Supplementary Information

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Section A. Data.

A1. Data Collection

The data collected for this study is a combination of data collected in previous studies led by coauthors[1], data gathered by authors specifically for this study, and aggregated data from other sources. The sections below describe the data collection process in more detail and the data itself.

HATCH Data

The Historical Adoption of TeCHnologies (HATCH) dataset is an unbalanced panel dataset. This data comes from publicly available sources (such as governmental databases, scientific literature, and other publicly available data aggregations) and supplemented with licensed data used in extended version of the HATCH dataset but not publicly shared. The proprietary data account for less than 0.001% of the time series included in the full dataset. For this study, we use version 1.5[1] and extend it with new data, which includes national level time series data on technology adoption. In this dataset, each row contains a unique country-technology pair and each column contains the level of adoption in that year for the country-technology pair.

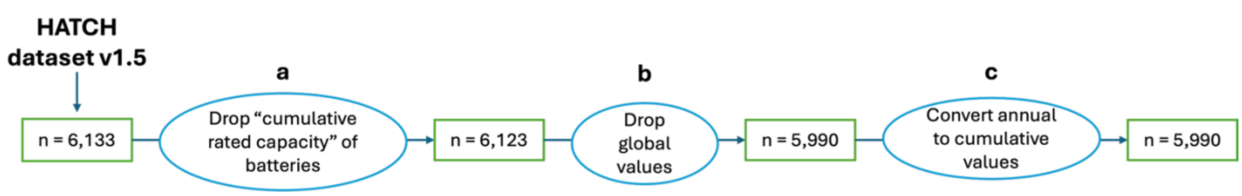
The technology adoption is measured by different units depending on the original source: annual production, cumulative capacity, total number of units, and the market share of a technology, shown in Supplementary Table 1. Home air conditioning is included in version 1.5 of the HATCH dataset as market share and number of units for the USA. We use number of units to align with measurements in other countries.

Production	Capacity	Cumulative Totals	Market Share
Annual Production	**Cumulative Rated Power**	**Cumulative Acreage**	**Share of Boilers**
Air-Source Heat Pumps	Flywheel Battery Storage	Herbicide-Tolerant Corn	Nox Pollution Controls (Boilers)
All Biofuels	Latent Heat Storage	Herbicide-Tolerant Cotton	**Share of Market**
Ammonia Synthesis	Lead-Acid Battery Storage	Herbicide-Tolerant Soybeans	Automatic Transmission
Aquaculture Production	Lithium-Ion Battery Storage	Insect-Resistant Corn	Cable TV
Beer Production	Pumped Hydro Storage	Insect-Resistant Cotton	Color Television
Cadmium Refining	Sensible Heat Storage	**Cumulative Number (Calculated)**	Dishwashers
Cane Sugar	Sodium-Based Battery Storage	Ground Source Heat Pumps	Disk Brakes
Capture Fisheries	**Cumulative Total Capacity**	High Speed Rail	Flush Toilet
Caustic Soda	Electric Bicycles	Objects Launched Into Space	Freezer
Cement	Laundry Dryers	Passenger Cars	Home Computers
Coal Production	Refrigerators	Postal Traffic	Household Internet Access
Cobalt	Washing Machines	Telegraph Traffic	Microcomputers
Copper|Mining	Wet Flue Gas Desulfurization Systems	**Cumulative Number of Units**	Microwaves
Copper|Refining	**Installed Electricity Capacity**	Motorcycles	Power Steering
Crude Oil	Biogas	Natural Gas Pipelines	Radial Tires
Electric Bicycles	Geothermal Energy	Oil Pipelines	Real-Time Gross Settlement Adoption
Electricity	Liquid Biofuels	**Number of Units**	Stove
Ethanol	Marine Energy	Home Air Conditioning	Vacuums
Gold	Offshore Wind Energy	Jet Aircraft	**Share of Population**
Graphite	Onshore Wind Energy	**Total Length**	BCG Vaccine
Hydrochloric Acid	Solar Photovoltaic	Canals	DTP1 Vaccine
Hydroelectricity	Solar Thermal Energy	Pubilc Roads	DTP3 Vaccine
Iron Ore	Solid Biofuels	Railroad	Ebook Reader
Lead	**Total Capacity**	**Total Number**	HEPB3 Vaccine
Liquefied Natural Gas	Oil Refining Capacity	Cellphones	HEPBB Vaccine
Lithium Mine Production		Crop Harvester	HIB3 Vaccine
Milk		Nuclear Weapons	MCV1 Vaccine

Natural Gas Production		Radio	MCV2 Vaccine
Nickel		Steamships	PCV3 Vaccine
Nitric Acid		Telephones	Podcasting
Nitrogen Fertilizer		Television	POL3 Vaccine
Nuclear Energy			RCV1 Vaccine
Oil Production			ROTAC Vaccine
Phosphate Fertilizer			Social Media Usage
Potash Fertilizer			YFV Vaccine
Primary Aluminum Production			
Primary Bauxite Production			
Primary Copper			
Rare Earth Mine Production			
Raw Steel Production			
Renewable Power			
Salt Production			
Sand and Gravel|Construction			
Sand and Gravel|Industrial			
Shale Production			
Silver			
Sulphuric Acid			
Synthetic Filaments			
Tin			
Zinc			

Supplementary Table 1. Unit of each technology in the HATCH dataset.

For this study, the HATCH dataset is filtered through a multi-step process depicted below in Supplementary Figure 1. Step (a) drops the cumulative rated capacity time series for battery technologies and keeps cumulative rated power metric for each battery technology (dropping 10 points). Step (b) drops global values because these are not relevant for the national-level scale in this analysis (dropping 95 points). Step (c) converts some annual values to cumulative values if those annual values are measured as the "number of units". They are converted to cumulative number of units as a measure of total adoption (no points dropped; number of points transformed n = 329).



Supplementary Figure 1. Filtering process of HATCH dataset for use in this analysis. This diagram shows the process of cleaning and filtering the HATCH 1.5 dataset for this analysis. The three steps are displayed and labelled as step a, b. and c. In step a, time series measuring cumulative rated capacity of energy storage technologies are dropped. In step b, global time series are dropped. In step c, time series measuring annual values of technologies that are measured in terms of 'number of units' are converted to cumulative values.

This results in 5,990 country-technology pairs (unique time series). After fitting a logistic function to each country-technology pair to measure growth speed and filtering those fits based on goodness of fits and within bounds (0 < k < 1) (this process described further in Section A2), there are 1,750 country-technology pairs across 112 technologies. This technology list and the number of countries per technology after filtering is summarized below in Supplementary Table 2 and Supplementary Table 3 by the number of countries per technology and the number of technologies per country.

Technology	# of Countries	Technology	# of Countries
All Biofuels	10	Microwaves	1
Ammonia Synthesis	4	Milk	14
Aquaculture Production	46	Motorcycles	19
BCG Vaccine	10	Natural Gas Pipelines	16
Beer Production	27	Natural Gas Production	23
Biogas	30	Nickel	1
Cable TV	1	Nitric Acid	4
Cadmium Refining	1	Nitrogen Fertilizer	8
Canals	1	Nox Pollution Controls (Boilers)	1
Cane Sugar	7	Nuclear Energy	8
Capture Fisheries	15	Nuclear Weapons	4
Caustic Soda	9	Objects Launched Into Space	19
Cellphones	61	Offshore Wind Energy	7
Coal Production	4	Oil Pipelines	5
Color Television	1	Oil Production	6
Copper|Mining	3	Oil Refining Capacity	14
Copper|Refining	4	Onshore Wind Energy	48
Crop Harvester	44	PCV3 Vaccine	5
Crude Oil	8	POL3 Vaccine	15
DTP1 Vaccine	15	Passenger Cars	132
DTP3 Vaccine	20	Phosphate Fertilizer	6
Dishwashers	1	Podcasting	1
Disk Brakes	1	Postal Traffic	75
Electric Bicycles	2	Potash Fertilizer	3
Electricity	40	Power Steering	1
Ethanol	1	Primary Aluminum Production	3
Flush Toilet	4	Primary Bauxite Production	2
Flywheel Battery Storage	1	Public Roads	6
Freezer	1	Pumped Hydro Storage	7
Geothermal Energy	3	RCV1 Vaccine	4
Gold	1	ROTAC Vaccine	2
Ground Source Heat Pumps	1	Radio	119
HEPB3 Vaccine	8	Railroad	34
HEPBB Vaccine	2	Raw Steel Production	7

HIB3 Vaccine	3	Real-Time Gross Settlement Adoption	1
Herbicide-Tolerant Corn	1	Refrigerators	1
Herbicide-Tolerant Cotton	1	Renewable Power	48
Herbicide-Tolerant Soybeans	1	Salt Production	4
High Speed Rail	5	Sensible Heat Storage	1
Home Air Conditioning	3	Shale Production	1
Home Computers	1	Silver	1
Household Internet Access	192	Social Media Usage	1
Hydrochloric Acid	5	Sodium-Based Battery Storage	1
Hydroelectricity	8	Solar Photovoltaic	60
Insect-Resistant Corn	1	Solid Biofuels	17
Insect-Resistant Cotton	1	Steamships	7
Iron Ore	2	Stove	1
Jet Aircraft	1	Sulphuric Acid	10
Laundry Dryers	1	Synthetic Filaments	17
Lead	1	Telegraph Traffic	72
Lead-Acid Battery Storage	1	Telephones	120
Liquefied Natural Gas	1	Television	119
MCV1 Vaccine	14	Washing Machines	1
MCV2 Vaccine	6	Wet Flue Gas Desulfurization Systems	3
Marine Energy	1	YFV Vaccine	1
Microcomputers	1	Zinc	5

Supplementary Table 2. Number of countries for each technology included in the HATCH dataset. Filtered through process depicted by Supplementary Figure 1 and filtered based on logistic fit $R^2 > 0.95$ and $0 < k < 1$.

Country Code	# of Tech	Country Code	# of Tech	Country Code	# of Tech	Country Code	# of Tech	Country Code	# of Tech
ABW	1	CRI	9	IDN	21	MNE	2	SGP	12
AFG	5	CUB	10	IND	37	MNG	7	SLB	1
AGO	6	CYM	1	IRL	13	MNP	1	SLE	6
ALB	5	CYP	5	IRN	19	MOZ	9	SLV	8
AND	1	DEU	26	IRQ	6	MRT	5	SOM	3
ARE	11	DJI	1	ISL	9	MTQ	1	SRB	5
ARG	12	DMA	1	ISR	17	MUS	8	STP	1
ARM	1	DNK	12	ITA	21	MWI	6	SUR	5
ATG	2	DOM	8	JAM	5	MYS	17	SVK	6
AUS	21	DZA	10	JOR	6	NAM	3	SVN	7
AUT	13	ECU	11	JPN	27	NCL	3	SWE	15
AZE	5	EGY	11	KAZ	6	NER	7	SWZ	5
BDI	5	ERI	8	KEN	7	NGA	10	SYC	1
BEL	14	ESP	24	KGZ	3	NIC	7	SYR	6
BEN	4	EST	10	KHM	5	NIU	2	TCD	5
BFA	5	ETH	5	KIR	1	NLD	18	TGO	5
BGD	13	FIN	14	KNA	1	NOR	17	THA	29
BGR	8	FJI	1	KOR	22	NPL	8	TJK	2
BHR	6	FRA	25	KWT	7	NRU	1	TKM	3
BHS	1	FRO	1	LAO	8	NZL	13	TLS	1
BIH	3	FSM	2	LBN	8	OMN	11	TON	1
BLR	6	GAB	6	LBR	5	PAK	22	TTO	3
BLZ	5	GBR	19	LBY	6	PAN	6	TUN	14
BMU	1	GEO	3	LCA	1	PER	17	TUR	20
BOL	10	GHA	13	LIE	1	PHL	10	TUV	1
BRA	28	GIB	1	LKA	17	PLW	1	TWN	11
BRB	3	GIN	7	LSO	6	PNG	6	TZA	7
BRN	1	GLP	1	LTU	8	POL	13	UGA	10
BTN	4	GMB	5	LUX	11	PRI	2	UKR	7
BWA	7	GNB	2	LVA	9	PRT	18	URY	10
CAF	5	GNQ	4	MAC	1	PRY	8	USA	55
CAN	25	GRC	13	MAR	13	PSE	2	UZB	4
CHE	15	GRD	2	MDA	5	PYF	2	VCT	4
CHL	20	GRL	1	MDG	8	QAT	4	VEN	10
CHN	45	GTM	9	MDV	5	REU	1	VNM	16
CIV	7	GUM	1	MEX	21	ROU	9	VUT	1
CMR	7	GUY	6	MHL	1	RUS	19	WSM	1
COD	6	HKG	4	MKD	1	RWA	6	YEM	5
COG	8	HND	7	MLI	5	SAU	13	ZAF	15
COL	16	HRV	8	MLT	3	SDN	8	ZMB	8
COM	1	HTI	5	MMR	10	SEN	6	ZWE	9
CPV	1	HUN	11						

Supplementary Table 3. Number of technologies for each country included in the HATCH dataset. Filtered through process depicted by Supplementary Figure 1 and filtered based on logistic fit $R^2 > 0.95$ and $0 < k < 1$. The analysis is based on the 3-digit ISO code, thus shown here. We remove the country code of CZE from the analysis to avoid overlap with Czechia, Czech Republic, and Slovakia. There are four countries included in time series that are not assigned ISO-3 code because they were transitional: Czechoslovakia, Netherlands Antilles, Serbia and Montenegro, and Yugoslavia. East Germany and South Viet Nam do not have ISO-3 codes because they were deleted, so they are not included in the country analysis of this analysis. Kosovo does not have an official ISO-3 code so is not included in this analysis. Belgium-Luxembourg is a country name used in FAO data and is not included in this analysis as it is not a specific country.

The technologies in the HATCH dataset are highly diverse. While some are relevant for mitigating climate change, such as renewable energy technologies, others are not directly related to climate change (such as cellphones) and some are themselves high emitters of greenhouse gasses (such as coal production). We include a wide range of technologies in the HATCH dataset that cover many technological categories because climate technologies are also highly diverse. Climate technologies both in their technology characteristics as well as how they may contribute to mitigating climate change (through reducing energy use, electrifying energy use, replacing fossil fuels, or avoiding/removing greenhouse gasses). Supplementary Table 4 lists the technology categories included in the HATCH dataset as well as examples of climate technologies for each of those categories.

Category	**Example Climate Technology**
Appliances	Induction cooktops are appliances that can replace gas cookstoves, which can reduce greenhouse gas emissions through electrification.
Chemical and Industrial	Chemical energy storage, including hydrogen storage, can play a role in enabling electrification and renewable energy usage.
Digitalization	Smart meters are digital appliances that can enable more efficient energy use which can reduce emissions.
Energy Supply	Solar photovoltaic supplies renewable energy, reducing greenhouse gas emissions.
Food and Health	Cover crops can improve carbon storage in soils.
Infrastructure	CO_2 pipelines are infrastructural technologies used for the transport of carbon dioxide between carbon capture locations to storage locations. They can be important for avoiding or removing carbon dioxide from point sources or the atmosphere.
Materials	Rare earth minerals are important for the production of climate technologies such as batteries for electric vehicles.
Sea and Water	Marine carbon dioxide removal methods are ocean-based methods of removing carbon dioxide from the atmosphere.
Space and Defense	Satellites can provide data on climate-relevant metrics, such as greenhouse gas emissions sources.
Storage Technology	Lithium-ion batteries are one kind of battery storage technology for large-scale renewable energy systems.
Transportation	Electric busses can reduce carbon dioxide emissions by displacing diesel-powered busses with electric busses.

Supplementary Table 4. Technology Categories in HATCH and example climate technology for each category.

Technology Characteristic Data

The variables used in this analysis are from a variety of sources and gathered through different methods as there is no central source for this information. Supplementary Table 5 describes these data and Supplementary Table 6 summarizes the data gathering methods.

Variable	Description and hypothesis	Example	Type, Levels, Transformations	Source
First year of commercialization	Modern systems have enabled more recently developed technologies to grow faster.[2]	Digitalization and globalization allow for faster growth through more trade and communication.	Type: Numerical Unit: Year	Author historical and archival research
Technological Lifetime	Shorter technological lifetimes are associated with faster adoption speed.[3]	Shorter lifetimes allow for faster turnaround for technological improvements, leading to faster adoption.	Type: Numerical Unit: Number of years Transformation: log	Author historical and archival research
Material Use	Technologies with lower material intensity per dollar of value allow for faster growth.	Few materials per dollar allows for more improvements to be made, enabling faster growth.	Type: Numerical Unit: kilogram per dollar (2009) Transformation: log	Author historical and archival research
Granularity	Granular (cheaper, smaller) technologies are more easily replaced and produced, enabling more rapid growth.[3,4]	More granular technologies benefit from faster production, which allows for technology improvements and learning to happen faster, avoiding lock-in.	Type: Numerical Unit: 2009 US dollars Transformation: log	Author historical and archival research
Complexity	The number of design elements in a technology, as well as their interactions, impacts the speed of technology growth.[5]	Simple technologies allow for faster learning because of faster production times, faster improvements, and fewer coordination hurdles.	Type: Categorical Unit: Number of components Levels: Simple, Design-Intensive, Complex	Expert review
Need for Customization	The greater need to customize a technology in its installation or adoption will slow growth.[5]	Highly customized technologies may require long, site-specific design stages, which slows technology adoption speed.	Type: Categorical Unit: Design Specification Level: Standardized, Mass-Customized, Customized	Expert review
Type of Adopter	Technologies adopted by both individuals and firms may benefit from more markets for growth, enabling faster diffusion.	Technology learning can transfer between markets within countries, leading to faster growth as improvements occur.	Type: Categorical Level: Individuals, Firms, Both	Expert review
Requires Feedstock	Fuel requirement may be associated with slower growth if additional economic sectors are involved in production.[6]		Type: Binary Level: Yes, No	Author categorization
Replacement	If a technology is replacing another technology, then the infrastructure may already exist to support its growth, therefore leading to faster growth.[7]	If a technology is replacing a similar technology with large support networks and systems, it may benefit from past learning and grow faster.	Type: Binary Level: Yes, No	Author categorization
Category	Allows for interactions with other characteristics (control variable).[2]	See other examples.	Type: Categorical	Author categorization

Supplementary Table 5. Description of technology characteristic data. Includes summary, description, hypothesis of relationship with growth speed, and details on the data source.

Variable	Data Collection Method
Category Type	Author categorization
Complexity	Expert survey
Feedstock	Author categorization
Granularity	Archival and historical research
Material Use	Archival and historical research
Need for Customization	Expert survey
Replacement	Author categorization
Technology Lifetime	Archival and historical research
Type of Adopter	Expert survey
Year of First Commercialization	Archival and historical research

Supplementary Table 6. Summary of data collection for each technology characteristic.

Expert Judgment

Gathering three categorical variables (complexity, need for customization, and type of adopter) was done through a survey of four people who study technological change at University of Wisconsin-Madison. For this survey, two authors classified each technology and the assigned authors were staggered in order to avoid direct overlap. For example, person A was assigned technology 1-10, person B assigned 5-15, person C assigned 10 - 20, and person D assigned 15-20 and 1-5. When filling out the survey, each respondent was shown one technology at a time. Each respondent received instructions to only spend about one minute per technology to classify along these three characteristics. For each category, respondents could also select “I Don’t Know”. Each respondent also received a rubric on which to base their categorizations (provided below in Supplementary Table 7, Supplementary Table 8, and Supplementary Table 9). The respondents were anonymized in the collation of responses (identified as respondent 1 and respondent 2).

Once responses were gathered, if responses matched, this was the response used for the characteristics. If one respondent selected “I Don’t Know”, regardless of the other response, the lead author performed more research to classify the technology for that category based on the rubric. If the responses did not match but were not “I Don’t Know”, the respondents all met to discuss further and came to consensus.

Complexity

Technology complexity is described in Malhotra and Schmidt and the description of each complexity category is also based on this[5]. The description and rubric were given to each respondent (Supplementary Table 7).

The design complexity of each technology is characterized by two factors: the number of design elements and the extent to which these elements interact with one another. The rubric below will help to classify technologies as simple, design-intensive, and complex based on these two factors.

Category	Classification Notes	Examples
Simple	Number of components: Less than 1,000 ● Modular interfaces between components ● Few or no moving parts ● Readily mass-produced	● Solar PV modules: 36 to 72 connected solar cells ● Other technologies: LEDs, building envelope retrofits
Design-Intensive	Number of components: Between 1,000 and 1,000,000 ● High number of components, multiple interactions between parts	● Wind turbines: composed of between 15,000 and 20,000 parts that interact ● Electric vehicles: composed of about 11,000 parts
Complex	Number of components: Over a million components ● Higher number of components and interactions ● Many different actors and sectors involved in design, manufacturing, and assembly	● Airplanes: 6 million parts that interact in a Boeing 747 ● Biomass power plants: consist of many sub-systems, the design of which are dependent on one another and involve a large number of components ● Other technologies: CCGT power plants, carbon capture and storage plants

Supplementary Table 7. Levels of complexity.

Need for Customization

Need for customization is described in Malhotra and Schmidt and the description of each category is also based on that analysis[2]. Supplementary Table 8 displays the rubric given to each respondent.

Categorizing the need for customization involves two axes: design variation and site-specificity. Standardized technologies have little or no design variation and flexible site use cases. Mass-customized technologies have some design variation and adoption can be site-specific. Customized technologies do not have standardized parts and all project details are tailored to site-specific characteristics.

Category	Classification Notes	Examples
Standardized	● Little (or no) design variation ● Flexible – can be used in most environments with few changes	● Solar PV modules: mass-manufactured, operating principles do not change across contexts ● Electric vehicles: mass-manufactured, there is variation in types but classes of customers already exist from the production of ICE vehicles ● Other technology examples: CCGT power plants, LEDs
Mass-customized	● Typically built by modular pieces – some may need customization and others do not ● Some aspect of the adoption might be site-specific ● The technology has standardized, mass-produced, and highly customized product in one technology unit	● Rooftop solar PV: mix of standardized products (solar modules) and site-specific design characteristics (characteristics of roofs) ● Other technology examples: wind turbines, concentrated solar power, carbon capture and storage, small modular reactors (nuclear)
Customized	● Technology does not have standardized parts that can benefit from mass-customization ● Project details tailored to site-specific characteristics	● Building envelope retrofits: the materials are mass produced, but installation is customized by individual building (depending on building design, geography, existing building materials) ● Other technology examples: geothermal power, biomass power plants, nuclear plants

Supplementary Table 8. Need for customization levels.

Type of Adopter

Who makes the decision to adopt the technology is broadly categorized on three levels: individuals, firms, and both. These decisions may involve different considerations and may therefore impact the speed of adoption. The rubric in Supplementary Table 9 was given to each respondent.

Category	Classification Notes
Individuals	If there is an **individual consumer** market and it is the **dominant** market, classify as "individuals"
Firms	If consumer adopters (people making the decision to buy/adopt) cannot make a decision about purchasing, classify as "firms"
Both	Technologies are adopted by individuals and firms – might be on different scales, different unit sizes, etc.

Supplementary Table 9. Levels of adopter type.

Author Categorization

Feedstock

Whether a technology requires a feedstock – in the form of an inputted fuel needed for its use – is classified as a yes or a no. Each technology is categorized as yes or no about whether it requires a feedstock. The scale-up of one technology might require support from other technologies, including a feedstock. Whether the technology requires a feedstock that a country could import for its operation or otherwise requires industries for inputs (such as biofuels) or requires other inputs (such as solar photovoltaic relying on solar irradiance).

