ARTICLE IN PRESS

Nature Communications

https://doi.org/10.1038/s41467-026-73563-6

Article in Press

Drivers of technology diffusion speed in countries

Received: 25 November 2024

Accepted: 12 May 2026

[redacted]

Cite this article as: Greene, J.H., Gidden, M.J., Brutschin, E. *et al.* Drivers of technology diffusion speed in countries. *Nat Commun* (2026). https://doi.org/10.1038/s41467-026-73563-6

Jenna H. Greene, Matthew J. Gidden, Elina Brutschin & Gregory F. Nemet

We are providing an unedited version of this manuscript to give early access to its findings. Before final publication, the manuscript will undergo further editing. Please note there may be errors present which affect the content, and all legal disclaimers apply.

If this paper is publishing under a Transparent Peer Review model then Peer Review reports will publish with the final article.

ARTICLE IN PRESS

© The Author(s) 2026. **Open Access** This article is licensed under a Creative Commons Attribution-NonCommercial-NoDerivatives 4.0 International License, which permits any non-commercial use, sharing, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if you modified the licensed material. You do not have permission under this licence to share adapted material derived from this article or parts of it. The images or other third party material in this article are included in the article's Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit http://creativecommons.org/licenses/by-nc-nd/4.0/.

Drivers of Technology Diffusion Speed in Countries

Authors: Jenna H. Greene[1*], Matthew J. Gidden[2,3], Elina Brutschin[3,4], and Gregory F. Nemet[5]
1 Center for Sustainability and the Global Environment, University of Wisconsin-Madison, Madison WI USA
2 Center for Global Sustainability, University of Maryland, College Park, MD, USA
3 International Institute for Applied Systems Analysis (IIASA), Laxenburg, Austria
4 Webster Vienna Private University, Vienna, Austria
5 La Follette School of Public Affairs, University of Wisconsin-Madison, Madison WI USA
* Corresponding Author, jhgreene@wisc.edu

Abstract

Reducing greenhouse gas emissions and limiting global temperature increases require rapid, large-scale technological transitions. Historical trends in technology adoption can inform how quickly such transitions may occur. We analyse the effects of technology and country characteristics on diffusion speed using an expanded Historical Adoption of Technologies (HATCH) dataset, comprising 5,990 national-level time series across 130 technologies and 228 countries. Compared to previous studies, this dataset enables a broader and more integrated assessment of diffusion drivers. We observe substantial variation in growth rates: newer, simpler, more standardised, smaller, less materially intensive, and shorter-lived technologies diffuse more rapidly. These findings suggest that smaller-scale technologies may be adopted faster than complex, large-scale technologies, which may require greater support and longer timeframes for widespread adoption.

Introduction

Limiting global temperature increases to well below 2 degrees and making efforts for 1.5 degrees as set in the Paris Agreement will require the widespread adoption of low-carbon technologies, such as renewable energy technologies, energy efficiency, and carbon dioxide removal methods among others[1]. Meeting these goals requires systems to change, including growth of emerging technologies and the necessary political and institutional shifts required to facilitate such growth[2–5].

These technologies include artifacts like hardware – such as solar panels, wind turbines and batteries – but also can be considered more broadly as interconnected systems of hardware, software, and systems required to meet a goal[6]. This broad definition of technology encompasses transitions in multiple sectors required to meet temperature goals: from agricultural systems to the ways cities are designed to sources of energy generation.

As global carbon budgets are shrinking[7], zero-emissions and negative-emissions technologies must grow quickly to meet global temperature targets, thus the speed of adoption is paramount. Examining past trends of technology diffusion allows us to view history as an observational space available to draw lessons from and therefore understand factors that can encourage faster diffusion speeds[8].

We look to both the technology characteristics and national context to contextualize the growth speeds of technologies implied by integrated assessment model outputs[9], predicted in forecasts[10], or planned for by policymakers. This can also inform studies that focus on feasible targets for climate technology growth[11–16]. In this analysis, we expand on previous studies on technology diffusion by increasing the number of technologies considered and the breadth of technology characteristics considered that may impact diffusion speed.

