'dual use' technologies suggests some grounds for optimism.

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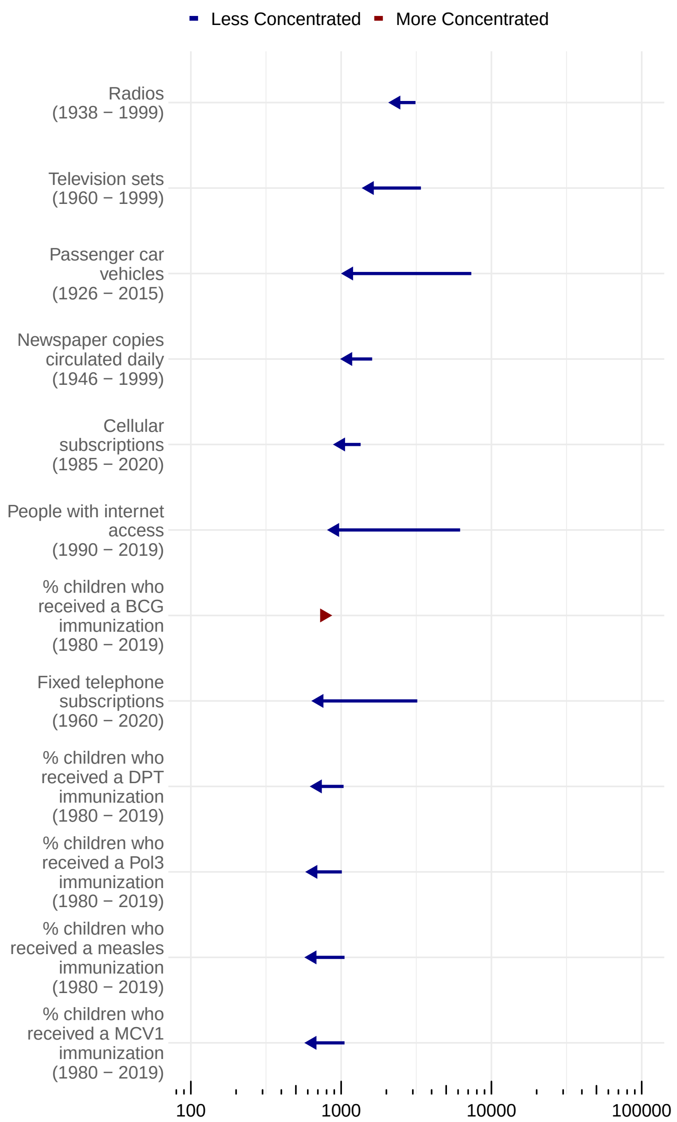
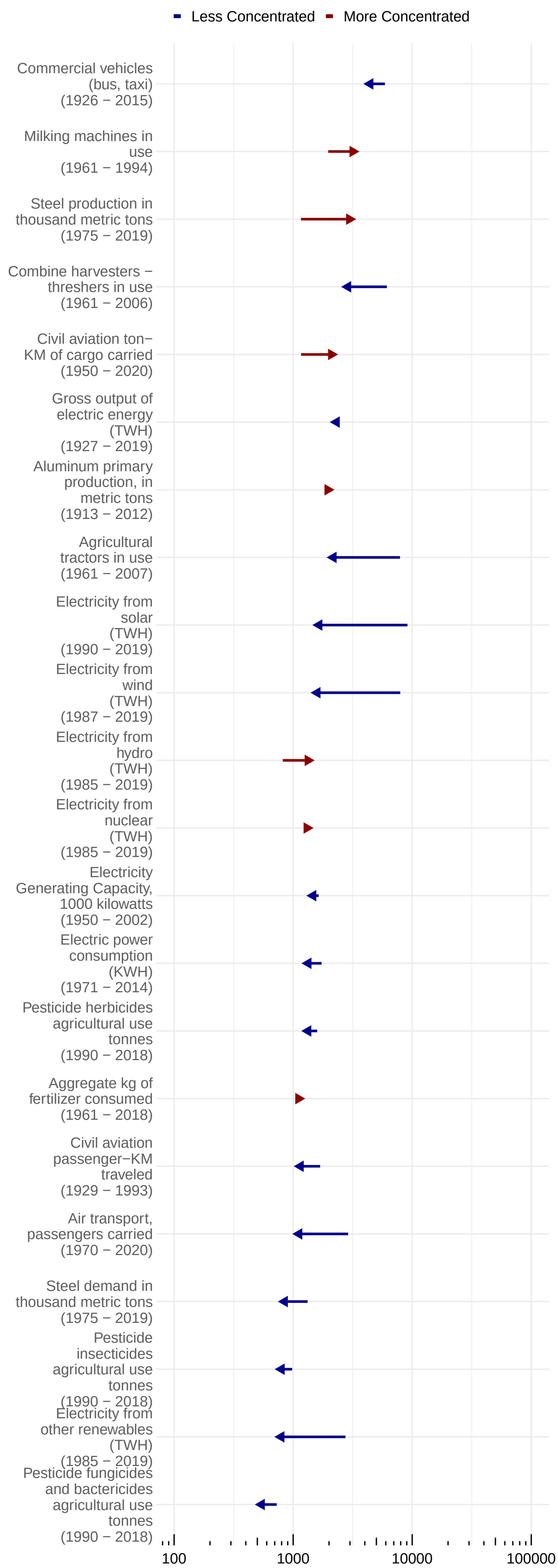
A Appendix