Granularity

Technology granularity is defined in terms of scale – either physical scale, economic scale, or both. More granular technologies are smaller in unit size, lower unit investment costs, and can therefore replicate more easily because of their modularity. On the other end of the spectrum are lumpy technologies that involve larger units and higher investment costs (Wilson et al 2020). For this data, the first level is numerical measures of granularity in terms of unit costs. Because this data is not available for all technologies, a second level of granularity is categorical: small, medium, and large. This classification can be determined from unit size where available (in terms of kilowatts, for energy technologies). If neither unit size nor unit cost are available, the technology is classified by authors according to the rubric below in Supplementary Table 10. For consistency in comparing technologies, the granularity of a technology is measured (where possible) in its first year of commercialization and converted to 2009 USD aligned with Wilson et al's classification of granularity[3]. Granularity is measured at the plant level where relevant.

Categorization (Cost) *Defined as unit investment cost at first year of commercialization in $09 USD*	**Categorization (Energy)** *Defined as unit size at first year of commercialization in KW*	**Granularity**
Cheap: Investment cost < $1000	Small: Unit size < 1 kW	High
Medium: Investment cost < $100,000	Medium: Unit size < 100 kW	Medium
Expensive: Investment cost > $100,000	Large: Unit size > 100 kW	Low

Supplementary Table 10. Levels of granularity.

These data are gathered through peer-reviewed articles and online sources for price or size estimates. Assumptions made for these measures are included in the granularity spreadsheet.

Material Use

The impact of material use, or material intensity, is measured as the amount of material (measured in kilograms) per dollar of value in a technology. This variable is also measured in two ways. The first is numerical and found by dividing the size of a technology in kilograms by the value of the technology (measured in unit price). Prices are converted to 2009 USD dollars. These data are gathered from peer-reviewed sources and publicly available online sources. When both measures are not available, technologies are classified according to the rubric displayed in Supplementary Table 11 as low, medium, and high levels of material use.

Low	Medium	High
Less than 1 kg per dollar	Between 0.1 and 1 kg per dollar	Over 1 kg per dollar
Example: *Vaccines* ● Milligrams per dollar	Example: *Wind Turbines* ● 0.2 kg per dollar	Example: *Iron Ore* ● 11 kg per dollar

Supplementary Table 11. Levels of material use.

Replacement

Technology replacement is operationalized as binary: yes or no. We define replacement broadly; whether the technology uses similar infrastructure and provides similar services to a preexisting technology. It is not meant in only a strict sense (for example, electric bicycles replacing analog bicycles) but rather broad replacement (for example, telephones replacing telegraphs). This is gathered through expert judgment by authors.

Technology Lifetime

Technology lifetime measures the technical lifetime of a technology to assess how frequently an adopter can make a decision to adopt a replacement technology or not. This data is measured in two ways. The first is numerical and is measured as the average number of years that a technology functions. The second is categorical and is classified as months, years (if more than 24 months or 2 years), and decades (if more than 20 years). For some technologies, average lifetime data was not available, so they are only measured as categorical variables.

Technology Category

The goal of this study is to investigate the underlying differences in technologies that impact speed of adoption, rather than just the technology category. But it is included as a characteristic to investigate alongside other characteristics. This characteristic was categorized by authors and used in previous analysis[8].

Year of First Commercialization

The year that a technology starts in a market can be measured through multiple metrics. We follow work in Bento et al to determining the beginning of the formative phase of a technology in four ways, defined in Supplementary Table 12[9]. For each technology, we use historical research to assess these four start year values. Values come from peer-reviewed literature, archival research, or other publicly-available sources to determine these start years. For this analysis we use the year of first commercialization as the definition of the start year because it is available for the most technologies and defines the beginning of market availability for the technology, which is most relevant for measuring technology growth. If the year of first sequential commercialization is unavailable but the year of first commercialization is available, we use that value for analysis.

Start Year	**Description**
Year of first invention	Year of first patent related to the technology or innovation.
Year of first embodiment of technology	Year of demonstration of the innovation
Year of first commercialization	Year of first technology application outside the lab or beginning of technology production
Year of first sequential commercialization	Year of first commercial application that then initiates the takeoff of the product

Supplementary Table 12. Methods to determine the start year of technologies. Includes four metrics to find the start year of each technology.

Technology	*Material Use (Num)*	*Material Use (Cat)*	*Year of First Comm.*	*Need for Custom-ization*	*Complexity*	*Type of Adopter*	*Granularity (Num.)*	*Granularity (Cat.)*	*Tech. Lifetime (Num.)*	*Tech. Lifetime (Cat.)*	*Strict replace-ment*	*Replace-ment*	*Feed-stock*	*Category Type*
All Biofuels	NA	Medium Material Use	NA	NA	Complex	Firms		Low	3	Years	No	No	Yes	Energy Supply
Ammonia Synthesis	0.6702	Medium Material Use	1913	Mass-customized	Complex	Firms	1122506000.00	Low	50	Decades	No	No	Yes	Food and Health
Aquaculture Production	0.6079	Medium Material Use	1950	Customized	Design-Intensive	Firms		Low	NA	NA	No	Yes	No	Sea and Water
BCG Vaccine	0.0004	Low Material Use	1927	Standardized	Simple	Individuals	2.50	High	0.167	Months	No	No	No	Food and Health
Beer Production	0.1565	Medium Material Use	NA	Mass-customized	Design-Intensive	Individuals	Expensive	Low	14	Years	No	No	No	Food and Health
Biogas	NA	Medium Material Use	1930	Mass-customized	Complex	Firms	Expensive	Low	20	Years	No	No	Yes	Energy Supply
Cable TV	NA	Low Material Use	1948	Standardized	Simple	Individuals	1232.26	Medium	15	Years	Yes	Yes	NA	Appliances
Cadmium Refining	0.4579	Medium Material Use	1880	Mass-customized	Complex	Firms	Expensive	Low	NA	Decades	No	No	No	Materials
Canals	NA	High Material Use	NA	Customized	Complex	Firms	1460317460.00	Low	NA	NA	No	No	NA	Transportation
Cane Sugar	0.0285	Low Material Use	NA	Customized	Design-Intensive	Firms	Expensive	Low	NA	Decades	No	Yes	No	Food and Health
Capture Fisheries	1.0638	High Material Use	1881	Mass-customized	Design-Intensive	Firms		Low	NA	Decades	No	No	No	Sea and Water
Caustic Soda	2.3148	High Material Use	1892	Customized	Complex	Firms	138105000.00	Low	30	Decades	No	No	Yes	Chemicals and Industrial
Cellphones	0.0008	Low Material Use	1977	Standardized	Design-Intensive	Individuals	67.87	High	3	Years	Yes	Yes	No	Appliances
Coal Production	1.5269	High Material Use	1884	Mass-customized	Complex	Firms	968444351.20	Low	40	Decades	No	Yes	No	Energy Supply
Color Television	0.0605	Low Material Use	1954	Standardized	Simple	Individuals	1461.99	Medium	12	Years	Yes	Yes	NA	Appliances
Copper|Mining	0.1558	Medium Material Use	1750	Customized	Complex	Firms	Expensive	Low	38	Decades	No	No	No	Materials

Copper|Refining	0.1554	Medium Material Use	1750	Customized	Complex	Firms	Expensive	Low	NA	Decades	No	No	No	Materials
Crop Harvester	0.0655	Low Material Use	1835	Standardized	Design-Intensive	Both	114500.00	Medium	NA	Years	No	Yes	Yes	Food and Health
Crude Oil	2.1887	High Material Use	1854	Customized	Complex	Firms	Expensive	Low	22.5	Decades	No	Yes	No	Energy Supply
DTP1 Vaccine	0.0000	Low Material Use	1949	Standardized	Simple	Individuals	24.36	High	0.125	Months	No	No	No	Food and Health
DTP3 Vaccine	0.0000	Low Material Use	1949	Standardized	Simple	Individuals	2.44	High	0.125	Months	No	No	No	Food and Health
Dishwashers	0.0696	Low Material Use	1929	Standardized	Simple	Both	675.98	High	12	Years	No	Yes	NA	Appliances
Disk Brakes	NA	NA	1956	Standardized	Simple	Both		High	8	Years	Yes	Yes	NA	Transportation
Electric Bicycles	0.0417	Low Material Use	NA	Standardized	Simple	Individuals	306.22	High	5	Years	Yes	Yes	NA	Transportation
Electricity	NA	Medium Material Use	1882	Customized	Complex	Both		Low	27.5	Decades	No	No	Yes	Energy Supply
Ethanol	1.8902	High Material Use	NA	Mass-customized	Design-Intensive	Firms	8600000.00	Low	45	Decades	No	Yes	NA	Food and Health
Flush Toilet	NA	NA	1840	Standardized	Simple	Individuals	341.32	High	5	Years	Yes	Yes	NA	Appliances
Flywheel Battery Storage	0.0018	Low Material Use	2011	Standardized	Design-Intensive	Firms	535521120.00	Low	20	Years	No	No	No	Storage Technology
Freezer	0.1984	Medium Material Use	1940	Standardized	Simple	Both	4081.61	Medium	21	Decades	Yes	Yes	NA	Appliances
Geothermal Energy	0.0000	Medium Material Use	1913	Mass-customized	Design-Intensive	Both	74000000.00	Low	30	Decades	No	No	No	Energy Supply
Gold	0.0000	Low Material Use	1851	Customized	Complex	Firms	Expensive	Low	20	Years	No	No	No	Materials
Ground Source Heat Pumps	0.0000	Medium Material Use	1945	NA	Design-Intensive	Both	10560.00	Medium	25	Decades	Yes	Yes	NA	Appliances
HEPB3 Vaccine	0.0000	Low Material Use	1986	Standardized	Simple	Individuals	14.92	High	3	Years	No	No	No	Food and Health
HEPBB Vaccine	0.0000	Low Material Use	1986	Standardized	Simple	Individuals	14.92	High	3	Years	No	No	No	Food and Health

HIB3 Vaccine	0.0001	Low Material Use	1987	Standardized	Simple	Individuals	12.40	High	3	Years	No	No	No	Food and Health
Herbicide-Tolerant Corn	5.4950	High Material Use	1997	Standardized	Simple	Firms	6.42	High	0.83	Months	Yes	Yes	NA	Food and Health
Herbicide-Tolerant Cotton	0.7508	Medium Material Use	1997	Standardized	Simple	Firms	1.85	High	0.83	Months	Yes	Yes	NA	Food and Health
Herbicide-Tolerant Soybeans	2.4901	High Material Use	1997	Standardized	Simple	Firms	15.18	High	0.83	Months	Yes	Yes	NA	Food and Health
High Speed Rail	0.0224	Low Material Use	1964	Customized	Complex	Firms	555555555.60	Low	55	Decades	Yes	Yes	NA	Infrastructure
Home Air Conditioning	0.0935	Low Material Use	1932	Standardized	Simple	Both	141100.00	Medium	18	Years	No	No	NA	Appliances
Home Computers	NA	Low Material Use	1977	Standardized	Design-Intensive	Individuals	3771.84	Medium	5	Years	No	No	NA	Digitalization
Household Internet Access	NA	NA	NA	Standardized	Simple	Individuals		Medium	NA	Decades	No	No	NA	Digitalization
Hydrochloric Acid	13.4844	High Material Use	1892	Customized	Complex	Firms	917260282.50	Low	30	Decades	No	No	Yes	Chemicals and Industrial
Hydroelectricity	NA	Medium Material Use	1882	Customized	Complex	Firms	124158017.90	Low	50	Decades	No	No	No	Energy Supply
Insect-Resistant Corn	5.4950	High Material Use	1995	Standardized	Simple	Firms	6.42	High	0.83	Months	Yes	Yes	NA	Food and Health
Insect-Resistant Cotton	0.7508	Medium Material Use	1995	Standardized	Simple	Firms	1.85	High	0.83	Months	Yes	Yes	NA	Food and Health
Iron Ore	11.4500	High Material Use	1855	Customized	Complex	Firms	Expensive	Low	15	Years	No	No	No	Materials
Jet Aircraft	0.0005	Low Material Use	1952	Standardized	Complex	Firms	65189048.24	Low	25	Decades	No	Yes	NA	Transportation
Laundry Dryers	0.1022	Medium Material Use	NA	Standardized	Simple	Individuals	656.90	High	14	Years	No	Yes	NA	Appliances
Lead	0.5535	Medium Material Use	1844	Customized	Complex	Firms	Expensive	Low	20	Years	No	No	No	Materials
Lead-Acid Battery Storage	0.3438	Medium Material Use	1997	Standardized	Simple	Both	207.60	High	7.5	Years	No	No	No	Storage Technology

Liquefied Natural Gas	2.4713	High Material Use	1941	Customized	Complex	Firms	54000000000.00	Low	30	Decades	No	Yes	NA	Energy Supply
MCV1 Vaccine	0.0000	Low Material Use	1963	Standardized	Simple	Individuals	24.96	High	0.167	Months	No	No	No	Food and Health
MCV2 Vaccine	0.0000	Low Material Use	1963	Standardized	Simple	Individuals	24.96	High	0.167	Months	No	No	No	Food and Health
Marine Energy	0.0264	Low Material Use	1965	Customized	Design-Intensive	Firms	6000000.00	Low	15	Years	No	No	No	Energy Supply
Microcomputers	NA	NA	1973	Standardized	Design-Intensive	Individuals	3771.84	Medium	NA	Years	No	Yes	NA	Digitalization
Microwaves	0.1286	Medium Material Use	1955	Standardized	Simple	Individuals	1082.90	Medium	7	Years	Yes	Yes	NA	Appliances
Milk	1.2897	High Material Use	NA	Customized	Complex	Both	Expensive	Low	NA	Decades	No	No	No	Food and Health
Motorcycles	0.0980	Low Material Use	1894	Standardized	Design-Intensive	Individuals	3826.23	Medium	15	Years	No	Yes	NA	Transportation
Natural Gas Pipelines	0.0495	Low Material Use	1872	Customized	Simple	Firms	159000000000.00	Low	50	Decades	No	Yes	NA	Infrastructure
Natural Gas Production	681.3476	High Material Use	1884	Mass-customized	Complex	Firms	226879159.80	Low	30	Decades	No	No	No	Energy Supply
Nickel	0.0538	Low Material Use	1880	Customized	Design-Intensive	Firms	1584000000.00	Low	21	Decades	No	No	No	Materials
Nitric Acid	2.3438	High Material Use	1905	Customized	Complex	Firms	181944000.00	Low	30	Decades	No	No	Yes	Chemicals and Industrial
Nitrogen Fertilizer	1.4594	High Material Use	1913	Mass-customized	Complex	Firms	Expensive	Low	0.83	Months	No	No	Yes	Food and Health
Nox Pollution Controls (Boilers)	NA	NA	NA	NA	Design-Intensive	Firms	Medium	Medium	NA	Decades	No	No	NA	Energy Supply
Nuclear Energy	NA	High Material Use	1954	Customized	Complex	Firms	2327131358.00	Low	40	Decades	No	No	Yes	Energy Supply
Nuclear Weapons	0.0000	Medium Material Use	1945	Customized	Complex	Firms	28000000.00	Low	25	Decades	No	No	Yes	Space and Defense
Objects Launched Into Space	NA	Medium Material Use	1957	Customized	Complex	Firms	8593593.50	Low	11	Years	No	No	Yes	Space and Defense

Offshore Wind Energy	0.2258	Medium Material Use	1991	Mass-customized	Design-Intensive	Firms	9000000.00	Low	25	Decades	No	No	No	Energy Supply
Oil Pipelines	0.0495	Low Material Use	1865	Customized	Simple	Firms	9628297362.00	Low	50	Decades	No	Yes	NA	Infrastructure
Oil Production	2.1887	High Material Use	1856	Mass-customized	Complex	Firms	Expensive	Low	22.5	Decades	No	No	No	Energy Supply
Oil Refining Capacity	2.1887	High Material Use	1856	Mass-customized	Complex	Firms	1928020566.00	Low	30	Decades	No	No	No	Energy Supply
Onshore Wind Energy	0.2030	Medium Material Use	1887	Mass-customized	Design-Intensive	Firms	4828242.20	Low	25	Decades	No	No	No	Energy Supply
PCV3 Vaccine	0.0000	Low Material Use	2000	Standardized	Simple	Individuals	128.75	High	0.125	Months	No	No	No	Food and Health
POL3 Vaccine	0.0000	Low Material Use	1955	Standardized	Simple	Individuals	15.98	High	0.83	Months	No	No	No	Food and Health
Passenger Cars	0.0495	Low Material Use	1886	Standardized	Design-Intensive	Both	55853.90	Low	15	Years	No	Yes	Yes	Transportation
Phosphate Fertilizer	1.3500	High Material Use	1843	Mass-customized	Design-Intensive	Firms	Expensive	Low	0.83	Months	No	No	No	Food and Health
Podcasting	NA	NA	2005	Standardized	Simple	Individuals		High	NA	NA	No	Yes	NA	Digitalization
Postal Traffic	NA	Medium Material Use	1830	Customized	Complex	Both	Expensive	Low	NA	Years	No	No	Yes	Infrastructure
Potash Fertilizer	3.4615	High Material Use	1861	Customized	Complex	Firms	Expensive	Low	0.83	Months	No	No	No	Food and Health
Power Steering	NA	NA	1951	Standardized	Design-Intensive	Both	1405.38	Medium	5	Years	Yes	Yes	NA	Transportation
Primary Aluminum Production	0.5239	Medium Material Use	1888	Mass-customized	Complex	Firms	478200000.00	Low	NA	Decades	No	No	Yes	Materials
Primary Bauxite Production	26.5041	High Material Use	1888	Customized	Complex	Firms	57500000.00	Low	72	Decades	No	No	No	Materials
Public Roads	2.3910	High Material Use	NA	Customized	Simple	Firms	3310989.00	Low	10	Years	No	No	NA	Infrastructure
Pumped Hydro Storage	0.0000	Medium Material Use	1907	Customized	Simple	Firms	2976000000.00	Low	40	Decades	No	No	No	Storage Technology
RCV1 Vaccine	0.0000	Low Material Use	1969	Standardized	Simple	Individuals	24.96	High	0.167	Months	No	No	No	Food and Health

ROTAC Vaccine	0.0000	Low Material Use	2006	Standardized	Simple	Individuals	87.98	High	3	Years	No	No	No	Food and Health
Radio	0.0277	Low Material Use	1910	Standardized	Simple	Individuals	139.76	High	10	Years	No	Yes	No	Appliances
Railroad	0.0811	Low Material Use	1825	Customized	Design-Intensive	Firms	29520.00	Low	55	Decades	No	Yes	Yes	Infrastructure
Raw Steel Production	0.3268	Medium Material Use	1855	Customized	Complex	Firms	1000000000.00	Low	40	Decades	No	No	Yes	Materials
Real-Time Gross Settlement Adoption	NA	NA	1985	Standardized	Simple	Individuals		High	NA	NA	No	Yes	NA	Digitalization
Refrigerators	0.1517	Medium Material Use	1918	Standardized	Simple	Both	8992.81	Medium	14	Years	Yes	Yes	NA	Appliances
Renewable Power	NA	Medium Material Use	NA	Customized	Complex	Both		Low	27.5	Decades	No	Yes	No	Energy Supply
Salt Production	19.2012	High Material Use	NA	Customized	Design-Intensive	Firms	Expensive	Low	NA	Decades	No	No	No	Materials
Sensible Heat Storage	2.1645	High Material Use	1982	Customized	Simple	Firms	1313300.00	Low	20	Years	No	No	No	Storage Technology
Shale Production	1.4316	High Material Use	1830	Mass-customized	Complex	Firms	Expensive	Low	NA	Decades	No	Yes	NA	Energy Supply
Silver	0.0017	Low Material Use	1874	Customized	Complex	Firms	Expensive	Low	NA	Decades	No	No	No	Materials
Social Media Usage	NA	NA	2003	NA	Simple	Individuals		High	NA	NA	No	Yes	NA	Digitalization
Sodium-Based Battery Storage	0.0282	Low Material Use	1970	Standardized	Simple	Both	20748000.00	Low	5	Years	No	No	No	Storage Technology
Solar Photovoltaic	0.3275	Medium Material Use	1957	Standardized	Simple	Both	615.30	High	33	Decades	No	No	No	Energy Supply
Solid Biofuels	NA	Medium Material Use	NA	Customized	Complex	Firms	Expensive	Low	25	Decades	No	No	Yes	Energy Supply
Steamships	3.9864	High Material Use	1807	Standardized	Design-Intensive	Firms	1183350.00	Low	30	Decades	Yes	Yes	Yes	Transportation
Stove	0.2016	Medium Material Use	1908	Standardized	Simple	Individuals	Cheap	Medium	14	Years	Yes	Yes	NA	Appliances

Sulphuric Acid	6.9911	High Material Use	1838	Customized	Complex	Firms	3048700.00	Low	30	Decades	No	No	Yes	Chemicals and Industrial
Synthetic Filaments	0.2685	Medium Material Use	1939	Mass-customized	Complex	Firms	236400000.00	Low	NA	Decades	Yes	Yes	Yes	Chemicals and Industrial
Telegraph Traffic	0.0295	Low Material Use	1845	Customized	Complex	Both	858000.00	Low	NA	Decades	No	Yes	No	Infrastructure
Telephones	0.0021	Low Material Use	1877	Standardized	Simple	Both	1088.64	High	6.5	Years	No	Yes	No	Appliances
Television	0.0605	Low Material Use	1936	Standardized	Simple	Individuals	1232.26	Medium	15	Years	No	Yes	No	Appliances
Washing Machines	0.1800	Medium Material Use	1908	Standardized	Simple	Individuals	1766.49	Medium	12	Years	Yes	Yes	NA	Appliances
Wet Flue Gas Desulfurization Systems	0.0000	Medium Material Use	1931	Mass-customized	Design-Intensive	Firms	2253160800.00	Low	NA	Decades	No	No	No	Energy Supply
YFV Vaccine	0.0000	Low Material Use	1937	Standardized	Simple	Individuals	16.70	High	3	Years	No	No	No	Food and Health
Zinc	0.4789	Medium Material Use	1743	Customized	Complex	Firms	Expensive	Low	NA	Decades	No	No	No	Materials

Supplementary Table 13. Technology Characteristics for each technology in the HATCH dataset with national data. All technology characteristics of each technology included in this analysis. Filtered through process depicted by Supplementary Figure 1 and filtered based on logistic fit R^2 > 0.95 and 0 < k < 1.

Country Data

Country-level data is summarized in Supplementary Table 14 and Supplementary Table 15.

Variable	Description and hypothesis	Example	Type, Metric, and Transformation	Metric and Source
Country income level	Countries with higher income can allow for faster adoption of technologies because of resources available to build out systems quickly.[2]	Countries with higher income may have resources to spend beyond meeting basic needs, for example on technology adoption.	Metric 1 (numerical): GDP per capita Transformation: mean value in sample, logged. Metric 2 (categorical): Income Group, Level: Low, High Transformation: Most common value in sample	Metric 1: Log GDP per capita[10] Metric 2: Income group[11]
Spending on technology development	Spending on technology research and development may be associated with faster technology adoption. [12],[13]	Countries with a strong R&D sector and support infrastructure may have higher trust in technology and resources to scale-up a technology quickly after its discovery.	Metric: Spending as percent of GDP (numerical) Transformation: Mean value in sample	R&D spending as % of GDP[14]
Type of government	The types of political regimes may influence their support or lack thereof for technology adoption depending on whether it threatens their power or ability to be reelected. Different regimes may have different impacts on speed depending on the technology type. [2],[15]	Democracy can be an enabler of innovation[12], typically because of trade liberalization, educational attainment, and elections that allow for citizens to vote against politicians who may see technology adoption as hindering their power.	Metric: Democracy or non-democracy (categorical) Transformation: Derived from polity score	Polity index (democracy, not democracy)[16]
Institutional capacity to pass, support, coordinate policies	Stronger state capacity may impact the ability of the government to pass and implement policies to support technology adoption or adopt regulation to slow adoption depending on technology type. [17]	States with stronger ability to pass policy may allow for fast adoption of technologies with high costs but with societal benefits.	Metric: State Capacity Index (numerical) Transformation: Mean value in sample. High/low derived from state capacity index.	State capacity[18]
Public acceptance of technology	Higher public acceptance for technology and science allows for faster technology adoption. [19]	Attitudes about technologies influence individual's and, collectively, organization's intention to adopt technologies.	Responses to two questions from World Value Survey (numerical; scale of 1 to 10) Transformation: Mean value in sample	Responses to World Value Survey[20]

Supplementary Table 14. Description of country characteristic data. Each characteristic is described, including the hypothesis, metric, source, and a citation about why this characteristic is included.