Innovation literature describes technological growth as following a life cycle in which a technology moves sequentially through distinct phases with feedbacks of knowledge flows to earlier stages across countries[17]. A technology is first developed through a series of innovations, with a substantial innovation marking the start of the lifecycle. This is then followed by a period of uncertainty called a formative phase, in which iterative improvements are made and tested in small, niche markets before commercialization[18–20]. The end of the formative phase is marked when a technology diffuses more broadly into new markets and spreads across populations[19,20]. This widespread growth is known as technology diffusion[21,22]. This period is defined by accelerating growth when new markets and actors choose to adopt the technology followed by slowing growth until an eventual market saturation[6].

Technology diffusion, the period in which a technology has been established but has not yet saturated the market, happens across different temporal scales and spatial scales and occurs in the context of broader social, technological, economic, and institutional systems, all of which affects its diffusion[6]. The speed of this diffusion thus differs by technology and geography[23].

Technology cost is an important factor in technology diffusion[24], but a variety of technological characteristics[25–28], political and institutional factors[29,30], and social factors[31] also impact the speed of technology scale-up. Researchers have emphasized the importance of understanding the varied national contexts and landscapes that may impact the speed of technology diffusion, both historically and in future estimates of growth[23,30]. The adoption context in which a technology grows can influence technology growth in either direction: institutional and political measures can slow growth through regulations, tariffs, or bans and can accelerate growth through incentives or government programs to encourage adoption. Understanding the role of adoption contexts on national-level growth through country characteristics may explain the dispersion of technology diffusion speed at the national level beyond technology characteristics.

Previous studies have focused on a detailed analysis of the growth of a single technology, such as computers[32], or clusters of technologies, such as agricultural technologies[25] or renewable energy technologies[23,30], to understand the role of both technology and national contexts. Fewer studies assess trends in these characteristics across a broad set of technologies[26,28,33] and even those are limited in the number and sectoral range of technologies they consider.

In this study, we analyze trends in the speed of technology diffusion at the national level across a large, heterogenous set of technologies. We pose three research questions: what technological characteristics affect the speed of technology diffusion across a broad set of technologies, what country characteristics affect the speed of technology diffusion across adoption contexts and a wide range of technologies, and are there combinations of technology and country characteristics that affect technology diffusion speeds across a broad set of countries and technologies. To address these questions, we conduct empirical analyses on a broad set of technologies to understand the direction and strength of the effect of technology characteristics, country characteristics, and the combination of the two on technology diffusion speed. While this approach does not identify all the interactions and complex systems that impact technology diffusion, an empirical analysis can identify broad trends across national-level technology growth.

We describe the impact of temporal, technology, and country characteristics on technology diffusion through bivariate analyses and linear regression models for each unique technology-country time series. As technologies move through phases of development, the shape of the adoption over time follows an s-curve shape[17]. The logistic function approximates this path and has been used extensively in empirical analyses of technology diffusion[15,19,20]. We fit a logistic function on each technology adoption time series and use the steepness parameter as a measurement of technology diffusion speed (more details on fitting process in Methods section).

This study builds upon previous literature in two ways. The first is by assessing a large, heterogeneous set of technologies and the second is through examining both technology and country characteristics. We analyze data from the Historical Adoption of Technologies (HATCH) dataset[34], which differs from other datasets assembled both in the number and breadth of technologies included[35]. The heterogenous technologies included is especially relevant for climate mitigation technologies, which are themselves heterogeneous and do not necessarily share common characteristics with one another. Therefore, understanding diffusion speed across a wide set of technologies across many countries can allow us to explore broad drivers of growth that may be relevant for a wide set of mitigation measures.

Second, we combine the temporal context, technology characteristics and country characteristics as indicators of diffusion speed. Researchers have investigated the roles of technology characteristics on technology growth globally[28], typically investigating technologies within the same sector or those replacing one another[23]. In this analysis, we gather, clean, and analyze a set of ten technology characteristics for each of the 130 technologies in the HATCH dataset. This is an expanded dataset that allows for more detailed analysis of the drivers of diffusion speed. The dataset is publicly available for future studies on technology diffusion speed and technology characteristics (see data availability section). The large scale of the dataset, both in terms of the number of technologies and countries included and the number of characteristics in the extended dataset, builds upon previous research on historical technology diffusion and allows for a more expansive analysis in this study.

We use data from the Historical Adoption of Technologies (HATCH) dataset[34]. HATCH is a publicly available dataset, which contains yearly time series data on technology adoption of over 200 technologies at the global and national scale. The HATCH dataset includes a heterogeneous set of technologies, ranging from industrial, agricultural, energy, and digital technologies, for example. The technologies in the HATCH dataset are not necessarily themselves climate technologies, however climate technologies are diverse and cover a wide range of technology categories (further discussed in Supplementary Information Section A1 and Supplementary Table 4).