Figure A1: Herfindahl-Hirschman Index

(a) Consumption

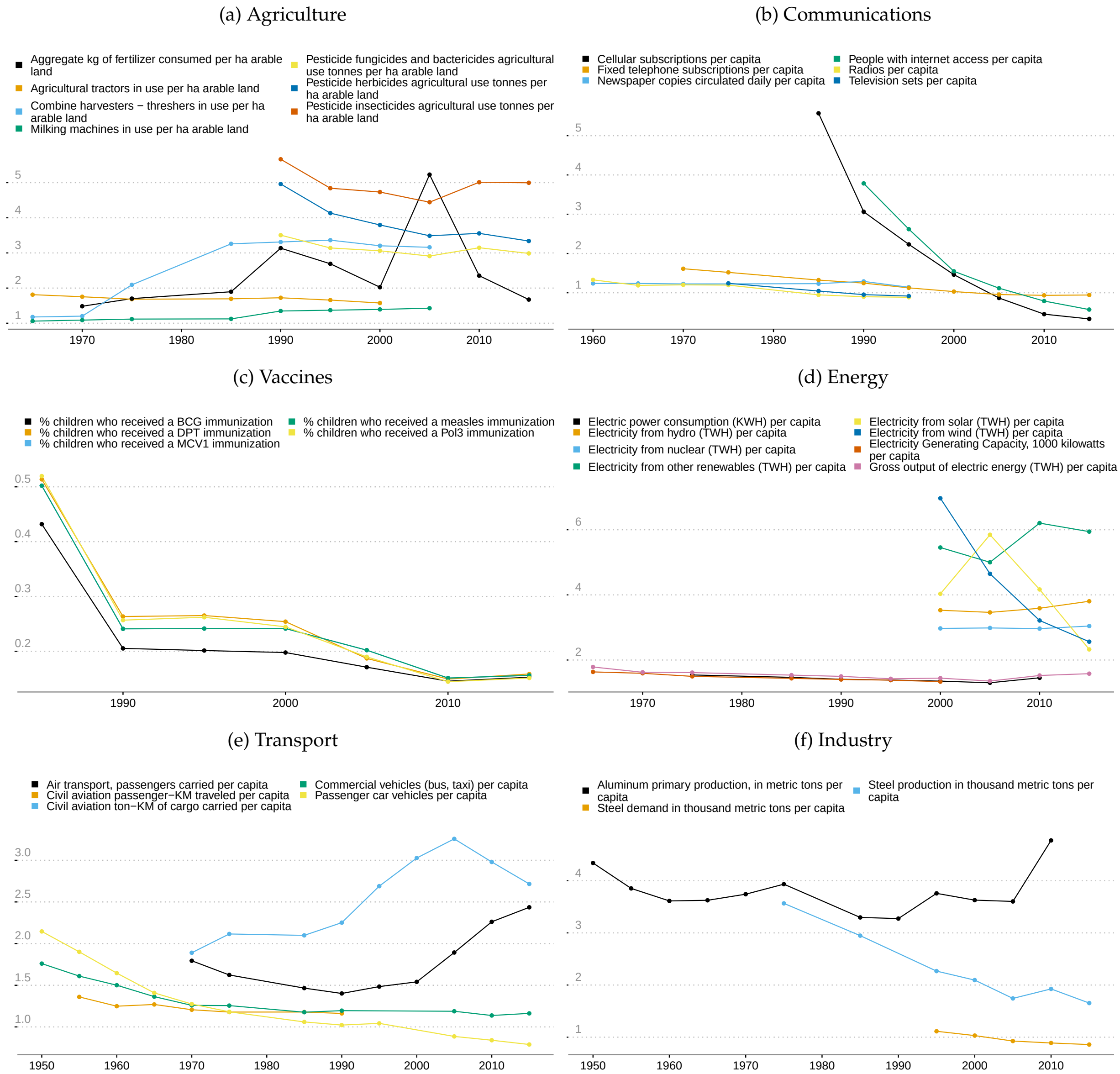


(b) Production



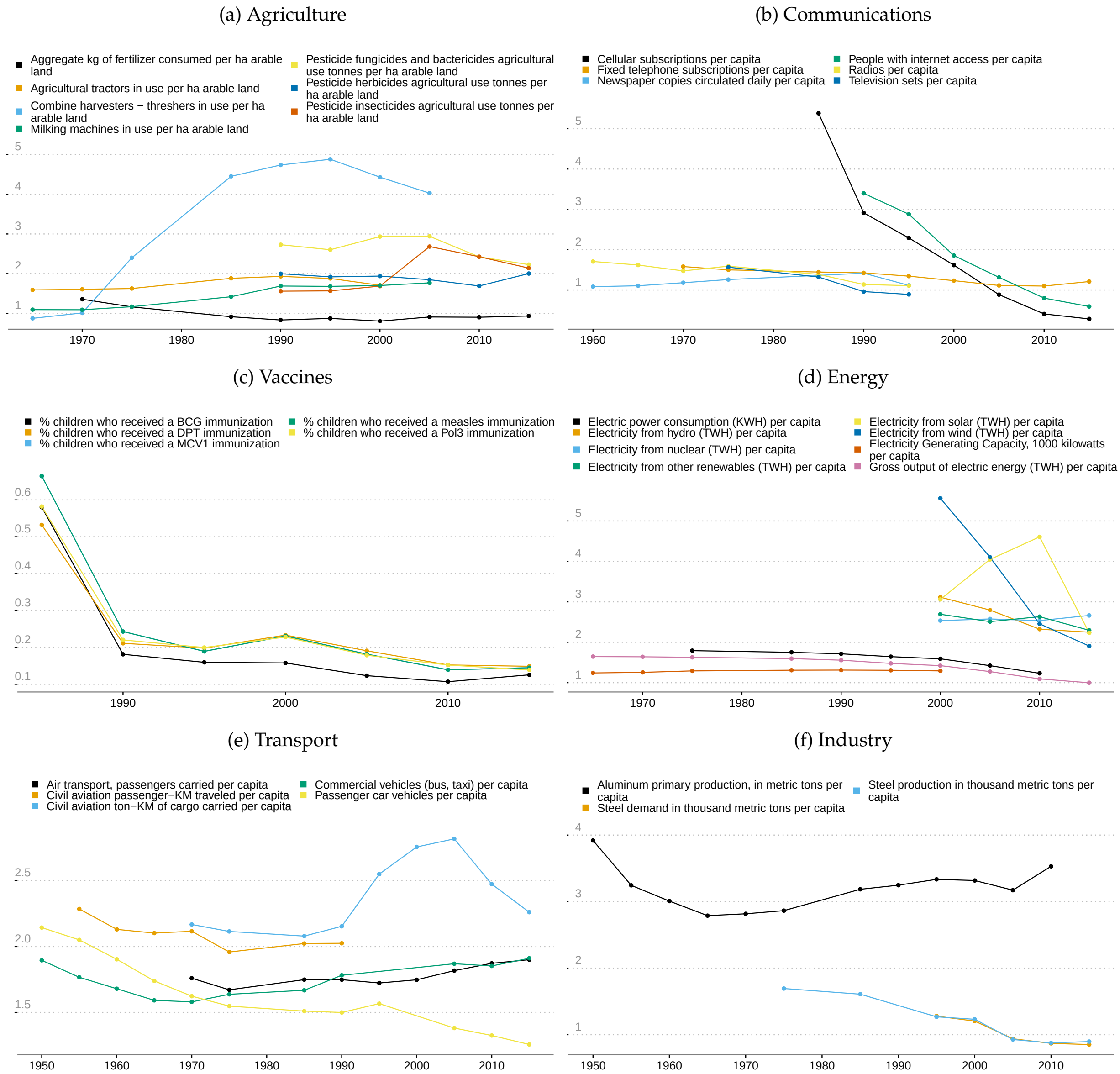
NOTE— This is the Herfindahl-Hirschman Index (HHI) for each variable in particular countries over time within a fixed sample of countries from the start to end dates. A declining HHI indicates that (absolute) stocks of a technology are more equally spread across countries.

Figure A2: **Unweighted** Coefficient of Variation across Time



NOTE— Plotted are the *unweighted* coefficients of variation across time within a fixed sample of countries across five-year periods. A lower coefficient of variation across time indicates greater cross-country convergence.

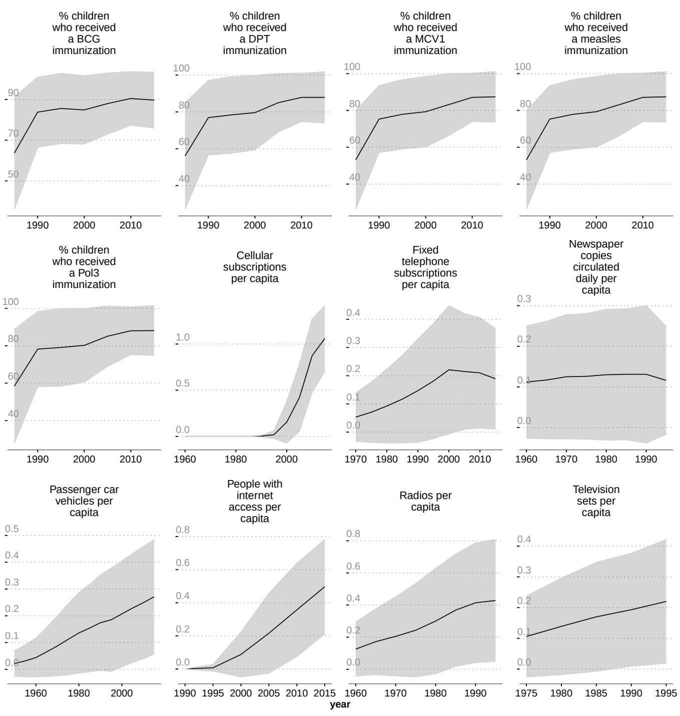
Figure A3: **Weighted** Coefficient of Variation across Time