Variable	Metric	Country Coverage	First Year	Last Year	Source
Income	GDP per capita	169	Varies by country, but many begin in1820, almost all by 1950.	2018	Maddison Project Database[21]
	Income group	218	1987	2022	World Bank[11]
Spending on Technology Development	R&D Spending (% of GDP)	218	1996	2023	World Bank
Type of government	Polity score	167	1800	2018	Polity5 Dataset[16]
State capacity	State capacity	177	1960	2015	Hanson & Sigman[18]
Public acceptance of technology	Response to question: Is science and technology making life easier?	90	1981	2022	World Value Survey (Question Q158)[20]
Public acceptance of technology	Response to question: Is the world better off because of science and technology?	90	1981	2022	World Value Survey (question Q163 2022 version)[20]

Supplementary Table 15. Coverage of each country characteristic. Table describes the start year, last year, and number of countries included in the source.

This analysis is based on a static dependent variable (the logistic steepness growth rate *k*), therefore the explanatory variables cannot be time-varying. But, the country characteristics in this analysis vary over time and differ depending on the time frame relevant for each technology. Because of this, we transform the time-varying characteristics to a time-invariant measure.

For each country-technology pair, the country characteristic is calculated from the first year of data for that country-technology pair until the inflection point calculated from the logistic function fit onto that time series. The values between these two points are averaged (for numerical variables) or the most common value (for categorical variables) is used for the country characteristic for that country-technology pair.

Income

The country's economic status is measured through two variables. The first is the average GDP per capita (logged) between the first year of the technology until the inflection point. This data comes from the Maddison Project Database, which covers 169 countries. The second is the income group of a country: lower, lower middle, upper middle, and upper, as classified by the World Bank. This is measured as the most common income level between the first year of data and the inflection year. If the inflection year is after 2022, the income level at 2022 is used. Because this measure is only available after 1989, if the technology inflection year is before then, this metric is not used. For this analysis, we group lower and lower middle into one category (low) and upper middle and upper into a second category (high).

Type of Government

The type of government in a country over a period of time is measured using the polity score. This score ranges from +10 (strongly democratic) to -10 (strongly autocratic). To measure this, we calculate the average polity score between the first year and inflection year for each country-technology pair. Then, if the average polity score is above a 6, it is considered a democracy and if it is below 6, it is categorized as not a democracy. This data is from the Polity5 Project.

State Capacity

The index for state capacity measures the ability of a state to create and enforce policies, relevant for our analysis if those policies either regulate the use of (and thus slow down) technology adoption or spur the use of (and thus speed up) technology adoption. We use the state capacity dataset from Hanson and Sigman which covers 177 countries[9]. We average the level of state capacity from the first year of a country-technology time series until the inflection year of that time series.

For our analysis, we also use a categorization of state capacity (low and high). A state capacity measure below 0 is categorized as low, and above 0 is categorized as high.

Public Acceptance of Technology

To operationalize the socio-cultural values of a country and the association with technology adoption, we use responses from two questions in the World Values Survey (WVS). The WVS is conducted in waves every five years in 90 countries and asks a wide variety of questions to respondents. We use the following two questions as measures of the acceptability of new technologies:

> *Question Q158: Science and technology are making our lives healthier, easier, and more comfortable.*
>
> *Scale of 1 (completely disagree) to 10 (completely agree)*
>
> *Question Q163: The world is better off, or worse off, because of science and technology*

Scale of 1 (a lot worse off) to 10 (a lot better off)

We remove values below 1, as these responses indicate respondents selected “I Don’t Know (-1), No answer/refused (-2), Not applicable (-3), or otherwise missing or not applicable (-5).

A2. Data Processing

Country Codes.

The sources of country characteristic data use different definitions of states for many reasons. First, there are different naming conventions for the same country (for example, United States vs. United States of America). Second, territories change over time, thus datasets that cover different periods of times contain different countries and have different data protocols about including these changes in their data. Lastly, some datasets only include countries of a certain population (for example, polity score is only measured for states with a population above 500,000).

To address this, we use ISO-3c country codes. We use the countrycode package to convert other country naming conventions to ISO-3c country codes[22]. In the World Value Survey, Northern Ireland contains a blank country code. We combine with the GBR ISO3c country code because this country code includes the United Kingdom of Great Britain and Northern Ireland. We remove the country code of CZE from the analysis to avoid overlap with Czechia, Czech Republic, and Slovakia.

There are an additional eight countries that are not included in the country analysis of the main analysis because of issues with the ISO-3 code process. There are four countries included in time series that are not assigned ISO-3 code because they were transitional: Czechoslovakia, Netherlands Antilles, Serbia and Montenegro, and Yugoslavia. East Germany and South Viet Nam do not have ISO-3 codes because they were deleted, so they are not included in the country analysis of this analysis. Kosovo does not have an official ISO-3 code so is not included in this analysis. Belgium-Luxembourg is a country name used in the Food and Agriculture Organization data and is not included in this analysis as it is not a specific country.

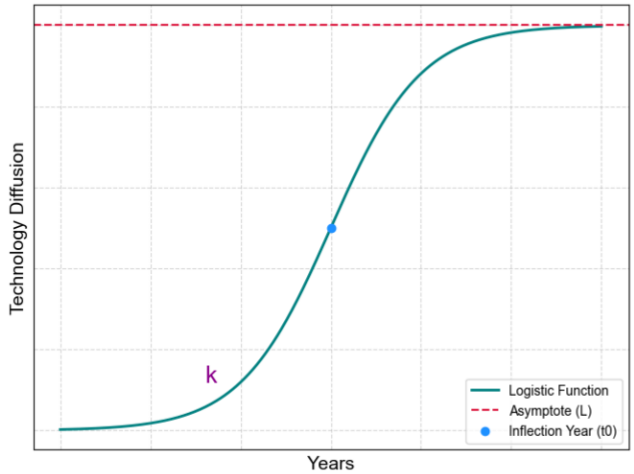
Measuring Speed

Logistic Function

The primary function used in this analysis to measure the speed of adoption is using the steepness parameter (k) found from fitting a logistic function (Supplementary Equation 1) onto the country-technology time series. Supplementary Figure 2 shows a stylized representation of this logistic function.

$$f(t) = \frac{L}{1 + e^{-k(t-t_0)}}$$

Supplementary Equation 1. Logistic function with three free parameters. L is the function's asymptote (upper bound), t0 is the inflection point (the point at which the absolute growth switches from increasing to decreasing; also at half of the asymptote's value), and k is the steepness parameter (growth rate for small t).



Supplementary Figure 2. Stylized logistic function. Green line shows the logistic function, with the k parameter shown in purple, the asymptote at the dotted pink line, and the inflection point shown in a blue dot.

To fit a logistic function onto each time series, we use the curve_fit function from the scipy.optimize package, using a nonlinear least squares optimization method[23]. We specify 5,000 function calls to attempt a fit. The initial parameters used in function fitting are based on Cherp et al shown in table Supplementary Table 16, calculated for each time series[24].

Parameter	Starting Value
L	Highest value of f(t) in time series
t0	Maximum absolute growth rate (difference in two consecutive values) in time series
k	0.5

Supplementary Table 16. Initial logistic fitting parameters. These parameters are used in the curve_fit function for the logistic function.

To filter time series and only include those with good logistic fits, we drop time series from the analysis through a four step process. First, we drop any time series where the curve_fit function could not converge on a fit, resulting in an error. This is based on Wilson et al (Wilson et al., 2013) to drop fits where than $R^2 < 0.95$. We also drop the time series if the steepness parameter estimated (*k*) is below 0 (since this analysis is focused on technology growth rather than decline) or above 1 (an indication of bad fit, potentially). This process, and the number of time series dropped in each step, is outlined in Supplementary Table 17.

Reasons for dropping	Number Dropped	Number of Points Remaining
Initial	–	5990
Error in function fitting	202	5788
$R^2 < 0.95$	3809	1979
$k > 1$	221	1758
$k < 0$	8	1750
Total Time Series with Growth Measurement	-	*1750*

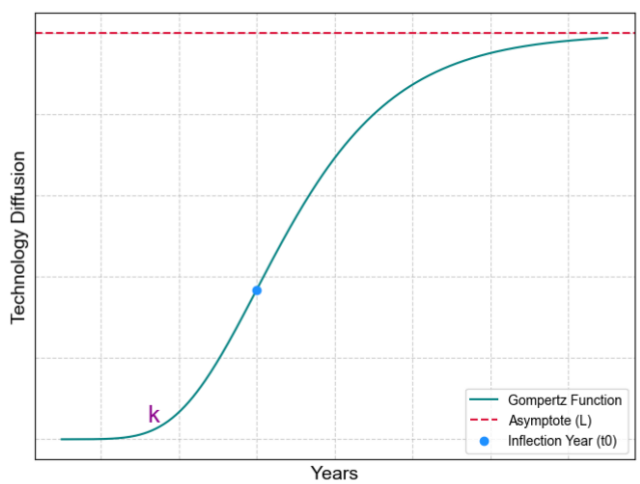
Supplementary Table 17. Filtering Process of function fitting. Description of process for dropping country-technology time series, the number of points dropped in each step, and the number of points remaining after each step.

Gompertz Function

For the sensitivity analysis, described in Supplementary Section C, we also fit a Gompertz function on each time series (Supplementary Equation 2). A stylized representation of the Gompertz function is shown in Supplementary Figure 3. This function is similar to the logistic function but is not symmetrical around the inflection point. Rather, the Gompertz function estimates slower growth after the inflection point to approach the asymptote.

$$f(t) = Le^{-e^{-k(t-t_0)}}$$

Supplementary Equation 2. Gompertz function with three free parameters. L is the function's asymptote (upper bound), t0 is the inflection point, and the k is the steepness parameter for small t.



Supplementary Figure 3. Stylized Gompertz function. Green line shows the Gompertz function, with the k parameter shown in purple, the asymptote at the dotted pink line, and the inflection point shown in a blue dot.

To fit a Gompertz function onto each time series, we use the curve_fit function from the scipy.optimize package, using a nonlinear least squares optimization method. We specify 5,000 function calls to attempt a fit. The initial parameters used in function fitting are the same as the logistic function, described in Supplementary Table 16.

We filter the time series for good Gompertz fits in the same process as the logistic function described above. This process, the number of points dropped, and the number remaining are outlined in Supplementary Table 18. The number of points remaining after this fitting process (n = 1628) is similar to the number of points in the main analysis using the logistic function fitting (n = 1750).

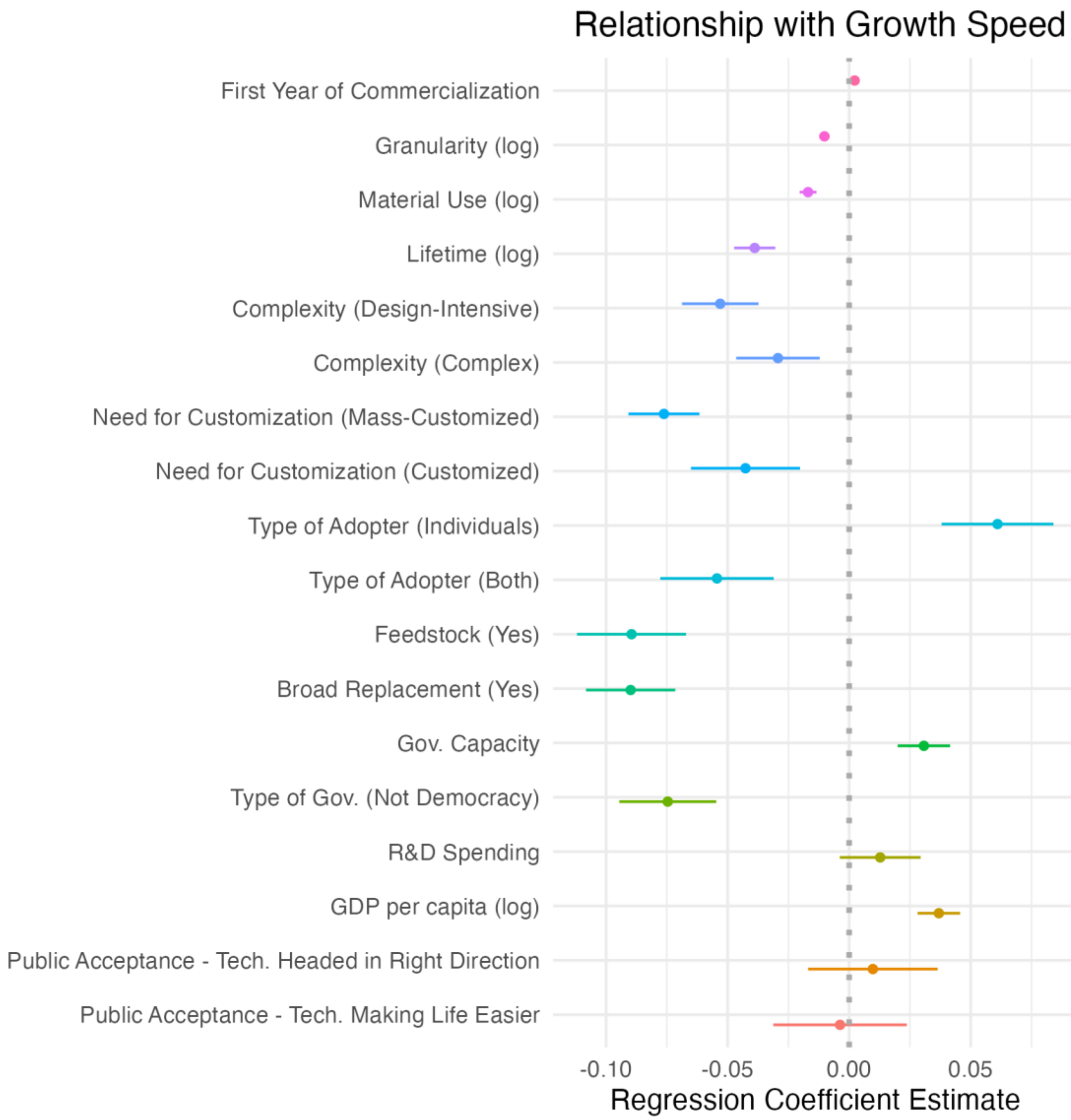
Reasons for dropping	**Number Dropped**	**Number of Points Remaining**
Initial	–	5990
Error in function fitting	953	5037
$R^2 < 0.95$	3262	1775
$k > 1$	143	1632
$k < 0$	4	1628
Total Time Series with Growth Measurement	-	*1628*

Supplementary Table 18. Filtering process of function fitting for Gompertz function. Description of process for dropping country-technology time series, the number of points dropped in each step, and the number of points remaining after each step.

Section B. Extended Analysis

B1. Bivariate Analysis

A summary of the independent bivariate of each characteristic with technology growth speed is shown in Supplementary Figure 4. First year of commercialization, granularity, material use, technology lifetime, complexity, need for customization, type of adopter, feedstock, replacement, state capacity, type of government, and GDP per capita are significantly related to growth speed. R&D spending and socio-cultural acceptance of technology (shown with two variables on public acceptance from World Value Survey) do not have a significant relationship with growth speed.



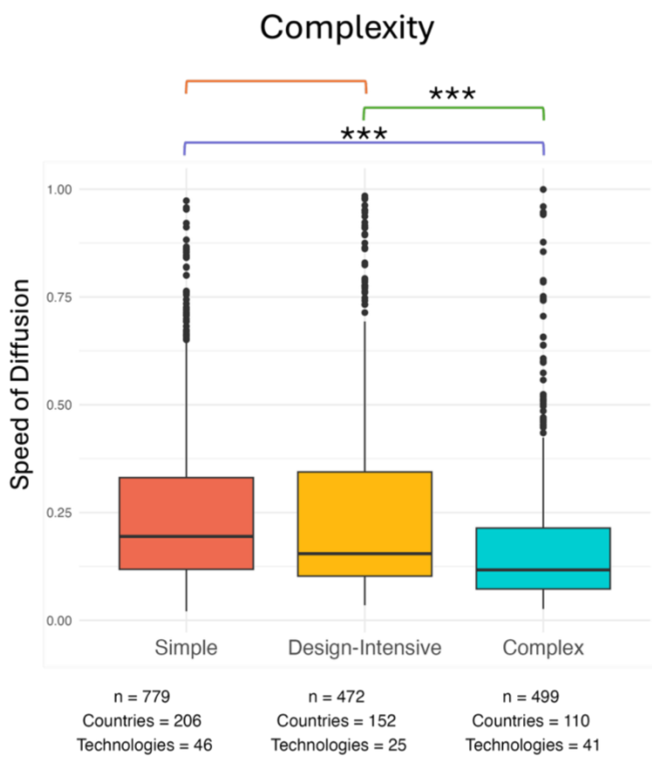
Supplementary Figure 4. Linear regression coefficients between independent variables and growth speed. Dots represent the estimated regression coefficients for each bivariate regression between each variable and technology growth speed. The dot represents the regression coefficient estimate for each variable with technology growth speed. Whiskers denote the 95% confidence intervals calculated through a two-sided t test. The dashed line shows a null effect. If confidence intervals cross the dotted line, these variables are not significant predictors for logistic fit in the respective model at the 95% confidence level (p < 0.05).

B2. Technology Characteristics

Complexity

Technological complexity is a categorical variable in the HATCH dataset (n = 112). Supplementary Figure 5 shows the speed of diffusion measured through the logistic function fit (filtered to only include those points with $R^2 > 95\%$ and $1 > y > 0$; n = 1,555). To test the difference across groups, we use the Kruskal-Wallis test because the diffusion speeds are not normally distributed (Supplementary Figure 6, for each group the Shapiro-Wilk test of normality $p < 0.05$).

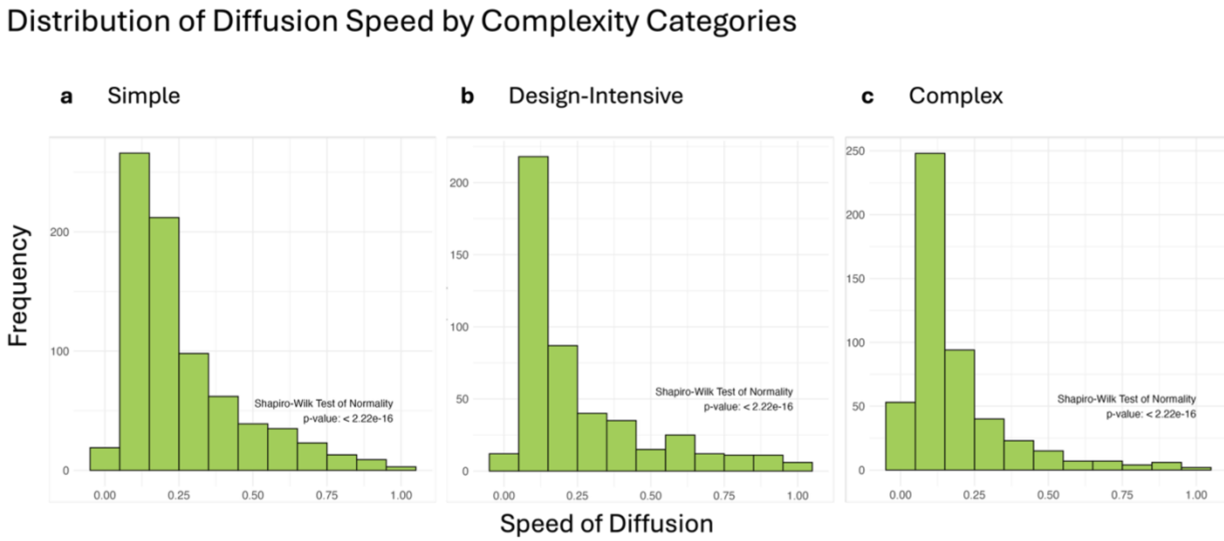
The complexity levels have significantly different mean diffusion speeds (Supplementary Table 20, Kruskal-Wallis Tests). Specifically, complex technologies have a significantly slower median speed of diffusion (0.117) than simple (0.195) and design-intensive (0.155) technologies (Supplementary Table 21, Dunn's Multiple Comparison Test).



*Supplementary Figure 5. Comparison of diffusion sped across complexity categories. Comparison of group variance using Dunn's Test; * = p < 0.05, ** = p < 0.01, *** = p < 0.001. Box edges show the inter-quartile range, line within box indicates median, solid lines extend from the interquartile range to the nonoutlier minimum or maximum (1.5 * inter-quartile range), and dots indicate outliers.*

Group	Min	25th Pct.	Median	Mean	75th Pct.	Max
Simple	0.021	0.118	0.195	0.256	0.331	0.973
Design-Intensive	0.035	0.102	0.155	0.255	0.344	0.984
Complex	0.026	0.073	0.117	0.181	0.214	0.999

Supplementary Table 19. Summary statistics of the diffusion speed for each category of complexity.



Supplementary Figure 6. Histograms of the distribution of speed of diffusion across categories of complexity. The Shapiro-Wilk tests the hypothesis that data is normally distributed. A p-value less than 0.05 indicates that data deviates from a normal distribution and that non-parametric methods such as a Dunn's multiple comparison test multiple comparison test. Panel a displays a histogram for the growth rates of simple technologies (n = 779), panel b displays a histogram for the growth rates of design-intensive technologies (n = 472), and panel c displays a histogram for the growth rates of complex technologies (n = 499).

Chi-Square Statistic	P Value	DF
95.7	0.00***	2

Supplementary Table 20. Results of the Kruskal-Wallis test for complexity categories. The median growth speed of groups is significantly different if p < 0.05.

Results of Dunn's Multiple Comparison Test

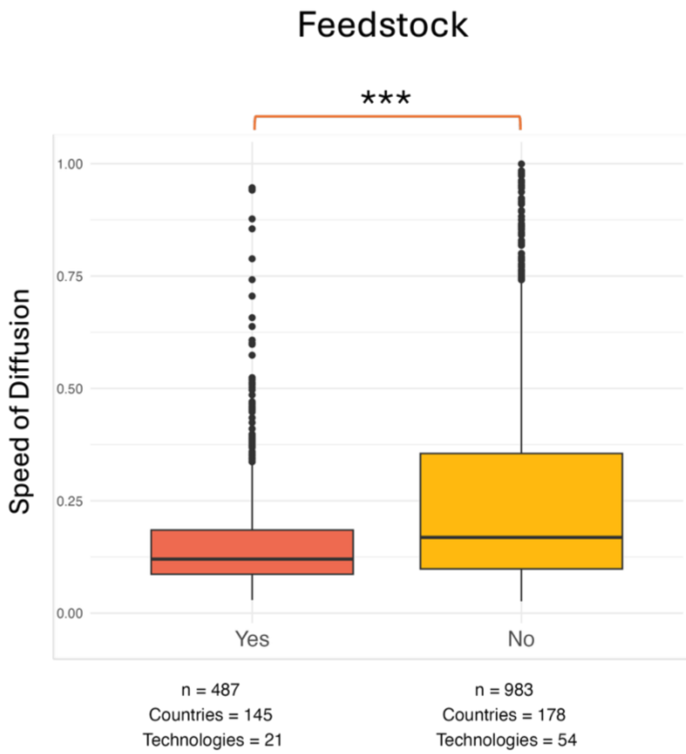
Comparison	Z Statistic	P Value	Adjusted P Value
Complex - Design-Intensive	-6.49	0.00	0.00***
Complex - Simple	-9.67	0.00	0.00***
Design-Intensive - Simple	-2.37	0.01	0.01

*Supplementary Table 21. Results of pairwise comparisons of levels of complexity using Dunn's post-hoc test. Z test statistic shows the standardized difference in mean ranks between groups. P values were adjusted for multiple comparisons using the Holm-Bonferroni method. Significance is defined at the 99% confidence level (*** indicates that p < 0.001).*

Feedstock

Whether a technology requires a feedstock is a categorical variable in the HATCH dataset with either a 'yes' or 'no' classification (n = 75). Supplementary Figure 7 shows the speed of diffusion measured through the logistic function fit (filtered to only include those points with R^2 > 95% and 1 > y > 0; n = 1,470). To test the difference across groups, we use the Kruskal-Wallis test because the diffusion speeds are not normally distributed (Supplementary Figure 8, for each group the Shapiro-Wilk test of normality $p < 0.05$).

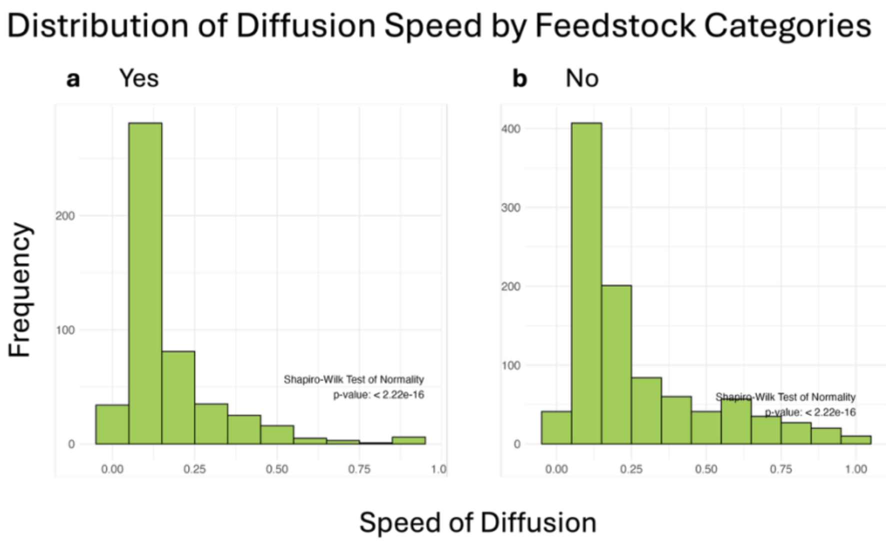
When comparing these groups of technologies, technologies that do not require a feedstock have a significantly faster speed of diffusion (0.17) than those that do require a feedstock (0.12) (Supplementary Table 23, Kruskal-Wallis Test).



*Supplementary Figure 7. Comparison of diffusion sped across feedstock requirement categories. Comparison of group variance using Kruskal Wallis Test; * = p < 0.05, ** = p < 0.01, *** = p < 0.001. Box edges show the inter-quartile range, line within box indicates median, solid lines extend from the interquartile range to the nonoutlier minimum or maximum (1.5 * inter-quartile range), and dots indicate outliers.*

Group	**Min**	**25th Pct.**	**Median**	**Mean**	**75th Pct.**	**Max**
Yes	0.03	0.09	0.12	0.17	0.19	0.95
No	0.03	0.10	0.17	0.26	0.36	1.00

Supplementary Table 22. Summary statistics of the diffusion speed for each category of feedstock requirements.



Supplementary Figure 8. Histograms of the distribution of speed of diffusion across categories of feedstock requirements. The Shapiro-Wilk tests the hypothesis that data is normally distributed. A p-value less than 0.05 indicates that data deviates from a normal distribution and that non-parametric methods such as a Dunn's multiple comparison test multiple comparison test. Panel a displays a histogram for the growth rates of simple technologies (n = 487) and panel b displays a histogram for the growth rates of design-intensive technologies (n = 983).

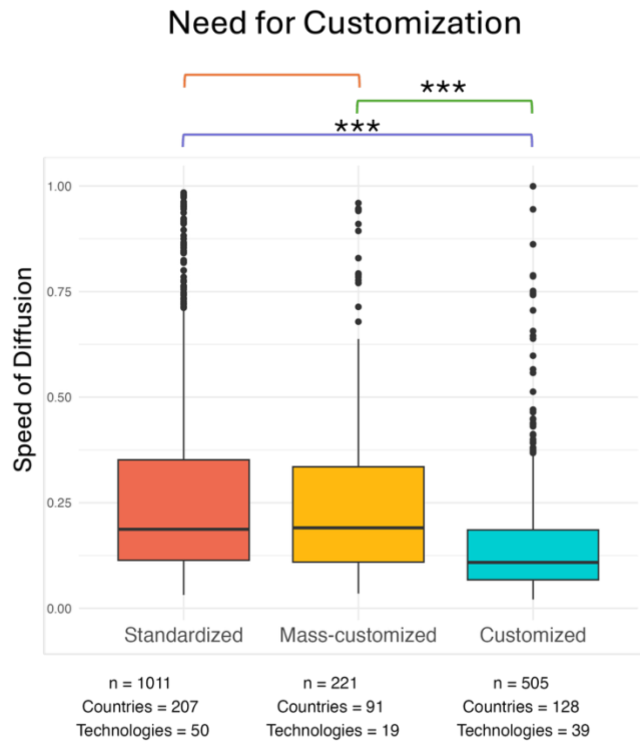
Chi-Square Statistic	P Value	DF
51.46	0.00***	1

Supplementary Table 23. Results of the Kruskal-Wallis test for feedstock categories. Tests the differences in medians across feedstock requirements in non-parametric distributions. The median growth speed of groups is significantly different if p < 0.05.

Need for Customization

Need for customization is a categorical variable in the HATCH dataset (n = 108). Supplementary Figure 9 shows the speed of diffusion measured through the logistic function fit (filtered to only include those points with $R^2 > 95\%$ and $1 > y > 0$; n = 1,737). To test the difference across groups, we use the Kruskal-Wallis test because the diffusion speeds are not normally distributed (Supplementary Figure 9, for each group the Shapiro-Wilk test of normality $p < 0.05$).

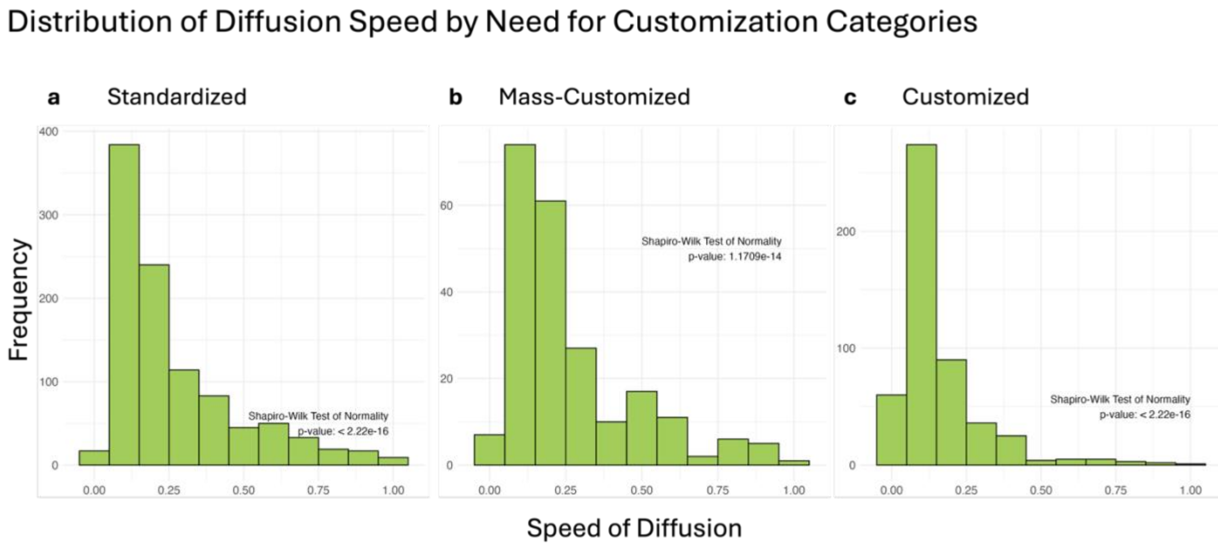
The levels of customization have significantly different diffusion speeds (Supplementary Table 25). Specifically, customized technologies have a significantly slower median speed of diffusion (0.11) than standardized (0.19) and Mass-customized (0.19) technologies (Supplementary Table 26).



*Supplementary Figure 9. Comparison of diffusion sped across need for customization categories. Comparison of group variance using Dunn's Test; * = p < 0.05, ** = p < 0.01, *** = p < 0.001. Box edges show the inter-quartile range, line within box indicates median, solid lines extend from the interquartile range to the nonoutlier minimum or maximum (1.5 * inter-quartile range), and dots indicate outliers.*

Group	Min	25th Pct.	Median	Mean	75th Pct.	Max
Standardized	0.03	0.11	0.19	0.26	0.35	0.98
Mass-customized	0.03	0.11	0.19	0.26	0.34	0.96
Customized	0.02	0.07	0.11	0.16	0.19	1.00

Supplementary Table 24. Summary statistics of the diffusion speed for each category of need for customization.



Supplementary Figure 10. Histograms of the distribution of speed of diffusion across categories of need for customization. The Shapiro-Wilk tests the hypothesis that data is normally distributed. A p-value less than 0.05 indicates that data deviates from a normal distribution and that non-parametric methods such as a Dunn's multiple comparison test multiple comparison test. Panel a displays a histogram for the growth rates of standardized technologies (n = 1,011), panel b displays a histogram for the growth rates of mass-customized technologies (n = 221), and panel c displays a histogram for the growth rates of customized technologies (n = 505).

Chi-Square Statistic	**P Value**	**DF**
162.68	0.00***	2

Supplementary Table 25. Results of the Kruskal-Wallis test need for customization. Tests the differences in medians across need for customization levels in non-parametric distributions. The median growth speed of groups is significantly different if p < 0.05.

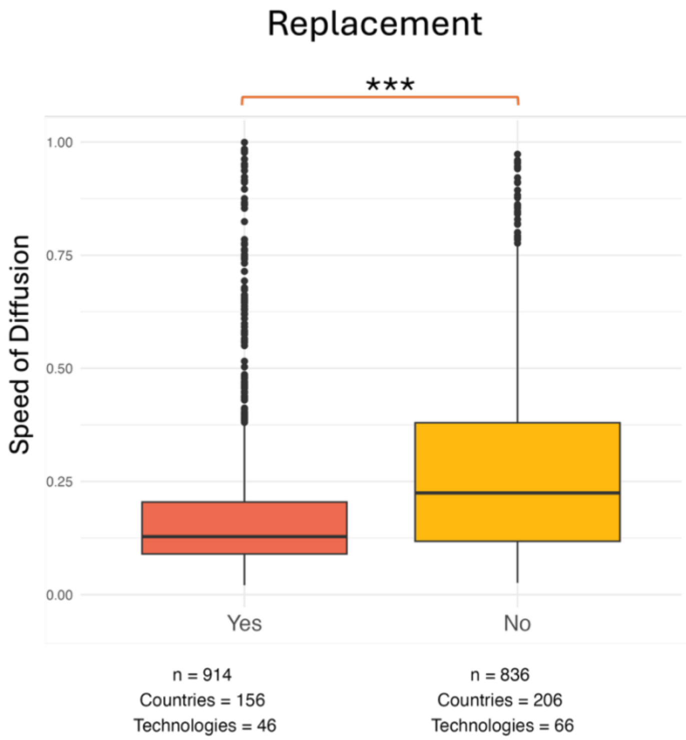
Comparison	**Z Statistic**	**P Value**	**Adjusted P Value**
Customized - Mass-customized	-8.171	0.000***	0.000***
Customized - Standardized	-12.425	0.000***	0.000***
Mass-customized - Standardized	-0.243	0.404	0.404

*Supplementary Table 26. Results of pairwise comparisons of levels of need for customization using Dunn's post-hoc test. Z test statistic shows the standardized difference in mean ranks between groups. P values were adjusted for multiple comparisons using the Holm-Bonferroni method. Significance is defined at the 99% confidence level (*** indicates that p < 0.001).*

Replacement

Whether a technology replaces another existing technology is a categorical variable in the HATCH dataset with either a 'yes' or 'no' classification (n = 112). Supplementary Figure 11 shows the speed of diffusion measured through the logistic function fit (filtered to only include those points with R^2 > 95% and 1 > y > 0; n = 1,750). We use the Kruskal-Wallis test to test the assumption that the groups grew at different speeds because the diffusion speeds are not normally distributed (Supplementary Figure 12).

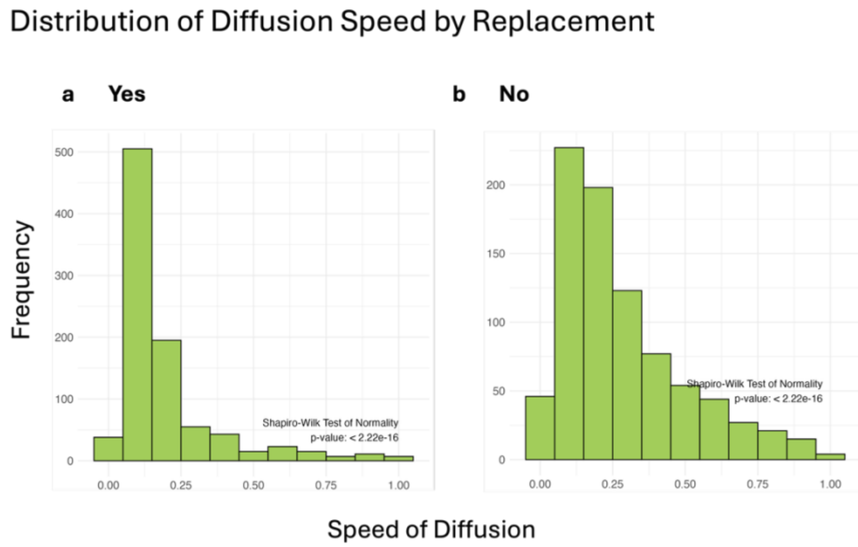
When comparing these groups of technologies, technologies that do not replace other technologies have a significantly faster speed of diffusion (0.22) than those that do require a feedstock (0.13) (Supplementary Table 28).



*Supplementary Figure 11. Comparison of diffusion sped across replacement categories. Comparison of group variance using Kruskal-Wallis Test; * = p < 0.05, ** = p < 0.01, *** = p < 0.001. Box edges show the inter-quartile range, line within box indicates median, solid lines extend from the interquartile range to the nonoutlier minimum or maximum (1.5 * inter-quartile range), and dots indicate outliers.*

Group	Min	25th Pct.	Median	Mean	75th Pct.	Max
Yes	0.02	0.09	0.13	0.19	0.2	1
No	0.03	0.12	0.22	0.28	0.38	0.97

Supplementary Table 27. Summary statistics of the diffusion speed for each category of replacement type.



Supplementary Figure 12. Histograms of the distribution of speed of diffusion across categories of replacement. The Shapiro-Wilk tests the hypothesis that data is normally distributed. A p-value less than 0.05 indicates that data deviates from a normal distribution and that non-parametric methods such as a Dunn's multiple comparison test multiple comparison test. Panel a displays a histogram for the growth rates of technologies that are replacing another (n = 914) and panel b displays a histogram for the growth rates of technologies that are not replacing another (n = 836.

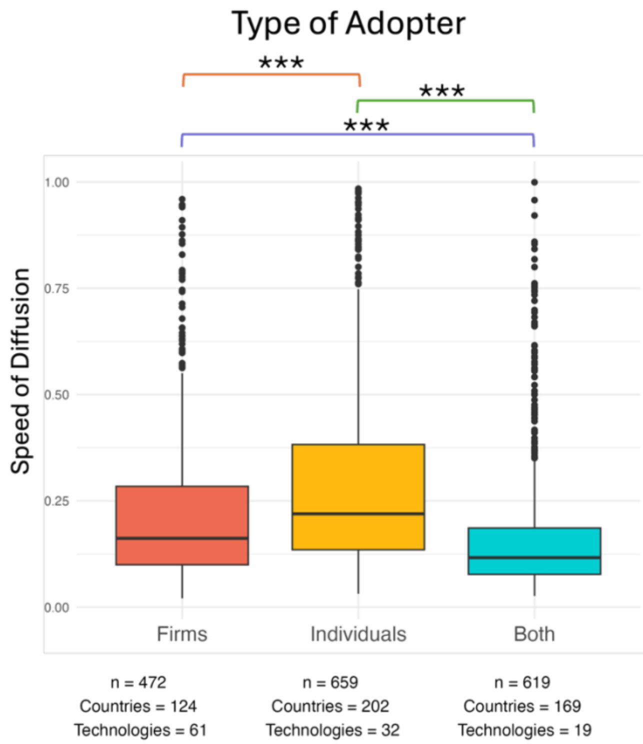
Chi-Square	P Value	DF	method
114.47	0.00***	1	Kruskal-Wallis rank sum test

Supplementary Table 28. Results of the Kruskal-Wallis test for technology replacement. Tests the differences in medians across replacement levels in non-parametric distributions. The median growth speed of groups is significantly different if p < 0.05.

Type of Adopter

The type of adopter for each technology is a categorical variable in the HATCH dataset (n = 112). Supplementary Figure 13 shows the speed of diffusion measured through the logistic function fit (filtered to only include those points with $R^2 > 95\%$ and $1 > y > 0$; n = 1,555). To test the difference across groups, we use the Kruskal-Wallis test because the diffusion speeds are not normally distributed (Supplementary Figure 14).

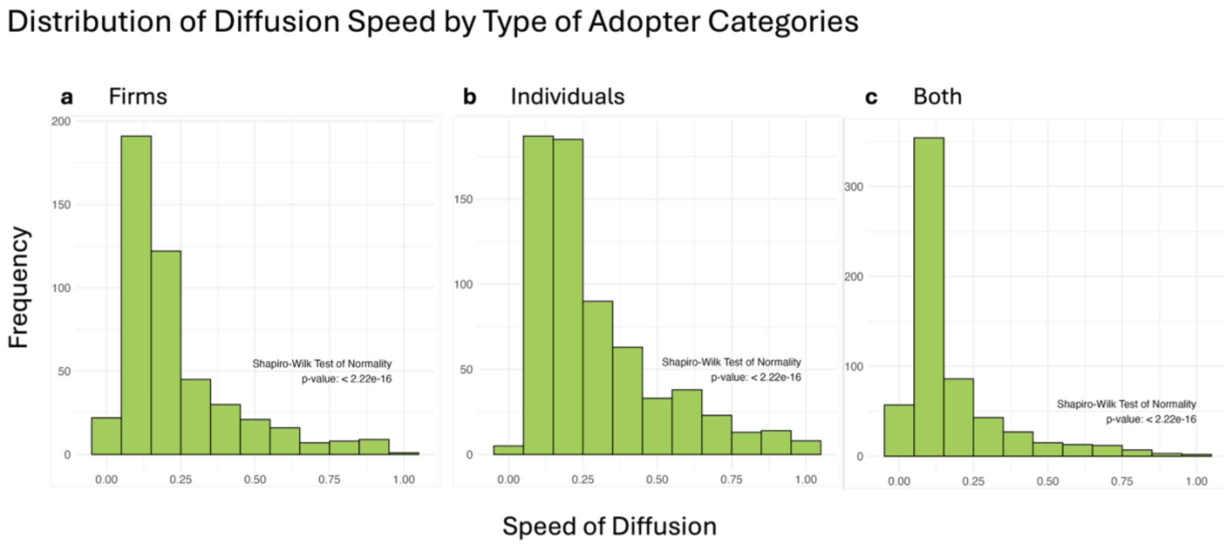
The levels of customization have significantly different diffusion speeds (Supplementary Table 30). Specifically, technologies adopted primarily by individuals grew faster (0.22) than technologies adopted primarily by firms (0.16) and by both (0.12). Further, technologies adopted by firms grew faster than those adopted by both) (Supplementary Table 31). This result does not match our hypothesis, that technologies available in both markets would be adopted faster than those restricted to individual markets.



*Supplementary Figure 13. Comparison of diffusion sped across adopter type categories. Comparison of group variance using Dunn Test; * = p < 0.05, ** = p < 0.01, *** = p < 0.001. Box edges show the inter-quartile range, line within box indicates median, solid lines extend from the interquartile range to the nonoutlier minimum or maximum (1.5 * inter-quartile range), and dots indicate outliers.*

Group	**Min**	**25th Pct.**	**Median**	**Mean**	**75th Pct.**	**Max**
Firms	0.02	0.1	0.16	0.23	0.28	0.96
Individuals	0.03	0.13	0.22	0.29	0.38	0.98
Both	0.03	0.08	0.12	0.18	0.19	1

Supplementary Table 29. Summary statistics of the diffusion speed for each category of adopter type.



Supplementary Figure 14. Histograms of the distribution of speed of diffusion across categories of type of adopter. The Shapiro-Wilk tests the hypothesis that data is normally distributed. A p-value less than 0.05 indicates that data deviates from a normal distribution and that non-parametric methods such as a Dunn's multiple comparison test multiple comparison test. Panel a displays a histogram for the growth rates of technologies that are primarily adopted by firms (n = 472), panel b displays a histogram for the growth rates of technologies that are primarily adopted by individuals (n = 659), and panel c displays a histogram for the growth rates of technologies that are adopted by both (n = 619).

Chi-Square Statistic	P Value	DF
177.73	0.00***	2

Supplementary Table 30. Results of the Kruskal-Wallis test for type of adopters. Tests the differences in medians across type of adopter levels in non-parametric distributions. The median growth speed of groups is significantly different if p < 0.05.