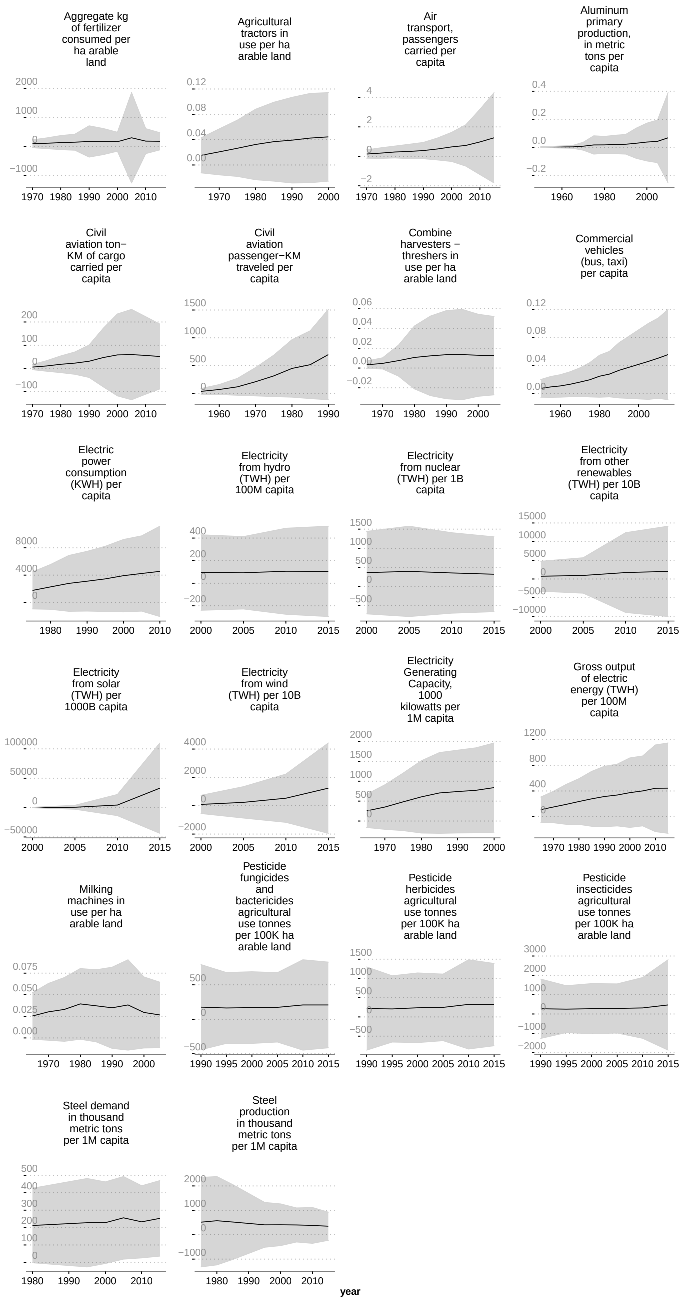
NOTE— Plotted are the *weighted* coefficients of variation across time within a fixed sample of countries across five-year periods. For agricultural technologies, values are weighted by hectares of arable land. Otherwise, values are weighted by population. A lower coefficient of variation across time indicates greater cross-country convergence.

Figure A4: Average adoption across time

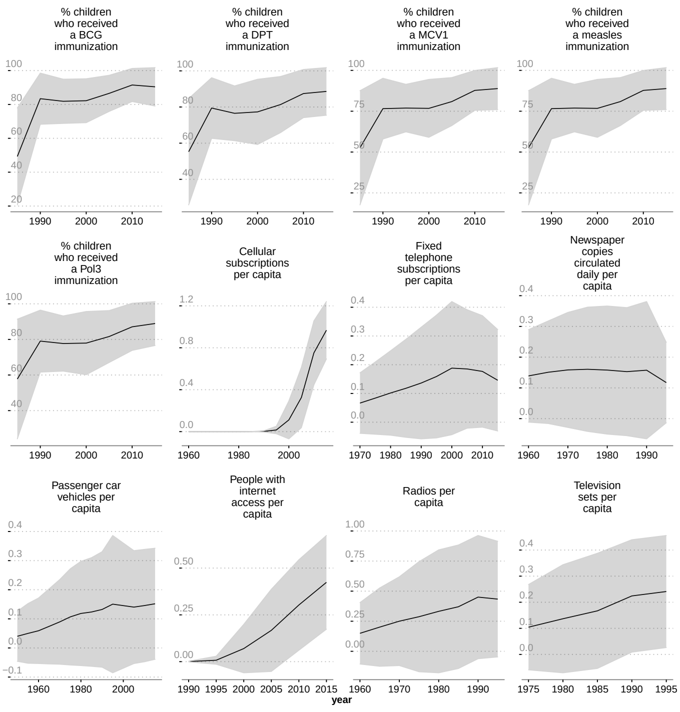
(a) Consumption (Unweighted)



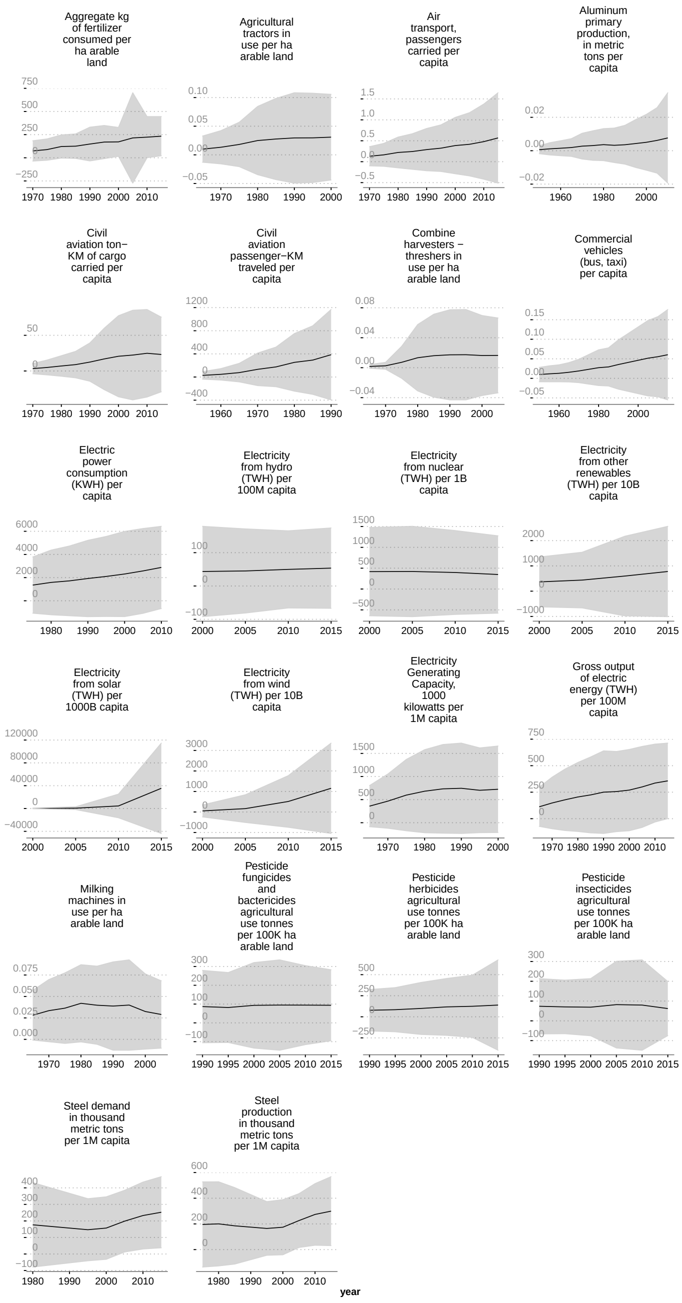
(b) Production (Unweighted)



(c) Consumption (Weighted)