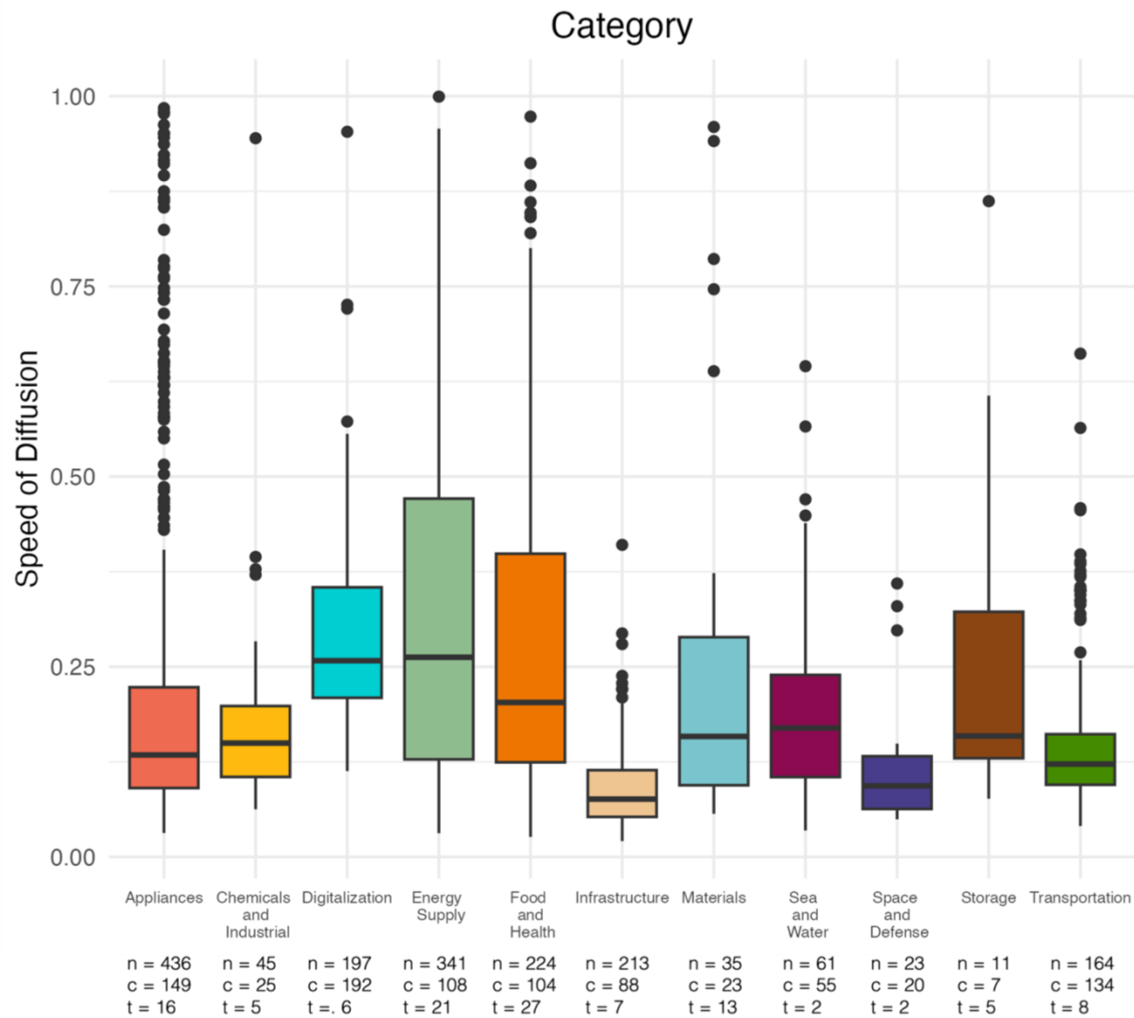
Results of Dunn's Multiple Comparison Test

Comparison	Z Statistic	P Value	Adjusted P Value
Both - Firms	-6.36	0.00***	0.00***
Both - Individuals	-13.33	0.00***	0.00***
Firms - Individuals	-5.92	0.00***	0.00***

*Supplementary Table 31. Results of pairwise comparisons of levels of type of adopters using Dunn's post-hoc test. Z test statistic shows the standardized difference in mean ranks between groups. P values were adjusted for multiple comparisons using the Holm-Bonferroni method. Significance is defined at the 99% confidence level (*** indicates that p < 0.001).*

Technology Category

Each technology in the HATCH dataset is categorized as one of eleven categories (n = 112 technologies and n = 1,750 time series). This variable is included both as justification for further investigation of other characteristics that drive differences across categories and a control variable for other analyses.



*Supplementary Figure 15. Comparison of Speed of Diffusion across technology categories. Under each category shows the number of observations (n), number of countries (c), and number of technologies (t). Box edges show the inter-quartile range, line within box indicates median, solid lines extend from the interquartile range to the nonoutlier minimum or maximum (1.5 * inter-quartile range), and dots indicate outliers.*

B3. Interaction of Technology Characteristics

Beyond individual bivariate analyses of technology characteristics and technology growth speeds, we also test the interaction of technology characteristics on growth speed (Supplementary Table 32). Because we include such a wide range of technologies in the HATCH dataset, from large industrial technologies to small household appliances, we examine the relationship between type of adopter and granularity, both of which are individually significantly related to growth speed. We find that within the subset of technologies primarily adopted by individuals, smaller, cheaper technologies grow faster ($n = 436$, $p < 0.05$). This is the same relationship between granularity and logistic fit as the entire dataset. We find the same relationship between granularity and growth speed for technologies adopted by both firms and individuals ($n = 441$, $p < 0.05$). However, for technologies primarily adopted by firms, we do not find a significant relationship between granularity and growth speed ($n = 292$, $p = 0.67$). This suggests that granularity may be a more important consideration for individuals than for firms during adoption decisions.

We find similar trends for material intensity and technology lifetime – these characteristics are not associated with faster growth speeds for technologies primarily adopted by firms, but the relationships remain significant for technologies primarily adopted by individuals. For technologies with markets for both individuals and firms, the relationship flips for both material intensity and technology lifetime. For these technologies, more material intensive technologies are associated with faster growth speeds ($n = 450$, $p < 0.05$) and longer lived technologies are associated with faster growth speeds ($n = 414$, $p < 0.05$).

We also test the interactions of first year of commercialization with granularity, material intensity, and lifetime and find that first year of commercialization remains a robust predictor of growth speed as these variables are held constant. This suggests that across diverse technologies, modern systems like increased trade and globalized communication have increased technology diffusion speed across technology characteristics.

In their analysis of cost curves of low-carbon technologies, Malhotra and Schmidt (2020) propose a framework based on the interaction between complexity and need for customization of technologies[2]. They present a typology of technologies across these two dimensions along three levels each. While their study is focused on cost dynamics and cumulative capacity, ours focuses on speed of diffusion. We therefore test the interaction between technological complexity and need for customization using an Analysis of Variance test where we include the interaction between the two variables and the relationship with technology growth speed. We find that complexity and need for customization remain significantly associated with growth speed, but the interaction of these two variables is not significantly associated with growth speed ($p = 0.82$). We therefore do not find empirical support for this typology related to technology diffusion speed.

Finally, we also test the impact of the first year of commercialization when complexity is held constant. We find that even when we account for the different complexity in technologies, more recently commercialized technologies have grown more quickly ($n = 1,419$, $p < 0.05$). This result suggests that the observed acceleration is not solely driven by differences in measured complexity across historical periods. At the same time, we recognize that complexity proxies cannot fully capture all qualitative differences between technologies, and therefore this analysis cannot fully eliminate selection effects.

Multiple Technology Characteristics and Growth Speed							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
First Year of Commercialization	0.003*** (0.0001) p = 0.000	0.002*** (0.0001) p = 0.000	0.003*** (0.0001) p = 0.000				0.002*** (0.0001) p = 0.000
Granularity (log)	-0.001 (0.001) p = 0.200			-0.016*** (0.002) p = 0.000			
Material Use (log)		-0.005*** (0.002) p = 0.002			-0.018*** (0.002) p = 0.000		
Lifetime (log)			-0.005 (0.004) p = 0.216			-0.038*** (0.005) p = 0.000	
Type of Adopter (Individual)				-0.102*** (0.028) p = 0.0004	-0.003 (0.017) p = 0.865	-0.006 (0.017) p = 0.702	
Type of Adopter (Firms)				-0.138*** (0.021) p = 0.000	-0.084*** (0.016) p = 0.000	-0.036** (0.015) p = 0.017	
Complexity (Design Intensive)							0.021** (0.009) p = 0.018
Complexity (Complex)							-0.053*** (0.008) p = 0.000
Constant	-4.765*** (0.251) p = 0.000	-4.047*** (0.222) p = 0.000	-5.034*** (0.281) p = 0.000	0.485*** (0.036) p = 0.000	0.203*** (0.010) p = 0.000	0.353*** (0.019) p = 0.000	-4.342*** (0.204) p = 0.000
Observations	1,158	1,213	1,128	1,169	1,275	1,240	1,419
R^2	0.315	0.278	0.296	0.111	0.102	0.067	0.296
Adjusted R^2	0.314	0.276	0.295	0.109	0.100	0.064	0.294
Residual Std.	0.177 (df = 1155)	0.181 (df = 1210)	0.183 (df = 1125)	0.202 (df = 1165)	0.199 (df = 1271)	0.210 (df = 1236)	0.175 (df = 1415)
F Statistic	266.148*** (df = 2; 1155)	232.532*** (df = 2; 1210)	236.535*** (df = 2; 1125)	48.675*** (df = 3; 1165)	48.242*** (df = 3; 1271)	29.455*** (df = 3; 1236)	198.066*** (df = 3; 1415)
Note:	*p<0.1; **p<0.05; ***p<0.01						

Supplementary Table 32. Multiple linear regression results of technology characteristic interactions for speed of diffusion. Value for each variable represents the unstandardized regression coefficient with the standard error in parentheses underneath. Statistical significance for predictor variables was determined through a two-sided t-test.

B4. Polynomial Approximations

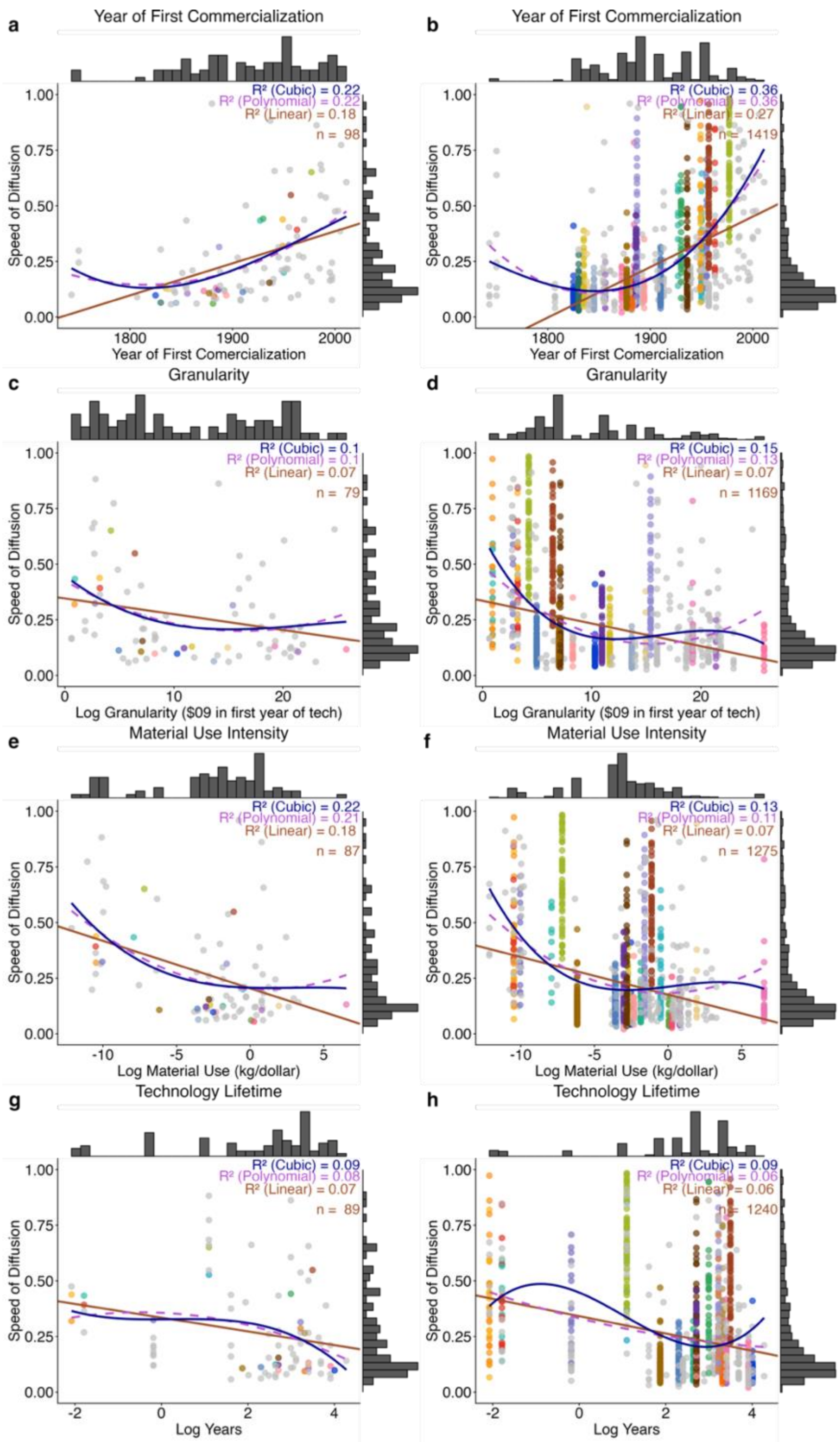
Beyond the linear regression approximation, we also add a polynomial regression with a squared term to each of the numerical technological characteristics as a test of robustness, shown in Supplementary Figure 16. The R^2 values for the two-term polynomial regression approximation are higher than a linear regression approximation across all technology characteristics, although still only explain 36% of dispersion for year of first commercialization, 13% of dispersion for granularity, 11% of dispersion for material intensity, and 6% for technology lifetime.

Using a polynomial approximation with a squared term, we find that for first year of commercialization, the earliest commercialized technologies in our analysis had a negative relationship between year of first commercialization and growth speed until the mid-1800s, at which time the relationship flipped, such that more recently commercialized technologies have grown more quickly. The coefficient for both the linear term (which is negative) and the squared term (which is positive) are both significant in the polynomial regression ($p < 0.05$).

For granularity, material use intensity, and technology lifetime, the polynomial approximation with a squared term provides a more nuanced understanding of the relationships between these characteristics and diffusion speed. We find increasing returns to these characteristics – at a certain level for these technology characteristics, the relationship flips from negatively correlated with growth speed to positively associated with growth speed. This suggests that the largest, most materially intensive, and longest lived technologies, are associated with faster diffusion speeds.

We also test the polynomial approximation with a cubic term using orthogonal polynomial approximations. We do not find a difference in the R^2 value between the two polynomial approximations for the year of first commercialization, and only a slight increase in granularity, material use intensity, and technology lifetime.

All terms are positive and significant in the three-term approximation for year of first commercialization and speed of diffusion, suggesting a positive, but non-linear, relationship (Supplementary Figure 16, panel b). For granularity, all of the terms are significant with mixed direction (linear and cubic terms are negative, and squared term is positive). This suggests a negative relationship between speed of diffusion and granularity for the smallest and largest technologies in the dataset, with a positive relationship for the middle technologies. This suggests that there is a generally negative, but non-linear, relationship between the granularity and diffusion speed of technologies. For material use intensity, all three terms are significant with the same patterns as granularity (both the linear and cubic terms are negative with a positive squared term). This suggests a generally negative, non-linear relationship between material use intensity and speed of diffusion. For average lifetime, we find that the cubic term is significant and positive, the linear term is significant and negative, and the squared term is not significant. This suggests a generally negative relationship that is non-linear.

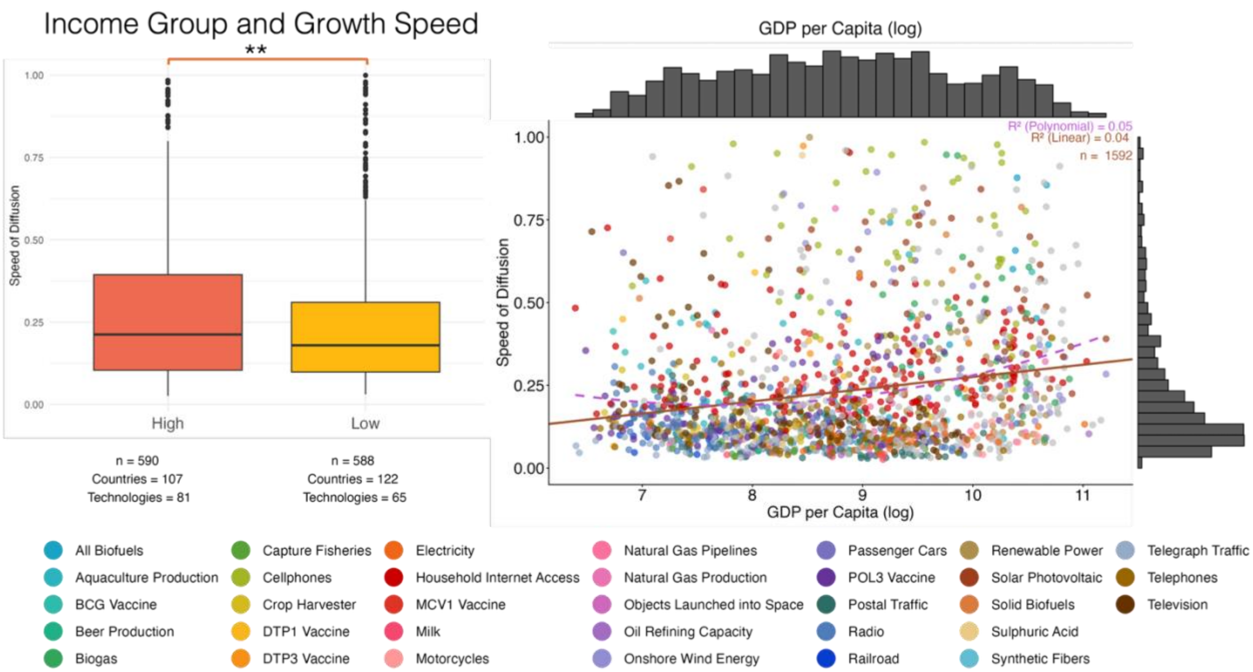


Supplementary Figure 16. Technology Characteristics and Diffusion Speeds with Polynomial Regression Approximations. Panels a, c, e, and g displays one point per technology (the median speed of diffusion across all countries with technology time series data). Panels b, d, f, and h displays dots for each technology-country pair. Each panel (a-h) displays the relationship between independent variables (first year of commercialization, granularity, material use, and technology lifetime) and speed of diffusion. Across all panels, the brown line shows the linear regression approximation, the purple dashed line shows the polynomial regression approximation with a squared term, and the navy blue line shows the polynomial approximation with a cubic term. Significance of each polynomial term was evaluated using a two-sided t-test on orthogonal coefficients.

B5. Country Characteristics

Income Group and GDP

Country-level income and average GDP per capita are included as control variables in the analysis. We find that higher income is associated with faster diffusion speeds than in lower income countries (n = 1,178, $p < 0.05$ from Dunn ad-hoc test). When income is measured using GDP per capita numerical data, we find a significantly positive relationship between average GDP per capita (measured in as log of average GDP per capita) and diffusion speed (n = 1,592, $p < 0.05$). However, this relationship only explains 5% of the dispersion of growth rates.

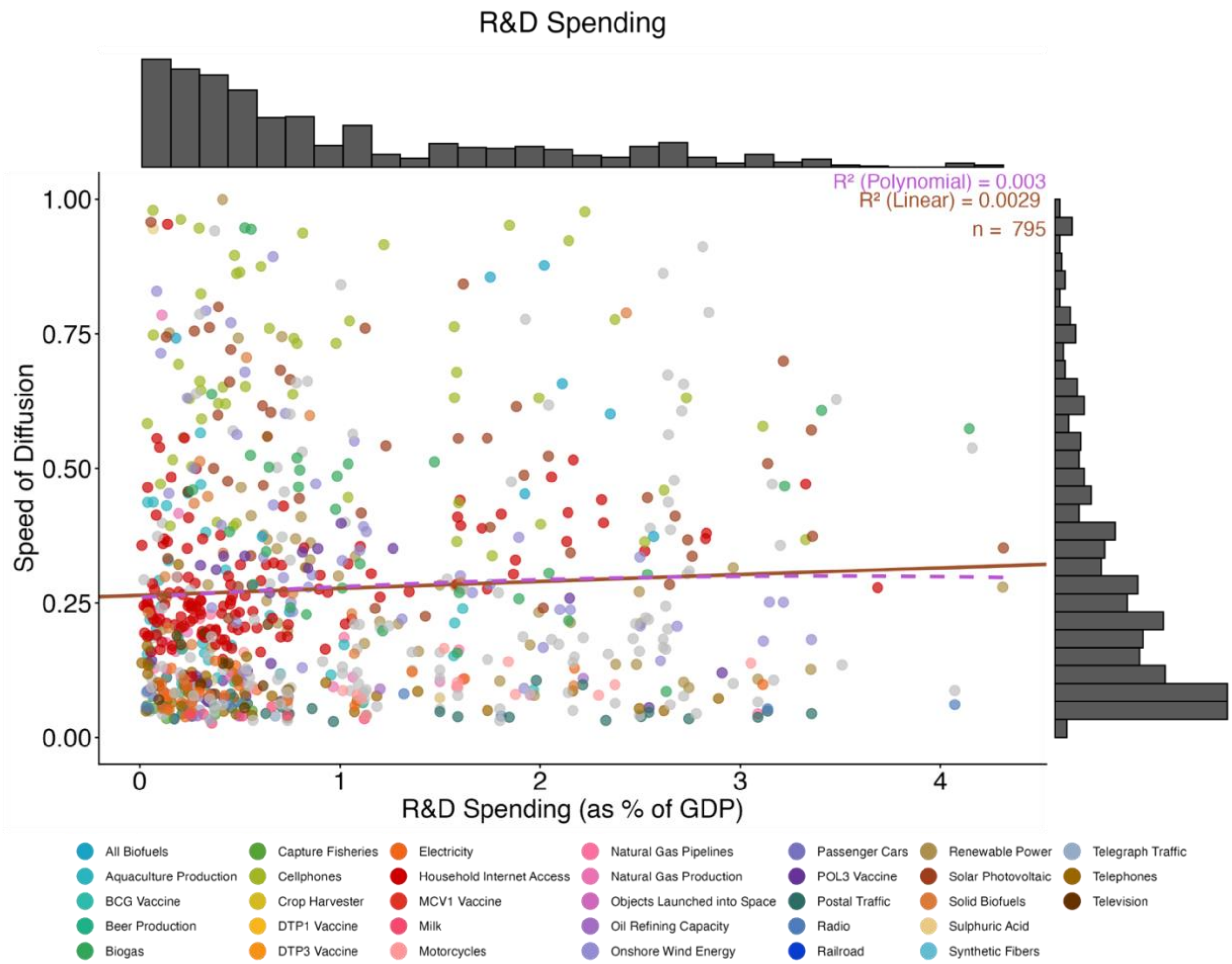


*Supplementary Figure 17. Relationship of economic characteristics and diffusion speed. Panel a shows the distribution of diffusion speed across income groups of countries (n= 1,178). Box edges show the inter-quartile range, line within box indicates median, solid lines extend from the interquartile range to the nonoutlier minimum or maximum (1.5 * inter-quartile range), and dots indicate outliers. Panel b shows GDP per capita and speed of diffusion. Gray points are technologies with fewer than 10 countries and non-gray points are described in the legend.*

Beyond a linear relationship, adding a squared term is also significant (n = 1,592, $p < 0.05$) and the effect accelerates: the highest GDP per capita levels are associated with the fastest speed of diffusion.

R&D Spending

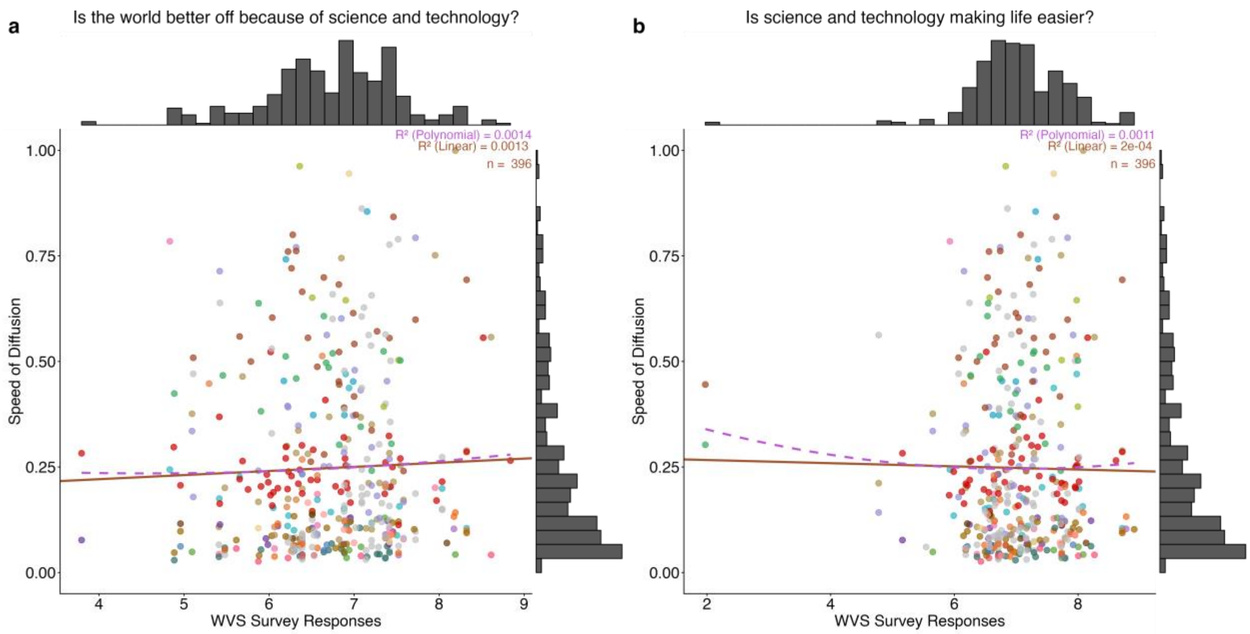
We include R&D spending as a percent of GDP to assess the relationship between R&D spending on new technologies and the speed of diffusion across technologies. We do not find a significant relationship between R&D spending and speed of diffusion with a linear relationship ($p = 0.13$), nor when we add a squared term to the estimate ($p = 0.13$ for linear term, $p = 0.69$ for quadratic term)



Supplementary Figure 18. Relationship between R&D spending in a country and the speed of diffusion. Gray dots show technologies with fewer than 10 countries; otherwise the color of the point shows the technology (see legend). The brown line shows the regression line of the bivariate. The relationship between R&D spending and speed of diffusion is not significant (n = 795).