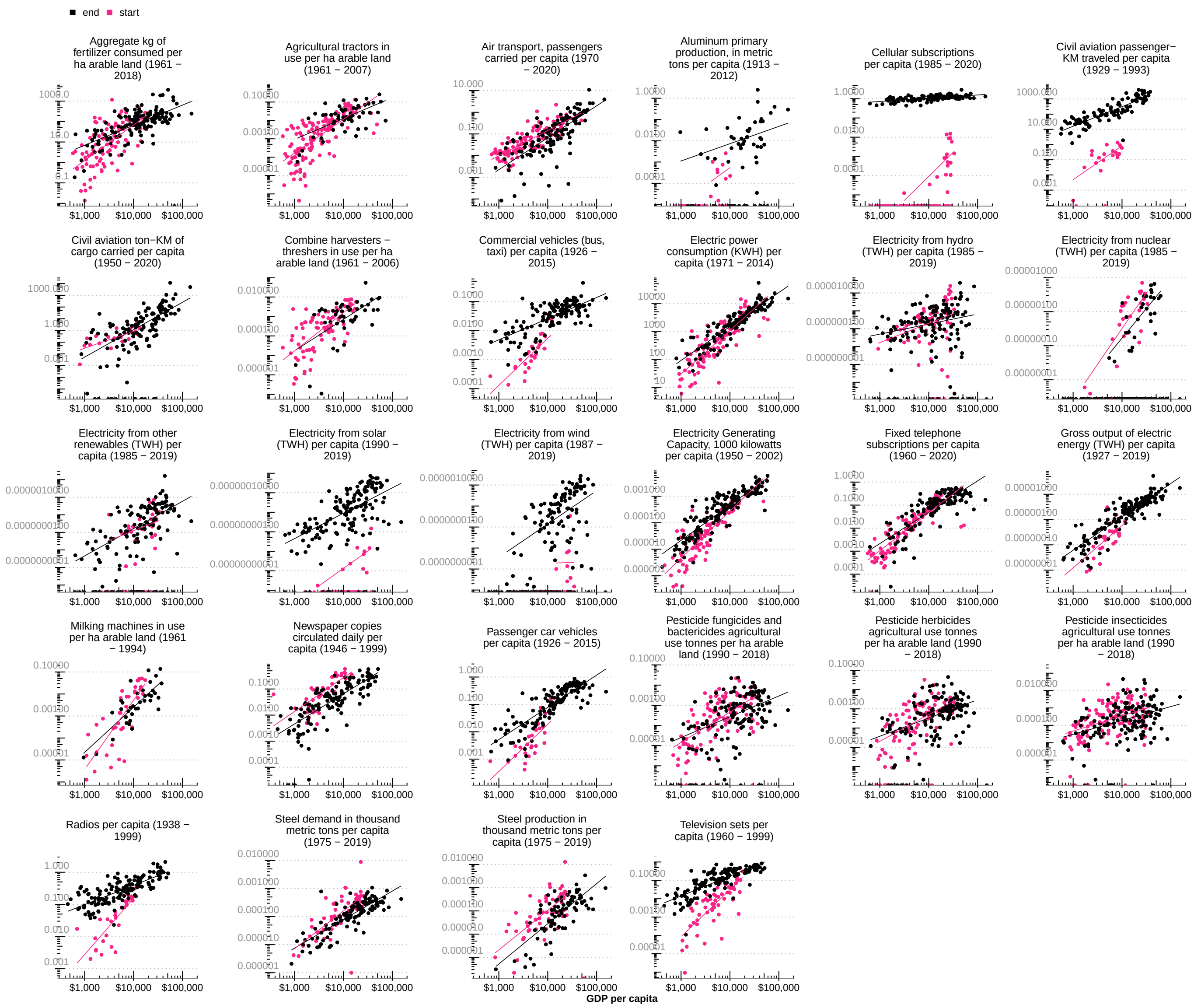
(d) Production (Weighted)



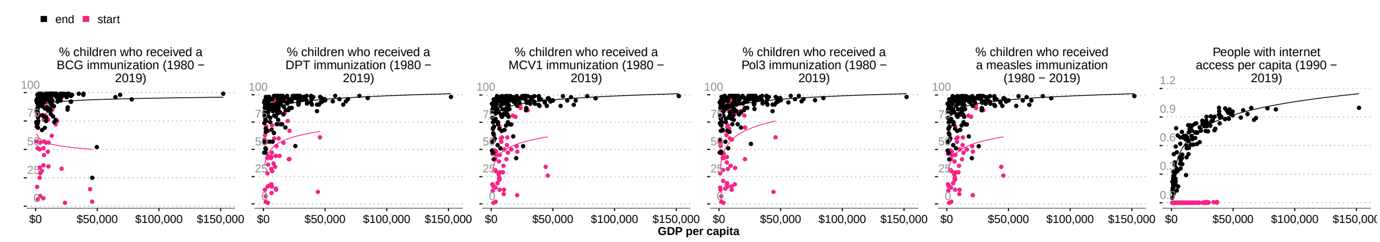
NOTE— Graphed are the mean adoption rates across 5 year periods for consumption and production technologies. Shaded areas indicate plus or minus one standard deviation. Samples across the entire dataset are fixed. The first row shows the adoption rates if an average across all countries is taken. The second row shows the adoption rates if a weighted average is taken. Weights are either population or hectares of arable land. On average, graphs show increased average adoption rates, though the adoption rate of some groups and categories of technologies have leveled, while for others, they continued to grow.

Figure A5: Preston Curves

(a) Log-Log

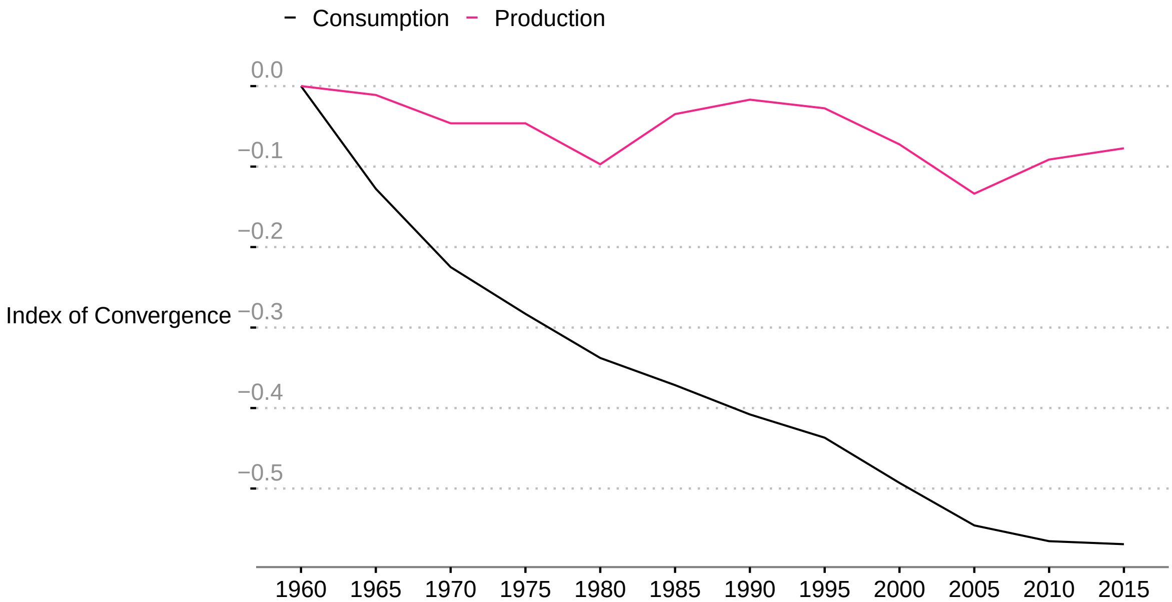


(b) Levels-Log



NOTE— Plotted is a scatter plot of adoption rates (Y) to GDP per capita (X) for the start and end periods of each technology. We fit the log of adoption rate to the log of GDP per capita for most variables. However, for the vaccines and internet access variables, we fit a levels-log curve. A shift upwards in the intercept and a flattening of the line of best fit indicates convergence.

Figure A6: Coefficient of Variation Index



NOTE— Plotted is an index of the coefficient of variation across time within a fixed sample of countries across five-year periods for a specific set of technologies. For production technologies the variables are gross output of electric energy (TWH) per capita, commercial vehicles (bus, taxi) per capita, thousand metric tons of steel produced, and aggregate kg of fertilizer consumed per hectare of arable land were included. For consumption technologies, fixed telephone subscriptions per capita, % children who received a DPT immunization, and passenger car vehicles per capita were included. The index is calculated by first computing an unweighted average of the coefficient of variation for each technology-year. Then, we divide each of those values by the initial coefficient of variation in 1960 (less 1). Finally, we average across technologies in the two bundles of consumption and production. A lower coefficient of variation index across time indicates convergence.

Table A.1: Table of Variable Origins

Group	Category	Variable	Variable Label	Is this a percentage?	Mean of the annual average GDP per capita (2011 dollars)	Median of the annual average GDP per capita (2011 dollars)	Mean of the annual average number of countries in sample	Median of the annual average number of countries in sample	Earliest date with available data	Most recent date with available data	How spliced	Source
Consumption	Communications	cabletv	Households that subscribe to cable	No	14802	14579	50	35	1975	2003		CHAT
Consumption	Communications	cell_subsc	Cellular subscriptions	No	11866	10122	160	161	1960	2020	replaced CHAT variable with our variable	WDI
Consumption	Communications	computer	Personal computers	No	12504	13909	60	43	1970	2009	replaced CHAT variable with our variable	WDI
Consumption	Communications	internetuser	People with internet access	No	10694	11204	100	156	1960	2020	replaced CHAT variable with our variable	WDI
Consumption	Communications	mail	Items mailed or received	No	5423	4012	37	39	1830	2000		CHAT
Consumption	Communications	newspaper	Newspaper copies circulated daily	No	7102	7134	80	104	1919	1999		CHAT
Consumption	Communications	radio	Radios	No	4560	3761	59	46	1820	2000		CHAT
Consumption	Communications	telegram	Telegrams	No	5463	4003	36	37	1830	2000		CHAT
Consumption	Communications	telephone	Fixed telephone subscriptions	No	6225	5344	57	44	1876	2003		CHAT
Consumption	Communications	telephone_canning_wdi	Fixed telephone subscriptions	No	10369	8900	157	191	1950	2020	arithmetic mean	Canning; WDI
Consumption	Communications	tv	Television sets	No	9440	8875	88	98	1946	2002		CHAT
Consumption	Financial	atm	ATMs	No	22297	21008	93	108	1988	2020	simple combine	WDI; CHAT
Consumption	Financial	cheque	Payments by cheque	No	26009	26411	24	27	1987	2003		CHAT
Consumption	Financial	creditdebit	Payments by credit and debit cards	No	26332	26599	22	22	1987	2003		CHAT
Consumption	Financial	creditdebit_number	Number of credit or debit cards in circulation	No	21127	21812	91	91	2002	2015		WB Global Payment Systems Survey (GPSS)
Consumption	Financial	creditdebit_value	Value of credit or debit card transactions (USD)	No	23011	24488	70	70	2002	2015		WB Global Payment Systems Survey (GPSS)
Consumption	Financial	creditdebit_volume	Number of credit or debit card transactions	No	23091	24488	67	70	2002	2015		WB Global Payment Systems Survey (GPSS)
Consumption	Financial	eft	Transactions using payment cards at points of service	No	27972	28119	22	18	1988	2003		CHAT
Consumption	Financial	pos	Retail locations at which payment cards can be used	No	27914	28482	22	19	1988	2003		CHAT
Consumption	Hospital (non-drug medical)	ct_scans	Computed Tomography exams, total	No	31718	32046	18	22	2000	2019		OECD
Consumption	Hospital (non-drug medical)	dgtsctam	Computed Tomography exams, in ambulatory care	No	34609	34499	14	18	2000	2019		OECD
Consumption	Hospital (non-drug medical)	dgtsctho	Computed Tomography exams, in hospitals	No	34149	33819	18	22	2000	2019		OECD

Table A.1: Table of Variable Origins *(continued)*

Group	Category	Variable	Variable Label	Is this a percentage?	Mean of the annual average GDP per capita (2011 dollars)	Median of the annual average GDP per capita (2011 dollars)	Mean of the annual average number of countries in sample	Median of the annual average number of countries in sample	Earliest date with available data	Most recent date with available data	How spliced	Source
Consumption	Hospital (non-drug medical)	dgtsmram	Magnetic Resonance Imaging exams, in ambulatory care	No	37045	36277	13	16	2000	2019		OECD
Consumption	Hospital (non-drug medical)	dgtsmrho	Magnetic Resonance Imaging exams, in hospitals	No	35982	35289	17	20	2000	2019		OECD
Consumption	Hospital (non-drug medical)	dgtspeam	Positron Emission Tomography (PET) exams, in ambulatory care	No	38423	37572	10	11	2000	2019		OECD
Consumption	Hospital (non-drug medical)	dgtspeex	Positron Emission Tomography (PET) exams, total	No	36808	35613	12	12	2000	2019		OECD
Consumption	Hospital (non-drug medical)	dgtspeho	Positron Emission Tomography (PET) exams, in hospitals	No	38374	37948	12	13	2000	2019		OECD
Consumption	Hospital (non-drug medical)	kidney_dialpat	Total patients receiving dialysis	No	22356	22697	20	23	1968	2002		CHAT
Consumption	Hospital (non-drug medical)	kidney_homedialpat	Total patients receiving home dialysis	No	24091	23102	18	21	1970	2002		CHAT
Consumption	Hospital (non-drug medical)	med_catscanner	CT scanners	No	25489	25026	14	13	1980	2002		CHAT
Consumption	Hospital (non-drug medical)	med_mammograph	Mammography machines	No	19320	20859	5	4	1968	2002		CHAT
Consumption	Hospital (non-drug medical)	med_mriunit	MRI units	No	26831	25751	12	15	1982	2002		CHAT
Consumption	Hospital (non-drug medical)	med_radiationequip	Equipment for x-ray or radionuclide treatment	No	17874	19608	8	7	1960	2002		CHAT
Consumption	Hospital (non-drug medical)	mri_scans	Magnetic Resonance Imaging exams, total	No	34708	34068	16	20	2000	2019		OECD
Consumption	Hospital (non-drug medical)	pctdaysurg_cataract	% Cataract surgeries without a hospital stay	Yes	27551	26210	5	3	1987	2001		CHAT
Consumption	Hospital (non-drug medical)	pctdaysurg_cholecyst	% Cholecystectomies without a hospital stay	Yes	28444	27799	6	7	1991	2001		CHAT
Consumption	Hospital (non-drug medical)	pctdaysurg_hernia	% Hernia procedures without a hospital stay	Yes	28536	27769	7	8	1991	2001		CHAT

Table A.1: Table of Variable Origins *(continued)*

Group	Category	Variable	Variable Label	Is this a percentage?	Mean of the annual average GDP per capita (2011 dollars)	Median of the annual average GDP per capita (2011 dollars)	Mean of the annual average number of countries in sample	Median of the annual average number of countries in sample	Earliest date with available data	Most recent date with available data	How spliced	Source
Consumption	Hospital (non-drug medical)	pctdaysurg_lapcholecyst	% Laparoscopic cholecystectomies without a hospital stay	Yes	29389	28804	5	6	1993	2001		CHAT
Consumption	Hospital (non-drug medical)	pctdaysurg_tonsil	% Tonsillectomies without a hospital stay	Yes	27748	27000	7	8	1993	2001		CHAT
Consumption	Hospital (non-drug medical)	pctdaysurg_varicosevein	% Varicose veins procedures without a hospital stay	Yes	28664	27533	6	7	1991	2001		CHAT
Consumption	Hospital (non-drug medical)	pcthomedialysis	% Dialysis patients who receive treatment at home	Yes	24697	23689	17	18	1970	2002		CHAT
Consumption	Hospital (non-drug medical)	surg_appendectomy	Appendectomies	No	29146	29316	11	10	1990	2001		CHAT
Consumption	Hospital (non-drug medical)	surg_breastcnsv	Breast conservation surgeries	No	29824	29555	7	7	1993	2001		CHAT
Consumption	Hospital (non-drug medical)	surg_cardcath	Cardiac catheterizations	No	28800	28103	10	10	1990	2001		CHAT
Consumption	Hospital (non-drug medical)	surg_cataract	Cataract surgeries	No	27426	26974	5	2	1980	2001		CHAT
Consumption	Hospital (non-drug medical)	surg_cholecyst	Cholecystectomies	No	28113	28681	4	1	1978	2001		CHAT
Consumption	Hospital (non-drug medical)	surg_corbypass	Coronary bypass surgeries	No	27169	26721	14	14	1980	2001		CHAT
Consumption	Hospital (non-drug medical)	surg_corinterven	Percutaneous coronary interventions	No	28143	27325	14	14	1990	2001		CHAT
Consumption	Hospital (non-drug medical)	surg_corstent	Coronary stenting procedures	No	28053	28671	6	6	1994	2001		CHAT
Consumption	Hospital (non-drug medical)	surg_csection	Caesarean sections	No	27739	27615	14	14	1990	2001		CHAT
Consumption	Hospital (non-drug medical)	surg_hernia	Number procedures to correct inguinal and femoral hernias	No	27285	26948	5	2	1980	2001		CHAT
Consumption	Hospital (non-drug medical)	surg_hipreplace	Hip replacement surgeries	No	29777	29362	11	10	1990	2001		CHAT