Socio-Cultural Acceptance

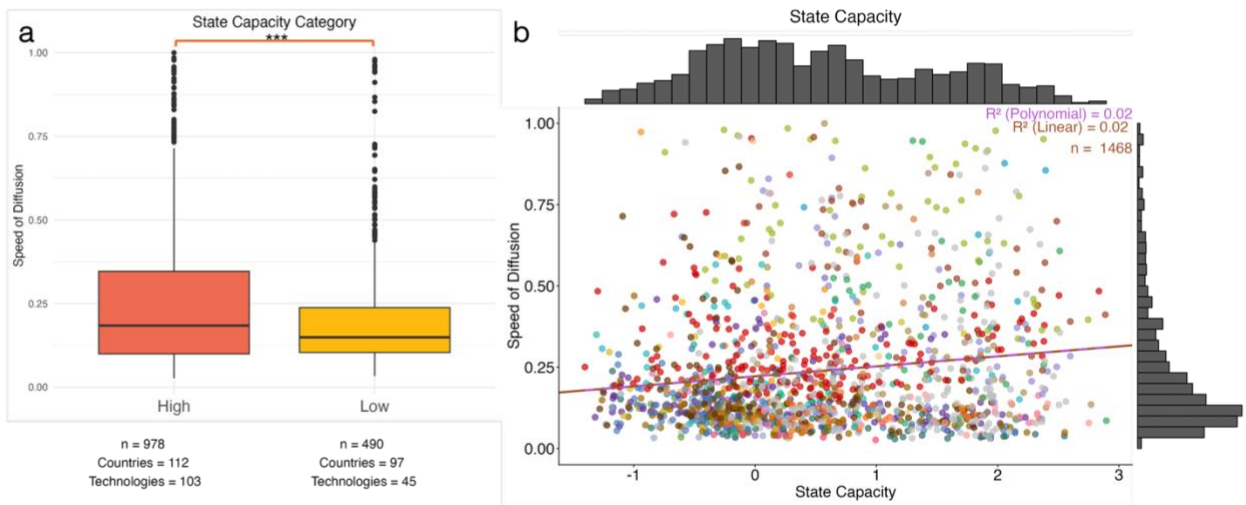
We operationalize socio-cultural acceptance of new technologies in a country through responses to two questions from the World Values Survey (WVS) (for more description of the data, see Supplementary Information Section A1). We find no significant relationship between responses to WVS questions and the speed of technology diffusion ($p > 0.05$). We also do not find a significant relationship when we add a squared term to the estimate ($p > 0.05$ for both quadratic terms and both linear terms). Supplementary Figure 19 show the scatter points of the diffusion speed of technologies in each country and the associated WVS response in that country over the relevant timeframe.



Supplementary Figure 19. Responses to World Value Survey and diffusion speed. Panel a displays the results of the World Value Survey question relating to whether respondents agree that the world is better off because of science and technology (scale of 1 to 10). Panel b displays the results of the World Value Survey question focused on whether respondants believe that science and technology are making life easier (scale of 1 to10). Brown line shows predicted levels of diffusion speed from the bivariate linear regression. Each dot shows the average response to the survey question over the temporal period of interest for each technology-country pair. Gray dots show technologies with fewer than 10 countries; otherwise the color of the point shows the technologies with more than 10 countries; There is no significant relationship between each of the WVS responses and speed of diffusion (n = 396).

Extended Analysis of State Capacity and Growth Speed

We find that state capacity is associated with faster growth speed. When we divide the state capacity into two groups (low state capacity if the capacity metric is below zero and high state capacity when the capacity metric is above zero), the median diffusion speed in countries with a high state capacity is higher than a low state capacity (Supplementary Figure 20 panel A). The trend is also significant for numerical metrics of state capacity, with a significant relationship between higher state capacity and faster technology diffusion (Supplementary Figure 20 panel B), although this only explains 2% of the dispersion in the data. We also estimate the relationship between state capacity and growth speed using a polynomial approximation. Although the linear term remains positive, implying a generally positive relationship, the squared term is not significant (p = 0.99)

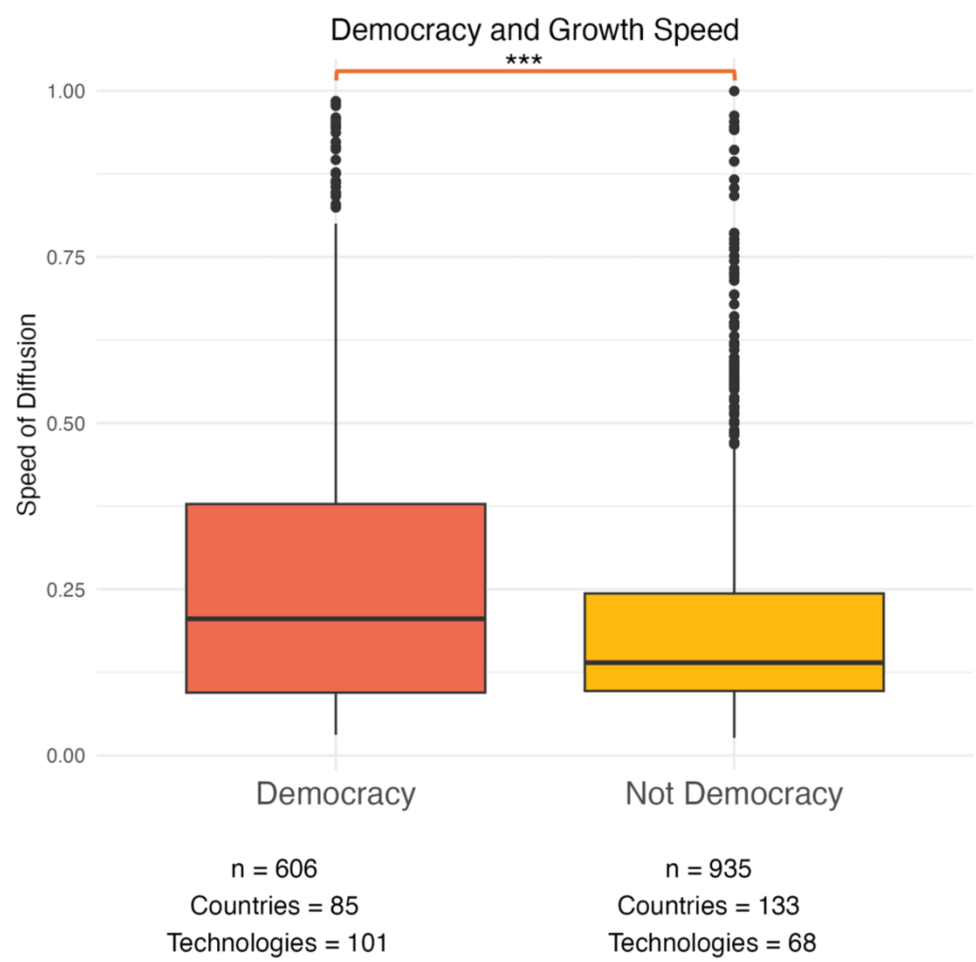


*Supplementary Figure 20. State Capacity and Diffusion Speed of Technologies. Panel A shows a comparison of states with low state capacity (average below zero) and high state capacity (average above zero). Box edges show the inter-quartile range, line within box indicates median, solid lines extend from the interquartile range to the nonoutlier minimum or maximum (1.5 * inter-quartile range), and dots indicate outliers. Panel B shows the average state capacity of a country between the first year of data and the inflection year for the relevant technology in the technology-country pair. Gray points represent technologies for which there are fewer than ten countries and non-gray points are technologies with more than ten countries shown in the legend. The brown line shows the bivariate regression estimate (n = 1,468).*

Extended Analysis of Democracy Type and Growth Speed

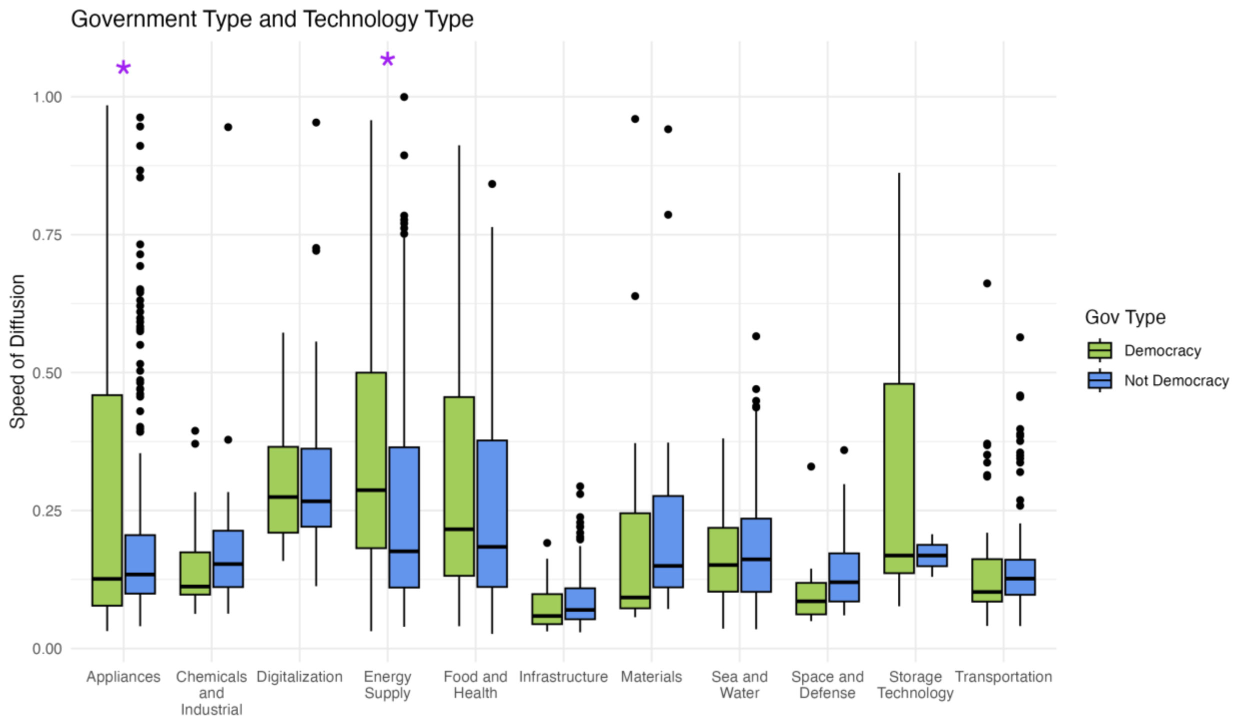
In our analysis, we find that technologies grow faster in democracies than in non-democracies ($p < 0.05$), measured as the average polity score over the period from the first year of data to the inflection year in each country for each technology (Supplementary Figure 21). That polity score is then converted to either democratic or non-democratic.

Several scholars have studied the relationship between technology diffusion and political institutions. Okada and Sumreth find that non-democratic dictatorships negatively impact diffusion speed[15]. Comin and Hobjin also find that countries with executive power that are military regimes or with an executive without a formal government post, or in which a national executive does not exist, have slower adoption[2]. Our findings align with this general trend.



*Supplementary Figure 21. Democracy status and diffusion speed. The difference in growth speed in democracies and non-democracies is significant ($p < 0.05$ from the Dunn ad-hoc test of difference, n = 1,541). Box edges show the inter-quartile range, line within box indicates median, solid lines extend from the interquartile range to the nonoutlier minimum or maximum (1.5 * inter-quartile range), and dots indicate outliers.*

However, we also find that this relationship is not robust across all technology types or as we consider individual technologies. This is aligned with Okada and Sumereth who find that the impact of democratic government regimes on the speed of technology diffusion depends on the type of technology[15]. When we divide the data in the HATCH dataset into broad technology types, we find that the difference between median growth speeds in democracies and non-democracies is not significant for most technology types (Supplementary Figure 22). The exceptions are appliances and energy supply technologies, both of which broadly grow faster in democracies than non-democracies. Even for these two categories, though, when we further focus on individual technologies, the finding is not robust. Rather, not all technologies have adequate data for both democracies and non-democracies to analyse the difference and many technologies within these categories have higher diffusion speeds in non-democracies than in democracies.

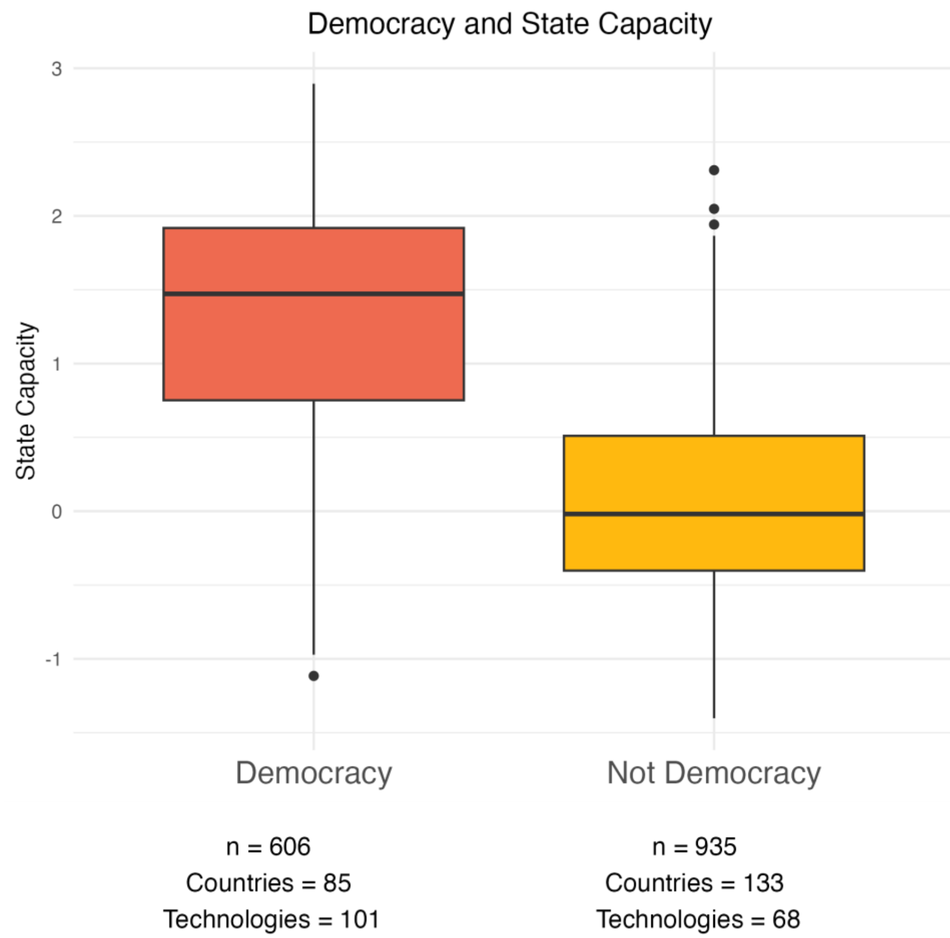


*Supplementary Figure 22. Government type by technology category and diffusion speed. Each technology category is divided into growth speeds depending on the government types (democracies in green and non-democracies in blue). Significance is determined through two-sided t-tests between government type categories. Purple asterisks above the box plots show significantly different growth speeds at a 95% confidence level ($p < 0.05$) between democracies and non-democracies for that technology category. Box edges show the inter-quartile range, line within box indicates median, solid lines extend from the interquartile range to the nonoutlier minimum or maximum (1.5 * inter-quartile range), and dots indicate outliers.*

Extended Analysis of Government Structure and State Capacity

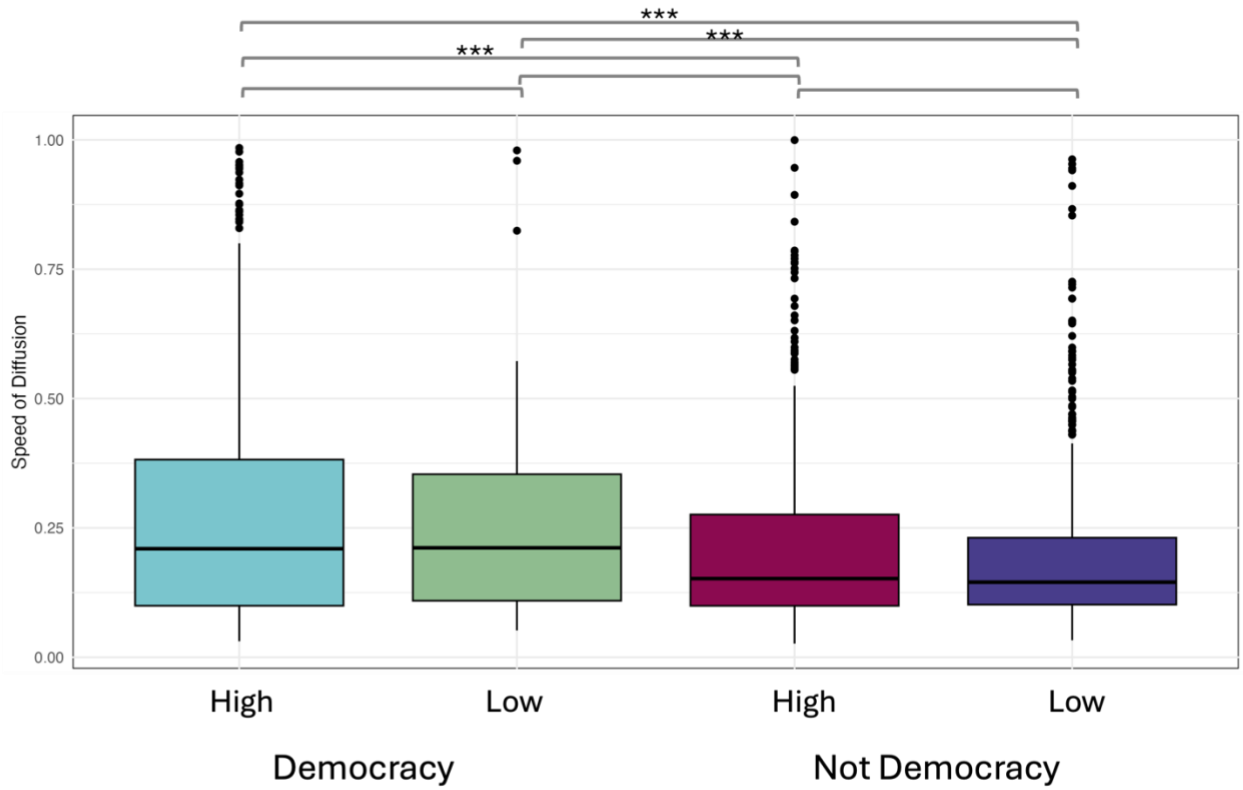
In our analysis, we find that diffusion speeds are faster in democracies than non-democracies and in countries with higher capacity than lower capacity. To further analyze these relationships, we look to the relationship between the three variables: government type, state capacity, and diffusion speed.

In Supplementary Figure 23, we find that in the HATCH dataset, democracies generally have higher levels of state capacities than in non-democracies. This is aligned with other studies that find these two variables are correlated[25]. In these studies, the relationship between polity score (measure of democracy) and levels of state capacity follow a J-shape, where the highest levels of state capacity are in the highest levels of democracies, but that lowest levels of democracies have higher state capacities than middle levels of democracies.



*Supplementary Figure 23. Relationship between government type and state capacity. In the HATCH dataset, democracies in the dataset have higher state capacity levels than non-democracies. Box edges show the inter-quartile range, line within box indicates median, solid lines extend from the interquartile range to the nonoutlier minimum or maximum (1.5 * inter-quartile range), and dots indicate outliers.*

We then explore the differences in median diffusion speeds across countries depending on whether they are democracies or non-democracies and with high or low state capacity (categorized based on the numerical measure). We find that the median difference in diffusion speeds between democracies with high and low state capacities is not significant, nor is the difference in median diffusion speed between non-democracies with high and low state capacities. This does not align with our hypothesis that high state capacity in both democracies and non-democracies have faster diffusion speed than states with low state capacity. This result, which considers the interaction between democracy level and state capacity, is robust even if we use numerical state capacity measures ($p < 0.05$).



*Supplementary Figure 24. Relationship between government type and state capacity. In the HATCH dataset, the median difference in technology diffusion speed between democracies with high and low state capacities are not significant. Statistical significance is determined using a two-sided Dunn ad-hoc test and shown above the boxplots with *** indicating that p < 0.05. The median difference in technology diffusion in non-democracies with high and low state capacity is also not significant, nor is the median difference in democracies with low state capacity and non-democracies with high state capacity. Box edges show the inter-quartile range, line within box indicates median, solid lines extend from the interquartile range to the nonoutlier minimum or maximum (1.5 * inter-quartile range), and dots indicate outliers.*

Section C. Sensitivity Analysis

Our analysis relies heavily on the fitting of the logistic function on each country-technology time series. We test the sensitivity of these results on three metrics: the type of fit (Logistic or Gompertz), the filtering of R^2 value, and a high filtering of the fitted steepness parameter. Rather, the Gompertz function estimates slower growth after the inflection point to approach the asymptote.

C1. Fit Type

The logistic function is a symmetrical s-curve centered at the inflection year, a parameter of the three-parameter logistic function. The Gompertz function is similar to the logistic function, except it is an asymmetrical model. It estimates slower growth after the inflection point approaching the asymptote. This fitting process is discussed in Supplementary Information section A2. We test the bivariate relationship between each technology and country characteristic with the steepness parameter for both the logistic and Gompertz fitted functions. Supplementary Table 33 and Supplementary Table 35 show the differences in regression estimates and differences in median levels across categorical levels for each variable across these two functional forms.