Table A.1: Table of Variable Origins *(continued)*

Group	Category	Variable	Variable Label	Is this a percentage?	Mean of the annual average GDP per capita (2011 dollars)	Median of the annual average GDP per capita (2011 dollars)	Mean of the annual average number of countries in sample	Median of the annual average number of countries in sample	Earliest date with available data	Most recent date with available data	How spliced	Source
Consumption	Hospital (non-drug medical)	surg_hysterectomy	Vaginal hysterectomies	No	29661	29114	10	10	1990	2001		CHAT
Consumption	Hospital (non-drug medical)	surg_kneereplace	Knee replacement surgeries	No	27876	26603	8	8	1990	2001		CHAT
Consumption	Hospital (non-drug medical)	surg_lapcholecyst	Cholecystectomies (gallbladder removals) laparoscopically	No	28491	28996	6	7	1993	2001		CHAT
Consumption	Hospital (non-drug medical)	surg_mastectomy	Mastectomies	No	29066	28818	10	10	1990	2001		CHAT
Consumption	Hospital (non-drug medical)	surg_pacemaker	Pacemaker implantation procedures	No	28120	27630	6	6	1990	2001		CHAT
Consumption	Hospital (non-drug medical)	surg_prostatetrans	Transurethral prostatectomy	No	28106	27471	8	8	1990	2001		CHAT
Consumption	Hospital (non-drug medical)	surg_prostatextrans	Non-transurethral prostatectomies	No	27331	26630	7	6	1990	2001		CHAT
Consumption	Hospital (non-drug medical)	surg_tonsil	Percent of tonsillectomies (with or without adenoidectomy) performed	No	27170	27006	4	2	1980	2001		CHAT
Consumption	Hospital (non-drug medical)	surg_varicosevein	Varicose vein correction	No	27903	25792	7	8	1991	2001		CHAT
Consumption	Hospital (non-drug medical)	transplant_bonemarrow	Bone marrow transplants	No	21007	22034	8	3	1960	2002		CHAT
Consumption	Hospital (non-drug medical)	transplant_heart	Heart transplants	No	25499	25234	15	15	1978	2002		CHAT
Consumption	Hospital (non-drug medical)	transplant_kidney	Kidney transplants	No	21033	20408	21	24	1963	2002		CHAT
Consumption	Hospital (non-drug medical)	transplant_liver	Liver transplants	No	21288	23571	10	5	1960	2002		CHAT
Consumption	Hospital (non-drug medical)	transplant_lung	Lung transplants	No	27692	27576	11	12	1980	2002		CHAT
Consumption	Transport	all_vehicles	Total vehicles (OICA)	No	19167	19257	141	141	2005	2015		OICA
Consumption	Transport	railp	Thousands of passenger journeys by railway	No	4850	4043	49	49	1834	1994		CHAT

Table A.1: Table of Variable Origins *(continued)*

Group	Category	Variable	Variable Label	Is this a percentage?	Mean of the annual average GDP per capita (2011 dollars)	Median of the annual average GDP per capita (2011 dollars)	Mean of the annual average number of countries in sample	Median of the annual average number of countries in sample	Earliest date with available data	Most recent date with available data	How spliced	Source
Consumption	Transport	railpkm	Passenger journeys by railway (passenger-km)	No	6716	4521	42	38	1834	2019	simple combine	WDI; CHAT
Consumption	Transport	vehicle_car	Passenger car vehicles	No	9330	6434	69	65	1895	2019	arithmetic mean of OECD and OICA data. then, weighted arithmetic mean of the most recent band of overlapping years with CHAT	OICA/OECD; CHAT
Consumption	Transport	vehicle_car_bts	Passenger cars (BTS)	No	24220	25880	26	27	1961	2015		World Motor Vehicle Production (BTS)
Consumption	Transport	vehicle_tot_bts	Total vehicles (BTS)	No	24222	25880	26	27	1961	2015		World Motor Vehicle Production (BTS)
Consumption	Vaccines	BCG	% children who received a BCG immunization	Yes	9115	8069	140	152	1980	2019		OWID
Consumption	Vaccines	DPT	% children who received a DPT immunization	Yes	12514	11419	171	187	1980	2019	replaced CHAT variable with our variable	OWID
Consumption	Vaccines	HepB3	% children who received a hepb3 immunization	Yes	14643	14699	118	143	1989	2019		OWID
Consumption	Vaccines	Hib3	% children who received a Hib3 immunization	Yes	21718	21504	101	98	1991	2019		OWID
Consumption	Vaccines	IPV1	% children who received a IPV1 immunization	Yes	20305	20075	165	162	2015	2019		OWID
Consumption	Vaccines	MCV1	% children who received a MCV1 immunization	Yes	12510	11419	171	187	1980	2019		OWID
Consumption	Vaccines	MCV2	% children who received a MCV2 immunization	Yes	19530	20392	121	122	2000	2019		OWID
Consumption	Vaccines	med_lithotriptor	Extracorporeal shock wave lithotripters	No	26477	24965	9	10	1982	2002		CHAT
Consumption	Vaccines	pctimmunizmeas	% children who received a measles immunization	Yes	12510	11419	171	187	1980	2019	replaced CHAT variable with our variable	WDI
Consumption	Vaccines	PCV3	% children who received a PCV3 immunization	Yes	26345	21687	88	95	2008	2019		OWID
Consumption	Vaccines	pharacid	A02A-Antacids (defined daily dosage)	No	33650	33843	17	17	2000	2019		OECD
Consumption	Vaccines	pharalim	A-Alimentary tract and metabolism (defined daily dosage)	No	34835	35440	21	21	2000	2019		OECD
Consumption	Vaccines	pharanal	N02-Analgesics (defined daily dosage)	No	35050	35440	21	21	2000	2019		OECD

Table A.1: Table of Variable Origins *(continued)*

Group	Category	Variable	Variable Label	Is this a percentage?	Mean of the annual average GDP per capita (2011 dollars)	Median of the annual average GDP per capita (2011 dollars)	Mean of the annual average number of countries in sample	Median of the annual average number of countries in sample	Earliest date with available data	Most recent date with available data	How spliced	Source
Consumption	Vaccines	pharanxo	N05B-Anxiolytics (defined daily dosage)	No	34749	35332	21	21	2000	2019		OECD
Consumption	Vaccines	phararas	C09-Agents acting on the Renin-Angiotensin system (defined daily dosage)	No	34808	35440	22	22	2000	2019		OECD
Consumption	Vaccines	phararit	C01B-Antiarrhythmics, Class I and III (defined daily dosage)	No	35076	35440	22	22	2000	2019		OECD
Consumption	Vaccines	pharbeta	C07-Beta blocking agents (defined daily dosage)	No	35041	35440	22	22	2000	2019		OECD
Consumption	Vaccines	pharbiot	J01-Antibacterials for systemic use (defined daily dosage)	No	34224	34494	26	28	2000	2019		OECD
Consumption	Vaccines	pharbloo	B-Blood and blood forming organs (defined daily dosage)	No	34531	35197	21	21	2000	2019		OECD
Consumption	Vaccines	pharcarv	C-Cardiovascular system (defined daily dosage)	No	34787	35440	21	21	2000	2019		OECD
Consumption	Vaccines	pharccbr	C08-Calcium channel blockers (defined daily dosage)	No	34864	35440	22	22	2000	2019		OECD
Consumption	Vaccines	pharchls	C10-Lipid modifying agents (defined daily dosage)	No	34988	35299	21	22	2000	2019		OECD
Consumption	Vaccines	pharcnsy	N-Nervous system (defined daily dosage)	No	34787	35440	21	21	2000	2019		OECD
Consumption	Vaccines	phardepr	N06A-Antidepressants (defined daily dosage)	No	34891	35440	22	22	2000	2019		OECD
Consumption	Vaccines	phardiab	A10-Drugs used in diabetes (defined daily dosage)	No	35041	35440	22	22	2000	2019		OECD
Consumption	Vaccines	phardiur	C03-Diuretics (defined daily dosage)	No	35011	35440	22	21	2000	2019		OECD
Consumption	Vaccines	pharflam	M01A-Antiinflammatory and antirheumatic products non-steroids (defined daily dosage)	No	35038	35440	22	22	2000	2019		OECD
Consumption	Vaccines	phargenu	G-Genito urinary system and sex hormones (defined daily dosage)	No	34902	35440	21	21	2000	2019		OECD
Consumption	Vaccines	pharglyc	C01A-Cardiac glycosides (defined daily dosage)	No	35048	35440	21	21	2000	2019		OECD
Consumption	Vaccines	pharhorm	H-Systemic hormonal preparations, excluding sex hormones and insulins (defined daily dosage)	No	34902	35440	21	21	2000	2019		OECD
Consumption	Vaccines	pharhypn	N05C-Hypnotics and sedatives (defined daily dosage)	No	34700	35332	21	20	2000	2019		OECD
Consumption	Vaccines	pharhypo	C02-Antihypertensives (defined daily dosage)	No	35079	35440	22	22	2000	2019		OECD
Consumption	Vaccines	pharinfc	J-Anti-infective for systemic use (defined daily dosage)	No	34787	35440	21	21	2000	2019		OECD

Table A.1: Table of Variable Origins *(continued)*

Group	Category	Variable	Variable Label	Is this a percentage?	Mean of the annual average GDP per capita (2011 dollars)	Median of the annual average GDP per capita (2011 dollars)	Mean of the annual average number of countries in sample	Median of the annual average number of countries in sample	Earliest date with available data	Most recent date with available data	How spliced	Source
Consumption	Vaccines	pharobai	R03-Drugs for obstructive airway diseases (defined daily dosage)	No	34822	35440	21	21	2000	2019		OECD
Consumption	Vaccines	pharpept	A02B-Drugs for peptic ulcer and gastro-esophageal reflux diseases (GERD) (defined daily dosage)	No	35038	35440	22	22	2000	2019		OECD
Consumption	Vaccines	pharress	R-Respiratory system (defined daily dosage)	No	34787	35440	21	21	2000	2019		OECD
Consumption	Vaccines	pharshmg	G03-Sex hormones and modulators of the genital system (defined daily dosage)	No	34850	35440	21	21	2000	2019		OECD
Consumption	Vaccines	pharskel	M-Musculo-skeletal system (defined daily dosage)	No	34787	35440	21	21	2000	2019		OECD
Consumption	Vaccines	Pol3	% children who received a Pol3 immunization	Yes	12497	11419	171	187	1980	2019		OWID
Consumption	Vaccines	RCV1	% children who received a RCV1 immunization	Yes	20446	19831	86	92	1980	2019		OWID
Consumption	Vaccines	RotaC	% children who received a rotac immunization	Yes	18955	18622	48	40	2006	2019		OWID
Consumption	Vaccines	YFV	% children who received a YFV immunization	Yes	5463	5223	27	31	1997	2019		OWID
Creation	Other	patents	Patent applications, residents	No	16417	15179	90	94	1980	2019		WDI
Non-Tech	Agriculture	ag_land	Land agricultural land area 1000 ha	No	10480	8604	206	192	1961	2018		FAO
Non-Tech	Agriculture	araland	Land arable land area 1000 ha	No	10480	8604	200	186	1961	2018		FAO
Non-Tech	Agriculture	forest	Land naturally regenerating forest area 1000 ha	No	13420	13551	211	211	1990	2018		FAO
Non-Tech	Agriculture	forest_planted	Land planted forest area 1000 ha	No	13420	13551	211	211	1990	2018		FAO
Non-Tech	Agriculture	pct_ag_ara_land	% Arable land share in agricultural land	Yes	10480	8604	200	186	1961	2018		FAO
Non-Tech	Agriculture	pctirrigated	% Irrigated area as a share of cultivated land	Yes	11057	8344	105	123	1961	2018	weighted arithmetic mean of the most recent band of overlapping years	FAO; CHAT
Non-Tech	Agriculture	pctmvbyarea	% Area of cropland planted with modern varieties	Yes	3654	3789	84	84	1960	2000		CHAT
Non-Tech	Hospital (non-drug medical)	bed_hosp	Beds in hospitals	No	16113	15176	59	64	1960	2019	replaced CHAT variable with our variable	WDI
Non-Tech	Hospital (non-drug medical)	bltcltcn	Beds in residential long-term care facilities	No	37399	36927	29	31	2005	2019		OECD
Non-Tech	Hospital (non-drug medical)	bltcltcn65	Beds in residential long-term care facilities aged 65 years old and over	No	37483	36927	29	31	2005	2019		OECD

Table A.1: Table of Variable Origins *(continued)*

Group	Category	Variable	Variable Label	Is this a percentage?	Mean of the annual average GDP per capita (2011 dollars)	Median of the annual average GDP per capita (2011 dollars)	Mean of the annual average number of countries in sample	Median of the annual average number of countries in sample	Earliest date with available data	Most recent date with available data	How spliced	Source
Non-Tech	Other	bed_acute	Beds for those seeking in-patient acute care	No	19455	19872	16	17	1960	2002		CHAT
Non-Tech	Other	bed_longterm	Beds for people who need continuing chronic care assistance	No	20428	19927	9	8	1960	2002		CHAT
Non-Tech	Other	visitorbeds	Visitor beds (hotels, etc.)	No	9895	9344	100	103	1977	2003		CHAT
Non-Tech	Other	visitorrooms	Visitor rooms (hotels, etc.)	No	10350	9579	106	105	1977	2003		CHAT
Production	Agriculture	ag_harvester	Combine harvesters - threshers in use	No	11352	11022	76	77	1961	2009	replaced CHAT variable with our variable	FAO
Production	Agriculture	ag_milkingmachine	Milking machines in use	No	14947	14091	39	40	1961	2009	replaced CHAT variable with our variable	FAO
Production	Agriculture	ag_tractor	Agricultural tractors in use	No	10023	8842	138	147	1961	2009	replaced CHAT variable with our variable	FAO
Production	Agriculture	fert_an	Fertilizer ammonium nitrate (AN) agricultural use tonnes	No	20006	17272	59	56	2002	2018		FAO
Production	Agriculture	fert_as	Fertilizer ammonium sulphate agricultural use tonnes	No	18471	16567	68	64	2002	2018		FAO
Production	Agriculture	fert_dap	Fertilizer diammonium phosphate (DAP) agricultural use tonnes	No	16701	14860	63	59	2002	2018		FAO
Production	Agriculture	fert_kcl	Fertilizer potassium chloride (muriate of potash) (MOP) agricultural use tonnes	No	20499	19016	67	63	2002	2018		FAO
Production	Agriculture	fert_npk	Fertilizer NPK fertilizers agricultural use tonnes	No	18452	16961	77	68	2002	2018		FAO
Production	Agriculture	fert_oth	Fertilizer other NP compounds agricultural use tonnes	No	18619	16869	53	48	2002	2018		FAO
Production	Agriculture	fert_phos	Fertilizer superphosphates above 35 percent agricultural use tonnes	No	19963	17376	51	44	2002	2018		FAO
Production	Agriculture	fert_sulph	Fertilizer potassium sulphate (sulphate of potash) (SOP) agricultural use tonnes	No	18858	17374	56	53	2002	2018		FAO
Production	Agriculture	fert_total	Aggregate kg of fertilizer consumed	No	11034	9209	139	131	1961	2018	replaced CHAT variable with our variable	WDI
Production	Agriculture	fert_urea	Fertilizer urea agricultural use tonnes	No	18893	17813	85	79	2002	2018		FAO
Production	Agriculture	irrigatedarea	Area equipped to provide water to crops	No	11057	8344	105	123	1961	2018	weighted arithmetic mean of the most recent band of overlapping years	FAO; CHAT