Variable Name	Fit Type - Regression Estimates	
	Logistic	*Gompertz*
Log Granularity	-0.010*** p = 0.000	-0.009***; p = 0.000
	n = 1,169	n = 1,119
Log Material Use	-0.017*** p = 0.000	-0.017***; p = 0.000
	n = 1,275	n = 1,212
Log Lifetime	-0.039*** p = 0.000	-0.038***; p = 0.000
	n = 1,240	n = 1,166
First Commercial Year	0.002*** p = 0.000	0.002***; p = 0.000
	n = 1,419	n = 1,333
Direction of Science and Technology	0.010; p = 0.472	-0.005; p = 0.726
	n = 396	n = 310
Ease of Life with Science and Technology	-0.004; p = 0.788	0.000; p = 0.995
	n = 396	n = 310
State Capacity (Numerical)	0.031***; p = .000	0.025***; p = 0.000
	n = 1,468	n = 1,351
R&D Spending	0.013; p = 0.132	0.000; p = 0.983
	n = 795	n = 683
Log GDP	0.037***; p = 0.000	0.031***; p = 0.000
	n = 1,592	n = 1,473
Gov Type (dem) - compared to not dem	-0.075***; p = 0.000	-0.053***; p = 0.000
	n = 1,541	n = 1,416
* p < 0.05, ** p < 0.01, *** p < 0.001		

*Supplementary Table 33. Sensitivity of bivariate regressions to fit type. Each cell shows the estimated coefficient of the linear regression with growth speed. Statistical significance is determined through two-sided t-tests. The significance of the relationship between the explanatory variable and the response variable is shown with: * p < 0.05, ** p < 0.01, *** p < 0.001.*

Of the significant regression coefficients, the direction and significance levels remain the same across logistic and Gompertz fitting estimates Supplementary Table 34.

Fit Type - Median Across Categorical Groups			
Variable Name	**Level**	**Logistic**	**Gompertz**
Complexity	Simple	0.19	0.10
		n = 779	n = 734
	Design-Intensive	0.15	0.08
		n = 472	n = 458
	Complex	0.12	0.05
		n = 499	n = 436
Need for Customization	Standardized	0.19	0.10
		n = 1,011	n = 968
	Mass-customized	0.19	0.10
		n = 221	n = 206
	Customized	0.11	0.05
		n = 505	n = 441
Type of Adopter	Firms	0.16	0.08
		n = 472	n = 422
	Individuals	0.22	0.12
		n= 659	n = 650
	Both	0.12	0.05
		n = 619	n = 556
Feedstock	Yes	0.12	0.06
		n = 487	n = 444
	No	0.17	0.09
		n = 983	n = 929
Replacement	Yes	0.13	0.06
		n = 914	n = 845
	No	0.23	0.12
		n = 836	n = 783

Supplementary Table 34. Comparison of median steepness parameter across categorical levels. Each cell shows the median of the steepness parameter for the observations in each level of each category.

We generally see the steepness levels estimated through the Gompertz function are lower than the logistic function. In Supplementary Table 34, the Gompertz steepness estimates are lower across each level of each category measured. In Supplementary Table 35, we see that the differences in median growth speed are the same direction between categorical groups using both the logistic and Gompertz functions.

Fit Type - Difference in Medians			
Variable Name	**Level**	**Logistic**	**Gompertz**
Complexity	Simple vs. Design-Intensive	0.04*** p = 0.000	0.02*** p = 0.000
	Simple vs. Complex	0.07*** p = 0.000	0.05*** p = 0.000
	Design-Intensive vs. Complex	0.03** p = 0.009	0.03*** p = 0.000
Need for Customization	Standardized vs. Mass-customized	0 p = 0.404	0 p = 0.422
	Standardized vs. Customized	0.8*** p = 0.000	0.05*** p = 0.000
	Mass-customized vs. Customized	0.8*** p = 0.000	0.05*** p = 0.000
Type of Adopter	Firms vs. Individuals	-0.06*** p = 0.000	-0.04*** p = 0.000
	Firms vs. Both	0.04*** p = 0.000	0.03*** p = 0.000
	Individuals vs. Both	0.1*** p = 0.000	0.07*** p = 0.000
Feedstock	Yes vs. No	-0.05*** p = 0.000	-0.03*** p = 0.000
Replacement	Yes vs. No	-0.9*** p = 0.000	-0.06*** p = 0.000
* p < 0.05, ** p < 0.01, *** p < 0.001			

Supplementary Table 35. Comparison of medians across categorical levels. Each cell shows the difference in medians of observations within each level of each category. Statistical significance is determined through two-sided t-tests. Significance levels show the significance of this difference using the non-parametric Dunn's test. P values were adjusted for multiple comparisons using the Holm-Bonferroni method.

C2. Goodness-of-Fit Filtering

The largest number of country-technology time series are dropped from the analysis because of an inadequate logistic function fit, measured with an R^2 value (described in Supplementary Information section A1). This filtering level, though, does not necessarily provide a guarantee of a good fit, but is rather an indicator of a fit that is adequate for comparison to other time series. By testing this assumption at different levels, we can test how sensitive the results are to this filtering level of the logistic fit.

In Supplementary Table 36 each explanatory variable is shown in the first column, followed by the estimated coefficient of the linear regression, the p-value of the bi-variate of this variable, and the speed of diffusion response variable, as well as the number of country-technology observations of that variable given the filtering level.

Numerical Variable Name	**R^2 Filter Level**			
	85%	**90%**	**95%**	**99%**
Log Granularity	-0.009*** p = 0.000	-0.010*** p = 0.000	-0.010*** p = 0.000	-0.021*** p = 0.000
	n = 1,745	n = 1,428	n = 1,169	n = 483
Log Material Use	-0.016*** p = 0.000	-0.018*** p = 0.000	-0.017*** p = 0.000	-0.025*** p = 0.000
	n = 2,078	n = 1,614	n = 1,275	n = 500
Log Lifetime	-0.028*** p = 0.000	-0.034*** p = 0.000	-0.039*** p = 0.000	-0.074*** p = 0.000
	n = 1,942	n = 1,542	n = 1,240	n = 464
First Commercial Year	0.002*** p = 0.000	0.002*** p = 0.000	0.002*** p = 0.000	0.003*** p = 0.000
	n = 2,190	n = 1,728	n = 1,419	n = 590
Direction of Science and Technology	0.008 p = 0.467	0.008 p = 0.496	0.010 p = 0.472	0.030 p = 0.240
	n = 571	n = 509	n = 396	n = 139
Ease of Life with Science and Technology	-0.008 p = 0.508	-0.003 p = 0.829	-0.004 p = 0.788	0.033 p = 0.263
	n = 571	n = 509	n = 396	n = 139
State Capacity (Numerical)	0.017*** p = 0.000	0.023*** p = 0.000	0.031*** p = 0.000	0.039*** p = 0.000
	n = 2,171	n = 1,909	n = 1,468	n = 621
R&D Spending	0.01 p = 0.148	0.012 p = 0.111	0.013 p = 0.132	0.006 p = 0.669
	n = 1,109	n = 1,005	n = 795	n = 312
Log GDP	0.024*** p = 0.024	0.030*** p = 0.000	0.037*** p = 0.000	0.055*** p = 0.000
	n = 2,329	n = 2,053	n = 1,592	n = 670
Gov Type (dem) - compared to not dem	-0.051*** p = 0.000	-0.061*** p = 0.000	-0.075*** p = 0.000	-0.116*** p = 0.000
	n = 2,255	n = 1,995	n = 1,541	n = 652
* p < 0.05, ** p < 0.01, *** p < 0.001				

Supplementary Table 36. Sensitivity of bivariate regressions to R^2 filtering level of logistic fit. Each cell shows the slope of the regression line between the explanatory variable in the first column and the logistic fit variable. Statistical significance is determined through two-sided t-tests. Significance levels show the significance of this difference using a two-sided t -test.

At a 95% confidence level, all variables in Supplementary Table 36 are associated with growth speed in the same direction and whether this relationship is significant or not regardless of the R^2 filter level. Overall, the relationship between individual variables and the diffusion speed is robust across R^2 cutoff levels between 85% and 99%.

R^2 Filtering Levels- Median Across Categorical Groups					
Variable Name	**Level**	**85%**	**90%**	**95%**	**99%**
Complexity	Simple	0.21	0.21	0.20	0.20
		n = 1,141	n = 1,000	n = 779	n = 279
	Design-Intensive	0.14	0.15	0.15	0.16
		n = 711	n = 609	n = 472	n = 234
	Complex	0.12	0.12	0.12	0.10
		n = 822	n = 704	n = 499	n = 194
Need for Customization	Standardized	0.20	0.20	0.19	0.18
		n = 1,370	n = 1,235	n = 1,011	n = 471
	Mass-customized	0.16	0.17	0.19	0.24
		n = 440	n = 352	n = 221	n = 46
	Customized	0.11	0.11	0.11	0.10
		n = 845	n = 708	n = 505	n = 188
Type of Adopter	Firms	0.15	0.16	0.16	0.20
		n = 947	n = 753	n = 472	n = 77
	Individuals	0.23	0.23	0.22	0.25
		n = 991	n = 862	n = 659	n = 239
	Both	0.12	0.12	0.12	0.11
		n = 736	n = 698	n = 619	n = 391
Feedstock	Yes	0.13	0.12	0.12	0.11
		n = 673	n = 599	n = 487	n = 245
	No	0.17	0.17	0.17	0.17
		n = 1,655	n = 1,394	n = 983	n = 349
Replacement	Yes	0.13	0.13	0.13	0.14
		n = 1,170	n = 1,073	n = 914	n = 448
	No	0.21	0.22	0.22	0.23
		n = 1,504	n = 1,240	n = 836	n = 259

Supplementary Table 37. Comparison of median steepness parameter across categorical levels. Each cell shows the median of the steepness parameter for the observations in each level of each category across R^2 filter level.

Supplementary Table 38 shows that across R^2 filtering level, the significance of the difference between growth speed across technological characteristic categories remain generally the same, with one exception. Standardized technologies grow more quickly than mass-customized technologies at the 85% and 90% level, and the relationship is flipped at the 99% filtering level (where mass-customized technologies grow more quickly than standardized technologies). The relationship is not significant at the 95% level.

Difference in medians across levels of categories and significance of difference					
		R^2 Filter Level			
Variable Name	**Level**	**85%**	**90%**	**95%**	**99%**
Complexity	Simple vs. Design-Intensive	0.07*** p = 0.000	0.06*** p = 0.000	0.05* p = 0.009	0.04 p = 0.140
	Simple vs. Complex	0.09*** p = 0.000	0.09*** p = 0.000	0.08*** p = 0.000	0.1*** p = 0.000
	Design-Intensive vs. Complex	0.02*** p = 0.000	0.03*** p = 0.000	0.03*** p = 0.000	0.06*** p = 0.000
Need for Customization	Standardized vs. Mass-customized	0.04*** p = 0.000	0.03*** p = 0.000	0 p = 0.404	-0.06* p = 0.097
	Standardized vs. Customized	0.09*** p = 0.000	0.09*** p = 0.000	0.08*** p = 0.000	0.08*** p = 0.000
	Mass-customized vs. Customized	0.05*** p = 0.000	0.06*** p = 0.000	0.08*** p = 0.000	0.14*** p = 0.000
Type of Adopter	Firms vs. Individuals	-0.08*** p = 0.000	-0.07*** p = 0.000	-0.06*** p = 0.000	-0.05* p = 0.012
	Firms vs. Both	0.03*** p = 0.000	0.04*** p = 0.000	0.04*** p = 0.000	0.09*** p = 0.000
	Individuals vs. Both	0.11*** p = 0.000	0.11*** p = 0.000	0.1*** p = 0.000	0.14*** p = 0.000
Feedstock	Yes vs. No	-0.04*** p = 0.000	-0.05*** p = 0.000	-0.05*** p = 0.000	-0.06*** p = 0.000
Replacement	Yes vs. No	-0.07*** p = 0.000	-0.09*** p = 0.000	-0.09*** p = 0.000	-0.09*** p = 0.000
* p < 0.05, ** p < 0.01, *** p < 0.001					

Supplementary Table 38. Sensitivity of median growth speeds across categorical levels to R^2 filtering level of logistic fit. Each cell shows the difference in median between two levels of each category. Statistical significance is determined through two-sided t-tests. Significance levels show the significance of this difference using the non-parametric Dunn's test. P values were adjusted for multiple comparisons using the Holm-Bonferroni method.

C3. Steepness Value Filtering

We also filter time series from the analysis based on the value of the logistic steepness parameter, k. If the logistic function fit onto the data gives a k value that is too high, we assume it is a bad fit and should not be included in this analysis. The level of an unreasonably high steepness parameter is unclear. We relax the assumption of the limit being $k = 1$ in this analysis to test the robustness of the upper fit level.

In Supplementary Table 39, the bivariate regression results between each numerical variable and the steepness parameter are shown along with the number of observations across different datasets depending on the upper limit of k. We see no difference in significance or in the direction of the relationship between each variable and the steepness parameter between the upper limit of 1 or 2. However, when the limit is increased to 5, the relationship between state capacity is not significantly associated with growth speed. Also, the relationship between R&D and technology growth is significant at the limit of 5, but is not significant at the 1 or 2 limit.

Numerical Variable Name	**Upper *k* Limit**		
	< 1	**< 2**	**< 5**
Log Granularity	-0.010*** p = 0.000	-0.019*** p = 0.000	-0.023*** p = 0.000
	n = 1,169	n = 1,260	n = 1,318
Log Material Use	-0.017*** p = 0.000	-0.030*** p = 0.000	-0.050*** p = 0.000
	n = 1,275	n = 1,368	n = 1,427
Log Lifetime	-0.039*** p = 0.000	-0.056*** p = 0.000	-0.077*** p = 0.000
	n = 1,240	n = 1,337	n = 1,399
First Commercial Year	0.002*** p = 0.000	0.004*** p = 0.000	0.005*** p = 0.000
	n = 1,419	n = 1,515	n = 1,575
Direction of Science and Technology	0.01 p = 0.472	0.011 p = 0.598	0.048 p = 0.240
	n = 396	n = 422	n = 441
Ease of Life with Science and Technology	-0.004 p = 0.788	0.003 p = 0.893	0.070 p = 0.100
	n = 396	n = 422	n = 441
State Capacity (Numerical)	0.031*** p = 0.000	0.034*** p = 0.000	0.019 p = 0.277
	n = 1,468	n = 1,561	n = 1,617
R&D Spending	0.013 p = 0.132	-0.002 p = 0.882	-0.066** p = 0.009
	n = 795	n = 857	n = 891
Log GDP	0.037*** p = 0.000	0.051*** p = 0.000	0.045** p = 0.001
	n = 1,592	n = 1,681	n = 1,740
Gov Type (dem) - compared to not dem	-0.075 p = 0.000	-0.095*** p = 0.000	-0.164*** p = 0.000
	n = 1,541	n = 1,633	n = 1,689
* p < 0.05, ** p < 0.01, *** p < 0.001			

Supplementary Table 39. Sensitivity of bivariate regressions to the upper limit of the logistic steepness parameter. Each cell shows the difference in medians of observations within each level of each category. Statistical significance is determined through two-sided t-tests. Significance levels show the significance of this difference using the non-parametric Dunn's test. P values were adjusted for multiple comparisons using the Holm-Bonferroni method.

Median Categorical Level Across Upper *k* Limit				
Variable Name	**Level**	**< 1**	**< 2**	**< 5**
Complexity	Simple	0.19	0.21	0.22
		n = 779	n = 840	n = 878
	Design-Intensive	0.15	0.16	0.17
		n = 472	n = 504	n = 526
	Complex	0.12	0.12	0.12
		n = 499	n = 510	n = 514
Need for Customization	Standardized	0.19	0.20	0.21
		n = 1,011	n = 1,092	n = 1,132
	Mass-customized	0.19	0.20	0.22
		n = 221	n = 233	n = 251
	Customized	0.11	0.11	0.11
		n = 505	n = 516	n = 522
Type of Adopter	Firms	0.16	0.17	0.18
		n = 472	n = 491	n = 514
	Individuals	0.22	0.24	0.25
		n = 659	n = 713	n = 744
	Both	0.12	0.12	0.12
		n = 619	n = 650	n = 660
Feedstock	Yes	0.12	0.12	0.12
		n = 487	n = 496	n = 499
	No	0.17	0.19	0.20
		n = 983	n = 1,074	n = 1,133
Replacement	Yes	0.13	0.13	0.13
		n = 914	n = 945	n = 953
	No	0.22	0.24	0.26
		n = 836	n = 909	n = 965

Supplementary Table 40. Comparison of median steepness parameter across categorical levels. Each cell shows the median of the steepness parameter for the observations in each level of each category across R^2 filter level.

For categorical variables, we measure the difference in median growth speed across levels of each categorical variable depending on different upper *k* limits in Supplementary Table 41. We also test whether the difference in medians across levels are significantly different. Across findings, we see no change in the direction of the relationship between levels nor do we see difference in the significance of these differences across upper *k* limit. In other words, the differences in growth speed across categorical levels is robust across upper limits of the *k* values.

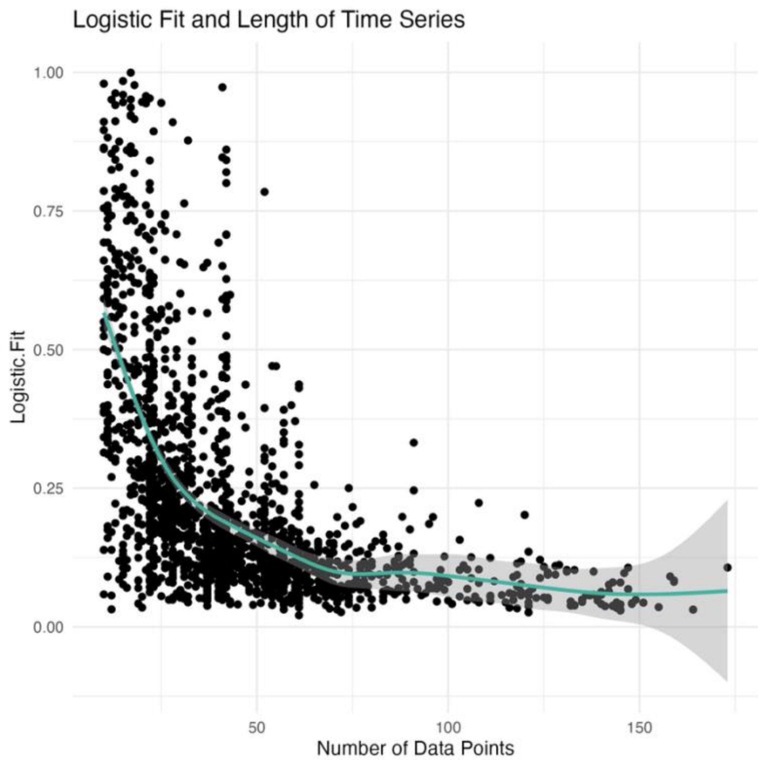
Difference in medians across levels of categories and significance of difference				
		Upper *k* Limit		
Variable Name	**Level**	**< 1**	**< 2**	**< 5**
Complexity	Simple vs. Design-Intensive	0.04** p = 0.009	0.05** p = 0.007	0.05* p = 0.010
	Simple vs. Complex	0.07*** p = 0.000	0.09*** p = 0.000	0.1*** p = 0.000
	Design-Intensive vs. Complex	0.03*** p = 0.000	0.04*** p = 0.000	0.05*** p = 0.000
Need for Customization	Standardized vs. Mass-customized	0 p = 0.404	0 p = 0.236	-0.01 p = 0.443
	Standardized vs. Customized	0.08*** p = 0.000	0.09*** p = 0.000	0.1*** p = 0.000
	Mass-customized vs. Customized	0.08*** p = 0.000	0.09*** p = 0.000	0.11*** p = 0.000
Type of Adopter	Firms vs. Individuals	-0.06*** p = 0.000	-0.07*** p = 0.000	-0.07*** p = 0.000
	Firms vs. Both	0.04*** p = 0.000	0.05*** p = 0.000	0.06*** p = 0.000
	Individuals vs. Both	0.1*** p = 0.000	0.12*** p = 0.000	0.13*** p = 0.000
Feedstock	Yes vs. No	-0.05*** p = 0.000	-0.07*** p = 0.000	-0.08*** p = 0.000
Replacement	Yes vs. No	-0.09*** p = 0.000	-0.11*** p = 0.000	-0.13*** p = 0.000
* p < 0.05, ** p < 0.01, *** p < 0.001				

Supplementary Table 41. Sensitivity of median growth speeds across categorical levels to upper limit of k parameter. Each cell shows the difference in median between two levels of each category. Statistical significance is determined through two-sided t-tests. Significance levels show the significance of this difference using the non-parametric Dunn's test. P values were adjusted for multiple comparisons using the Holm-Bonferroni method.

C4. Logistic Fit and Length of Time Series

The time series in the HATCH dataset, each a unique combination of technology diffusion in a certain country, differ in their length (the number of years included in the dataset) as well as the timing of the data. In some cases, the time series are long and capture many stages of technology diffusion. In others, the time series may only capture certain stages of growth. To address this difference, we only include time series in this analysis with at least 10 years of data. Beyond this filtering, we also analyze the impact of the length of time series on the logistic fit and the bivariate relationships in this paper.

First, we find a negative relationship between the length of the time series and the steepness parameter k. As the number of data points increases, the logistic steepness estimate (the speed of technology diffuses) decreases (shown in Supplementary Figure 25).



Supplementary Figure 25. Relationship between diffusion speed and number of data points. Each country-technology pair is shown by a black dot and the trend line, smoothed using locally estimated scatterplot smoothing, is shown in green. This shows a negative relationship between the number of data points and the steepness of the logistic fit function. The significance of this relationship was tested through a two-sided t-test of the linear regression coefficient estimate (coefficient estimate = -0.004; p = 0.000).

To investigate whether this relationship impacts the relationships we find with technology characteristics and country characteristics, we perform multiple linear regression analyses in which we add the number of data points constant while other variables change. The results are shown in Supplementary Table 42.

In model 1, we test the relationship between vintage (the first year of the time series) and the first commercial year of the given technology. These are not always the same for time series in which the technology is adopted later than the year of first commercialization for that technology in another place, or if the data starts later than the initial phase of technology diffusion. We see that the as the first year of commercialization increases, diffusion speed increases and this relationship remains significant even if we also account for the first year of data in the time series.

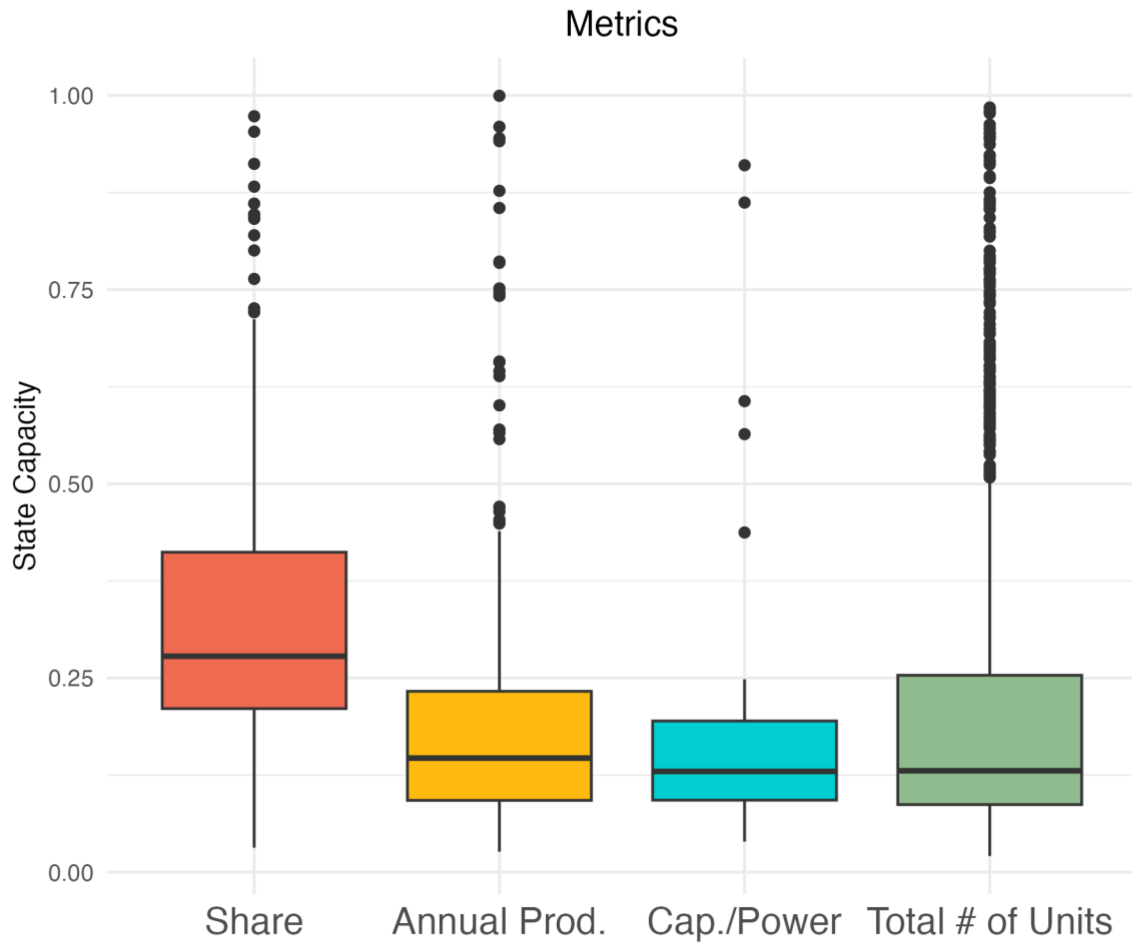
In models 2 through 7, we analyze the relationship between the speed of diffusion and each numerical variable while holding the number of data points in the series constant. The direction of each of these relationships and their significance remain the same as in the original analysis, even as we hold the number of points in the time series constant. The results are therefore robust to the length of the time series.