Table A.1: Table of Variable Origins *(continued)*

Group	Category	Variable	Variable Label	Is this a percentage?	Mean of the annual average GDP per capita (2011 dollars)	Median of the annual average GDP per capita (2011 dollars)	Mean of the annual average number of countries in sample	Median of the annual average number of countries in sample	Earliest date with available data	Most recent date with available data	How spliced	Source
Production	Agriculture	pest_fund_bact	Pesticide fungicides and bactericides agricultural use tonnes	No	14526	14604	159	161	1990	2018		FAO
Production	Agriculture	pest_herb	Pesticide herbicides agricultural use tonnes	No	14806	14885	156	157	1990	2018		FAO
Production	Agriculture	pest_insect	Pesticide insecticides agricultural use tonnes	No	14347	14423	161	163	1990	2018		FAO
Production	Agriculture	pest_minoil	Pesticide mineral oils agricultural use tonnes	No	19381	19829	71	73	1990	2018		FAO
Production	Agriculture	pest_other	Pesticide other pesticides nes agricultural use tonnes	No	17902	18197	83	85	1990	2018		FAO
Production	Agriculture	pest_pgr	Pesticide plant growth regulators agricultural use tonnes	No	15837	16091	105	107	1990	2018		FAO
Production	Agriculture	pest_rod	Pesticide rodenticides agricultural use tonnes	No	13654	13839	124	126	1990	2018		FAO
Production	Agriculture	pest_total	Total metric tons of pesticides in agricultural use	No	14296	14365	162	164	1990	2018	replaced CHAT variable with our variable	FAO
Production	Communications	servers	Secure internet servers	No	18129	18174	212	212	2010	2020		WDI
Production	Energy	elec_coal	Electricity from coal (TWH)	No	16282	16352	130	208	1985	2020		OWID
Production	Energy	elec_cons	Electric power consumption (KWH)	No	12667	11511	95	110	1960	2019		WDI
Production	Energy	elec_gas	Electricity from gas (TWH)	No	16282	16352	130	208	1985	2020		OWID
Production	Energy	elec_hydro	Electricity from hydro (TWH)	No	16381	16305	150	209	1985	2020		OWID
Production	Energy	elec_nuc	Electricity from nuclear (TWH)	No	16381	16305	150	209	1985	2020		OWID
Production	Energy	elec_oil	Electricity from oil (TWH)	No	16282	16352	130	208	1985	2020		OWID
Production	Energy	elec_renew_other	Electricity from other renewables (TWH)	No	16381	16305	150	209	1985	2020		OWID
Production	Energy	elec_solar	Electricity from solar (TWH)	No	16381	16305	150	209	1985	2020		OWID
Production	Energy	elec_wind	Electricity from wind (TWH)	No	16381	16305	150	209	1985	2020		OWID
Production	Energy	elecprod	Gross output of electric energy (TWH)	No	7923	5392	96	111	1895	2020	weighted arithmetic mean of the most recent band of overlapping years	CHAT; OWID
Production	Energy	electric_gen_capacity	Electricity Generating Capacity, 1000 kilowatts	No	7731	8114	147	125	1950	2002		Canning
Production	Industry	aluminum	Aluminum primary production, in metric tons	No	6971	4553	72	72	1850	2012		CLIO
Production	Industry	loom_auto	Automatic looms	No	8566	8536	67	59	1963	1979		CHAT
Production	Industry	loom_total	Ordinary and automatic looms	No	8571	8536	67	59	1963	1979		CHAT
Production	Industry	spindle_mule	Mule spindles	No	3964	2974	9	1	1903	1954		CHAT
Production	Industry	spindle_ring	Ring spindles	No	3750	2974	15	1	1903	1954		CHAT
Production	Industry	steel_demand	Steel demand in thousand metric tons	No	15119	13831	93	110	1967	2019		World Steel

Table A.1: Table of Variable Origins *(continued)*

Group	Category	Variable	Variable Label	Is this a percentage?	Mean of the annual average GDP per capita (2011 dollars)	Median of the annual average GDP per capita (2011 dollars)	Mean of the annual average number of countries in sample	Median of the annual average number of countries in sample	Earliest date with available data	Most recent date with available data	How spliced	Source
Production	Industry	steel_production	Steel production in thousand metric tons	No	16560	14165	74	88	1967	2019	replaced CHAT variable with our variable	World Steel
Production	Industry	steel_stainless	Stainless steel production	No	18077	17875	20	20	1981	1990		CHAT
Production	Industry	txtlmat_artif	Weight of artificial fibers in spindles	No	8915	8973	59	57	1962	1979		CHAT
Production	Industry	txtlmat_otherraw	Weight of other fibers in spindles	No	13509	13580	24	22	1968	1979		CHAT
Production	Industry	txtlmat_synth	Weight of synthetic fibers in spindles	No	9391	9231	53	54	1963	1979		CHAT
Production	Industry	txtlmat_totalraw	Weight of all fibers in spindles	No	8448	8595	66	59	1962	1979		CHAT
Production	Other	railline_wdi	Rail lines (total route-km)	No	17543	18883	81	83	1995	2019		WDI
Production	Transport	aviation_pass	Air transport, passengers carried	No	12463	10231	146	148	1970	2020		WDI
Production	Transport	aviationpkm	Civil aviation passenger-KM traveled	No	6845	6322	59	58	1920	1993		CHAT
Production	Transport	aviationtkm	Civil aviation ton-KM of cargo carried	No	9628	8410	95	125	1929	2020	growth	WDI; CHAT
Production	Transport	railline	Geographical/route lengths of line open at the end of the year	No	4666	3649	68	74	1825	2004		CHAT
Production	Transport	railt	Metric tons of freight carried on railways (excluding livestock and passenger baggage)	No	5073	4090	53	57	1850	1994		CHAT
Production	Transport	railtkm	Freight carried on railways (excluding livestock and passenger baggage) (ton-km)	No	7055	4755	49	50	1850	2019	simple combine	WDI; CHAT
Production	Transport	road	Length of Paved Road (km)	No	7858	7650	86	94	1950	2002		Canning
Production	Transport	ship_all	Ships of all kinds	No	5544	4243	27	26	1820	1998		CHAT
Production	Transport	ship_motor	Motor ship	No	11361	7526	5	5	1908	1994		CHAT
Production	Transport	ship_sail	Sail ships	No	6959	4309	12	9	1820	1993		CHAT
Production	Transport	ship_steam	Steam ships	No	7083	4184	8	8	1820	1998		CHAT
Production	Transport	ship_steammotor	Steam and motor ships	No	6019	5326	22	17	1870	1998		CHAT
Production	Transport	shipton_all	Tonnage of ships of all kinds	No	5467	4228	28	28	1820	1998		CHAT
Production	Transport	shipton_motor	Tonnage of motor ships	No	12318	7715	5	5	1906	1998		CHAT
Production	Transport	shipton_sail	Tonnage of sail ships	No	7161	4575	13	10	1820	1993		CHAT
Production	Transport	shipton_steam	Tonnage of steam ships	No	7185	4672	8	8	1820	1998		CHAT
Production	Transport	shipton_steammotor	Tonnage of steam and motor ships	No	6071	5685	24	18	1870	1998		CHAT
Production	Transport	vehicle_com	Commercial vehicles (bus, taxi)	No	8444	6732	71	82	1904	2015	simple combine	OICA; CHAT
Production	Transport	vehicle_commercial_bts	Commercial vehicles (BTS)	No	24222	25880	26	27	1961	2015		World Motor Vehicle Production (BTS)