		(1)	(2)	(3)	(4)	(5)	(6)	(7)
Control Variables	Vintage	0.002*** (0.0001) p = 0.000						
	Number.of.Points		-0.002*** (0.0002) p = 0.000	-0.004*** (0.0002) p = 0.000	-0.004*** (0.0002) p = 0.000	0.004*** (0.0002) p = 0.000	-0.003*** (0.0002) p = 0.000	-0.004*** (0.0002) p = 0.000
Temporal Context	FirstCommercialYr	0.001*** (0.0001) p = 0.000	0.002*** (0.0001) p = 0.000					
Technology Characteristics	log_granularity			-0.007*** (0.001) p = 0.000				
	log_material				-0.013*** (0.002) p = 0.000			
	log_lifetime					-0.028*** (0.004) p = 0.000		
Country Characteristics	Log_GDPavg						0.015*** (0.004) p = 0.0002	
	Capacity_Average							0.029*** (0.005) p = 0.000
	Constant	-5.921***	-2.634***	0.463***	0.359***	0.485***	0.252***	0.403***
		(0.233) p = 0.000	(0.213) p = 0.000	(0.013) p = 0.000	(0.011) p = 0.000	(0.013) p = 0.000	(0.038) p = 0.000	(0.009) p = 0.000
	Observations	1,419	1,419	1,169	1275	1,240	1,592	1,468
	R^2	0.341	0.343	0.281	0.302	0.275	0.269	0.289
	Adjusted R^2	0.340	0.342	0.280	0.301	0.274	0.268	0.288
	Residual Std. Error	0.169 (df = 1416)	0.169 (df = 1416)	0.182 (df = 1166)	0.175 (df = 1272)	0.185 (df = 1,237)	0.170 (df = 1589)	0.169 (df = 1465)
	F Statistic	365.997*** (df = 2; 1416)	369.485*** (df = 2; 1416)	227.605*** (df = 2; 1166)	274.911*** (df = 2; 1272)	234.11*** (df = 2; 1237)	291.82*** (df = 2; 1589)	297.607*** (df = 2; 1465)
		Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$						

Supplementary Table 42. Bivariate linear regressions of the relationship between numerical variables controlling for number of points in time series. Each cell shows the linear regression coefficient estimate between each variable and growth speed. Statistical significance is determined using a two-sided t-test.

C5. Impact of Technology Metric on Growth Rates

We test the relationship between growth rate and the technology metric in the technology time series data. We find that technologies measured in terms of market share are significantly higher than annual production, capacity/power, and number of units (shown in Supplementary Figure 26). The others are not significantly different from one another. The greatest number of technologies are measured in terms of annual production (n = 40) but the number of observations is highest for total number of units (n = 1,034) and market share (n = 315).



n = 315	n = 369	n = 32	n = 1034
Countries = 195	Countries = 116	Countries = 20	Countries = 171
Technologies = 29	Technologies = 40	Technologies = 11	Technologies = 33

*Supplementary Figure 26. Relationship between Type of Metric and Diffusion Speed of Technologies. Box edges show the inter-quartile range, line within box indicates median, solid lines extend from the interquartile range to the nonoutlier minimum or maximum (1.5 * inter-quartile range), and dots indicate outliers.*

If we drop the market share metric from the analysis, our bivariate results are the same with one exception: the type of adopter variable. Individuals and firms do not adopt at a significantly different level when market share technologies are not included (n = 1,435, p = 0.16). Bivariates for each metric and each variable are included in Supplementary Figure 27. The year of first commercialization remains a significant predictor of technology diffusion speed for technologies measured in terms of number of units, capacity, and market share (with more recently commercialized technologies associated with faster growth), but it is not significantly associated with faster technology diffusion speed for technologies measured in terms of annual production (Supplementary Figure 27, panel c).

Supplementary Figure 27. Results of bivariate analysis of each metric and each variable in the analysis. Plots show the estimated linear regression coefficient for each individual bivariate regression. Dots represent the estimated regression coefficients for each variable included in the linear regression analysis. Whiskers denote the 95% confidence intervals calculated through a two-sided t-test. The dashed line shows a null effect. If confidence intervals cross the dotted line, these variables are not significant predictors for logistic fit in the respective model at the 95% confidence level (p < 0.05). Variables that are significantly associated with growth speed at the 95% confidence level are also shown with filled dots and those that are not significantly associated with growth speed are shown with open dots in the coefficient estimates.

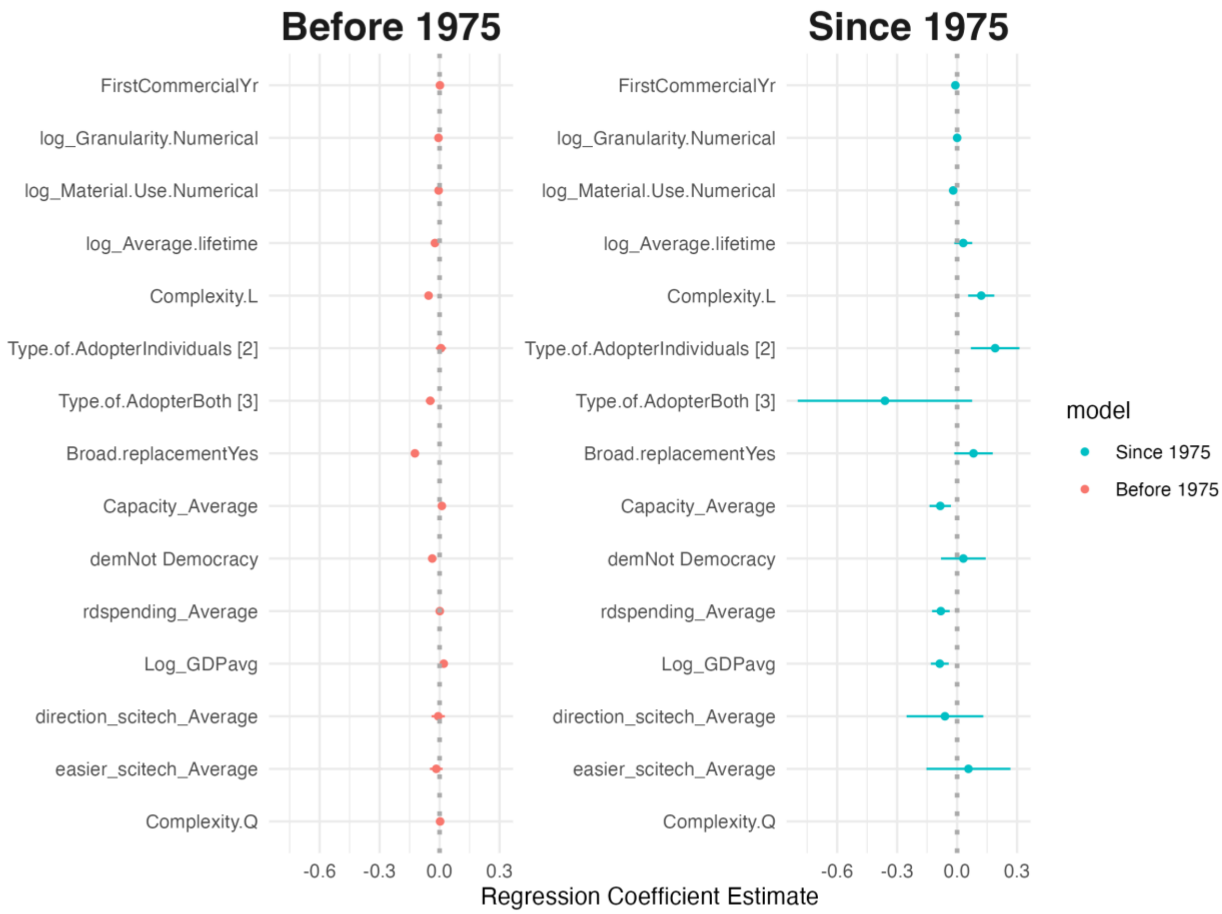
C6. Changing Relationships between Growth Rate and Technology and Country Characteristics Over Time

The HATCH dataset includes technologies from a wide range of time. The earliest technology in the filtered dataset used in this analysis was first commercialized in 1743 (zinc production) and the most recent was first commercialized in 2011 (flywheel battery storage). The year a technology was first commercialized is a robust predictor of growth, with more recently commercialized technologies growing faster than earlier commercialized technologies. Because the dataset includes data across centuries, we also examine the difference between predictor variables for technologies commercialized within the past 50 years (beginning in 1975) and before.

When we filter the dataset in this way, there are only 100 technology-country time series for technologies commercialized in the past 50 years, while the pre-1975 data includes 1,319 time series. We therefore include the findings here because they indicate potential future areas of research focused on technology diffusion in the past 50 years. But, such an analysis would need to either increase the number of technology-country observations included in the past 50 years (either through more specific data gathering efforts or through a different curve fitting exercise that is less strict about a logistic fit) or focus on a different methodology than bivariate correlations and multivariate regressions. The sample sizes are too different to directly compare for a robust finding in the main paper, but the exercise reveals interesting potential changes in the role of technology and country characteristics in different time periods.

The findings of the bivariate analysis are shown in Supplementary Figure 28. We find that since 1975, more recently commercialized technologies have grown slower – a reverse from the relationship found in the whole dataset. Granularity and technology lifetime do not have a significant relationship with growth speed in this time period. More materially intensive technologies are associated with slower growth since 1975, which is the same finding as the entire dataset. Surprisingly, design-intensive technologies (more complex, $p < 0.05$) have grown more quickly in the past 50 years than simple technologies. Technologies adopted by individuals have been adopted faster than those adopted by firms.

We also find that increased state capacity, R&D spending, and GDP per capita are associated with slower growth speed since 1975. This may indicate that more recently, countries with less capacity to pass policies, lower economic development, and lower R&D spending have leapfrogged wealthier countries that have developed policies to encourage innovation and spent money on R&D investment. Again, we caution that these findings are based on far fewer observations than the rest of this analysis, so these results are illustrative of future research directions, rather than robust across large observations. Future studies may focus on the role of country characteristics on technology diffusion in more recent decades, particularly focused on technology growth in the formative phase and differences in earlier and later adopting countries.



Supplementary Figure 28. Bivariate linear regression coefficients for growth speed across time periods. Dots represent the estimated regression coefficients for each variable included in the linear regression analysis. Whiskers denote the 95% confidence intervals calculated through a two-sided t-test. The dashed line shows a null effect. If confidence intervals cross the dotted line, these variables are not significant predictors for logistic fit in the respective model at the 95% confidence level ($p < 0.05$).

Beyond comparing the patterns in these two groups, we also test for heteroskedasticity in the analysis between the speed of diffusion and the year of first commercialization. We find that the residuals increase as the year of first commercialization increases, indicating heteroskedasticity in the analysis (p value in Bruesch-Pagan test < 0.05). In the presence of heteroskedasticity, we use the heteroskedasticity-robust standard errors using the Eicker-Huber-White standard error method and find that when accounting for the heteroskedasticity in the variance, the positive association between year of first commercialization and technology diffusion speed remains significant ($p < 0.05$). Therefore, although we find heteroskedasticity in this relationship, the positive trend remains robust regardless.

C7. Comparing Speed of Diffusion in HATCH with other studies

As a robustness test and benchmarking of the fitting process used in this analysis, we compare the growth rates found from the function fitting in this analysis with historical growth rates of a set of energy technologies in Iyer et al (2015)[26].

The Iyer et al analysis focuses primarily on energy technologies. Of the 38 technologies in the Iyer et al analysis, we found 26 with closely related technologies in the HATCH dataset. We include here a table with the technologies in Table 1 of Iyer et al (2015)[26] as well as the associated technologies in the HATCH dataset. For technologies in the HATCH dataset, we use the median growth speed of all countries for that technology as the logistic growth rate. Then, we calculate the average annual growth rate using the methodology in Iyer et al: growth_rate = 219.7 / ΔT with $\Delta T = \ln(81) / \text{logistic\_growth\_rate}$. After filtering out the technologies in the Iyer et al (2015) dataset for which there is not an associated technology in HATCH, we rank the growth rates by speed of each dataset (shown in the Supplementary Table 43).

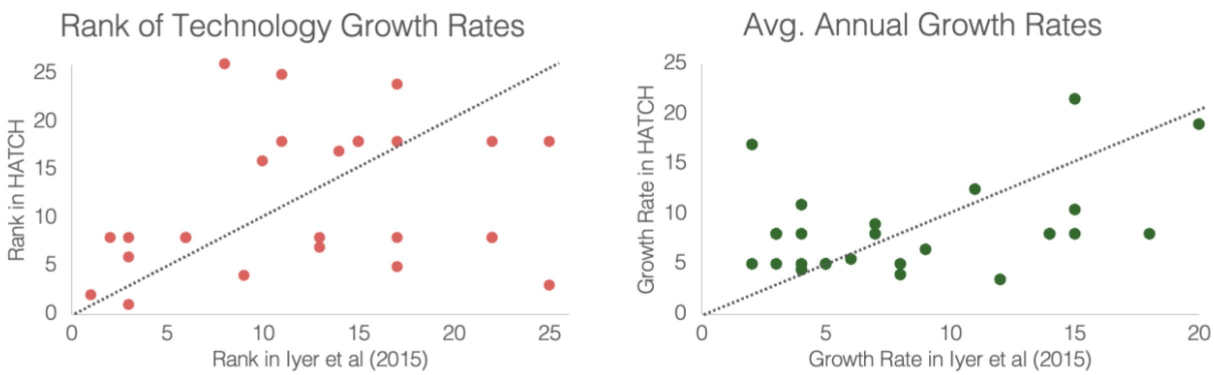
Technology in Iyer et al	Region in Iyer et al	Avg annual growth rate	Rank in Iyer et al	Associated Technology in HATCH	Logistic Growth Rate in HATCH	Calculated avg. annual growth rate	Rank in HATCH
Washing detergent (as a substitute for soap)	USA	24	--	No direct match	--	--	--
Flue gas Desulfurization	USA	15	3	Wet Flue Gas Desulfurization Systems	0.43	21	1
Locomotives	USA, Russia, and UK	18	--	No direct match	--	--	--
Wind Energy	Denmark	20	1	Onshore Wind Energy	0.38	19	2
Transistors in radios (as a substitute for vacuum tubes)	USA	15	--	No direct match	--	--	--
Compact fluorescent lamps	Japan	15	--	No direct match	--	--	--
Bioenergy	Global	2	25	Solid Biofuels	0.34	17	3
Nuclear energy	Global	11	9	Nuclear Energy	0.25	12	4
Aircrafts	Global	4	17	Jet Aircrafts	0.22	11	5
Black and white TV (as a substitute for color TV)	USA	15	3	Television	0.21	10	6
Natural gas power	Global	7	13	Natural Gas Production	0.18	9	7
Car air conditioners	USA	12	--	No direct match	--	--	--
Cars (as a substitute for horses)	USA	18	2	Passenger Cars	0.16	8	8
Basic oxygen steel furnace	USA	11	--	No direct match	--	--	--

Cars (as a substitute for horses)	France	15	3	Passenger Cars	0.16	8	8
Coal and Gas energy	Global	5-10	--	No direct match	--	--	--
Basic oxygen furnace	Global	9	--	No direct match	--	--	--
Automobiles (as a substitute for carriages)	UK	14	6	Passenger Cars	0.16	8	8
Railway track electrification	Russia	8	--	No direct match	--	--	
Cars (as a substitute for horses)	UK and France	14	6	Passenger Cars	0.16	8	8
Oil energy	Global	7	13	Oil Production	0.16	8	8
Air in intercity travel (as a substitute for rail)	USA	8	--	No direct match	--	--	--
Chemical preservation of railway ties	USA	8	--	No direct match	--	--	--
Open-heart steelmaking	USA	4	17	Raw Steel Production	0.16	8	8
Open-heart steelmaking	Global	3	22	Raw Steel Production	0.16	8	8
Cars	Global	3	22	Passenger Cars	0.16	8	8
Electrification of homes	USA	5	--	No direct match	--	--	--
Percentage of houses with radio	USA	9	10	Radio	0.13	6	16
Oil refineries	Global	6	14	Oil refining capacity	0.11	5	17
Mechanization in coal mining	Russia	8	11	Coal Production	0.1	5	18
Railways	France	5	15	Railroad	0.1	5	18
Coal power	Global	5	15	Coal Production	0.1	5	18
Railways	Global	4	17	Railroad	0.1	5	18
Coal (as a substitute for traditional energy)	USA	3	22	Coal Production	0.1	5	18
Coal (as a substitute for traditional energy)	Global	2	25	Coal Production	0.1	5	18
Steam (as a substitute for sail ships)	Global	4	17	Steamships	0.09	4	24
Hydropower	Global	<8	11	Hydroelectricity	0.08	4	25
Air conditioners in homes	Japan	12	8	Home Air Conditioning	0.07	3	26

Supplementary Table 43. Comparison of Growth Rates in Iyer et al 2015[26].

From this analysis, we found the median growth rate from the Iyer et al dataset and the selection of HATCH data that only includes technologies with matches in the Iyer et al dataset is the same (8% growth). The spread of the growth rate in the Iyer et al dataset is greater (5.7 standard deviation) than the selected HATCH dataset (4.6 standard deviation). The average difference between the average annual growth rates in the HATCH dataset and the average annual growth rates in the Iyer et al dataset is 0. The median difference is also 0. Although there is a wide spread of differences (shown in there is no clear bias.

The comparison of these ranks and the annual growth rates is shown in the Supplementary Figure 29, with the dotted line showing a 1:1 relationship between the ranks and average annual growth rates in Iyer et al. and HATCH dataset. We do not see a 1:1 match, but we also do not see a clear pattern. The data in the Iyer et al. dataset is primarily global, or it is focused in one country. We use the median growth rate in HATCH, but generally national growth rates are faster than global growth rates[27] so the comparison is skewed. Additionally, some technologies in Iyer et al. dataset are measured directly as a substitute for a different technology, rather than the growth of that technology generally. This distinction is not present in the HATCH dataset.



Supplementary Figure 29. Comparison of ranking of technology growth speed and average annual growth rates in HATCH dataset and Iyer et al (2015) dataset. Dotted line shows one-to-one relationship between ranks of technology growth rates and average annual growth rates in Iyer et al and HATCH data.

Section D. Extended Discussion of Limitations

The goal of this analysis is to explore patterns of temporal, technology, and country characteristics associated with technology growth speeds across a wide variety of technologies in the HATCH dataset. There are several limitations to this study, some of which are described in the main text. More substantial discussions of some limitations are included here.

D1. Omission of Variables

Technology diffusion is a complicated process that may be impacted by many factors. In this study, we include one temporal characteristic, nine technology characteristics, and five country characteristics. Our analysis is focused on one to four variables per indicator from the Steg et al. framework on the feasibility of climate mitigation options[28]. There are many other variables that could be included in such a broad analysis but are not included for three reasons: first, some are not included if they vary both by country and technology dimensions; second, some are not included because they are only relevant for certain technologies; and third, we rely on publicly available data, so some potential drivers may not be included if there is a lack of data.

Adding more variables may change the results of this analysis. Although we are deliberate in including many characteristics to explore differences in technology diffusion speed, it is not feasible to include all characteristics that may be relevant in the technology diffusion process. The goal of this analysis is to strike a balance between including enough characteristics to explore different hypotheses related to drivers of technology diffusion with including too many characteristics that may be relevant only to some technologies or that are not feasible to include at the scale necessary for this analysis.

D2. Metrics and Measures

This analysis focuses on the patterns that impact speed of technology diffusion across technologies in different countries. It is a quantitative analysis, which requires quantifying technology diffusion to compare speeds across a variety of technologies and markets. Fitting an s-shaped curve onto time series data is a common approach to measuring and comparing technology growth[29], although other metrics and techniques are sometimes used. In Supplementary Table 44, we summarize advantages and disadvantages of a few ways to measure technology diffusion. Many other studies have more deeply discussed different s-curve models[29–32]. For any metric that is derived from fitting a model (linear, exponential, logistic, and Gompertz), an overarching concern is a good model fit. Real-world technology diffusion processes may not exactly fit any of these models; any model is simply an approximation of the diffusion process. None of these metrics can completely capture the process of technology diffusion.

Measure	Advantage	Disadvantage
Linear	Simple model of growth	No theoretical basis in technology diffusion literature.
Exponential	Simple model of growth	Does not include any growth decline or slowing, which does not have a theoretical basis.
Logistic (S-Curve)	The *k* metric is unitless, thus it is comparable across markets and technologies. The logistic curve is the most commonly used diffusion curve across the technology literature[31]	The *k* metric measures the speed of diffusion relative to the asymptote, or ceiling, which varies by technology. Technology diffusion may not always be symmetrical around the inflection point as modelled in the logistic curve[31].
Gompertz (S-Curve)	Compared to a logistic curve, the asymmetric nature of the Gompertz model may fit some time series better, notably if adoption slows in later adopting users (firms or individuals).	The *k* metric measures the speed of diffusion relative to the asymptote, or ceiling, which varies by technology.
Compound annual growth rate (CAGR)	Simple measure of growth, requires less time series data	Not an s-shaped curve, not based in technology diffusion literature. Does not take into account the path of technology diffusion, rather the starting and ending points of growth

Supplementary Table 44. Measures of technology growth.

Ultimately, we chose the *k* metric of the logistic function as the main measure of technology diffusion in this analysis because of the logistic function's widespread use in the technology diffusion literature, the comparability of the *k* metric across technologies and markets, and the ability of an s-shaped model to capture underlying dynamics of technology diffusion that are beyond the scope of more simple models (linear, exponential, and CAGR metrics). We also include a robustness test using the Gompertz model in Supplementary Information Section C1 because of the asymmetrical nature of some technology diffusion process. Although the steepness measure we found using the Gompertz fitting process was generally slower than the logistic function steepness measure, the relationships between the temporal, technology, and country characteristics were the same across both measures.

It is beyond the scope of this analysis to robustly compare different measures and metrics while also analyzing the temporal, technology, and country characteristics that are associated with faster technology diffusion speed. Other studies have more specifically examined the use cases of using different growth metrics and models to measure technology diffusion[29,32,33]. In future work, researchers can go beyond the Gompertz and logistic function to test the temporal, technology, and country characteristics of technology diffusion measured using other models and metrics.

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