For this study, we use only technologies with national-level data that contain at least ten data points, which yields n = 5,990 time series consisting of 226,704 data points across 130 technologies and 228 countries. After filtering these time series to ensure quality fits for estimating growth speeds, we use 1,750 time series from 112 technologies for the analysis (see Supplementary Tables 1-3 and Supplementary Figure 1).

The HATCH dataset is an unbalanced panel dataset; each technology does not have the same number of national observations and not all countries have the same number of technologies in the dataset. Figure 1 shows a histogram of these two dimensions. Many technologies in the dataset only have data for one country (n = 42, panel A Figure 1) with a median of 18 countries per technology in the dataset. The United States has the most technologies in the dataset (n = 120, panel B Figure 1). The median number of technologies per country in the dataset is 23 technologies (panel B Figure 1).

Researchers have proposed a framework to assess barriers and enablers of climate mitigation options across multiple dimensions[36]. These dimensions are then operationalized through indicators. While our analysis is focused on a heterogenous set of technologies that do not necessarily mitigate climate change, mitigation technologies themselves are diverse. For example, some climate technologies such as direct air capture with carbon storage may share more characteristics with industrial technologies like ammonia synthesis[37] than with smart thermostats, for example. Although both examples may play a role in reaching climate targets, they may not share many other traits with one another, so it can be useful to look to a wide range of potential historical analogs because the differences amongst mitigation technologies themselves. Further, we hope to gain insight into potential diffusion speed of mitigation technologies using historical lessons through analysis of the HATCH dataset.

For this analysis, we therefore use the feasibility framework from Steg et al[36] along technological, economic, institutional, and socio-cultural dimensions and relevant indicators to understand the relationship between operationalized indicators and diffusion speed of historical technologies at the national level. Table 1 maps the dimensions and indicators from Steg et al[36] with variables that can be measured for technology-country pairs in the HATCH dataset. Because our analysis is focused on historical technology adoption, rather than projecting or predicting future growth, we also add an indicator of temporal context to Steg et al's feasibility framework. We measure temporal context using the year of first commercialization for each technology in the HATCH dataset. This analysis includes nine technology and temporal variables and a control variable of technology category. More details on the predictor variables used in this analysis is included in the Methods section.

Results

We find that technology characteristics explain a larger amount of dispersion in growth rates than country characteristics. We find that recently commercialized technologies grow faster than older technologies as do smaller and cheaper, less materially intensive, and short-lived technologies. The results of the multivariate regression analysis show that several technological and country characteristics significantly impact the speed of technology diffusion, but no combination we analyze explains more than 32% of dispersion of growth speed. The hypothesis and results of the bivariate analysis for each variable is summarized in Table 2 and Supplementary Figure 4.

The steepness parameter used to measure growth speed is unitless and can be difficult to contextualize (see Methods for further discussion). The metric can be transformed into the number of years that it takes to move from the early to later stages of adoption, defined as the growth duration and calculated as the number of years that a technology takes to grow from 10 to 90% of its asymptote (further described in Methods section)[13]. For example, the steepness parameter $k = 0.16$ (the median diffusion speed of the filtered HATCH dataset) corresponds to a growth duration of 27.5 years.

Technology Characteristics

In the HATCH dataset, we observe that more recently commercialized technologies have faster diffusion speeds ($n = 1{,}419$, $p < 0.05$) (Figure 2, panel b). This finding is robust for the median diffusion speed in the dataset (median level of each country for a given technology) ($n = 98$, $p < 0.05$) (Figure 2, panel a). We find heteroskedasticity in this relationship, with residuals increasing with more recently commercialized technologies, but the general trend remains robust despite this heteroskedasticity ($t = 17.84$, $p < 0.05$ using White's robust standard errors). As the first year of commercialization increases by one, the predicted speed of diffusion increases by 0.002. In other words, a technology that is commercialized a decade later than another has a predicted diffusion speed increase of 0.02. In aggregate, the median diffusion speed has increased from 0.10 to 0.61 between 1743 (the earliest commercialized technology in the dataset) and 2011 (the most recently commercialized technology in the dataset). This translates to a difference in median growth duration of 44 years in 1743 to 7.2 years in 2011. Beyond a linear relationship, we also observe a significant quadratic relationship between the year of first commercialization and diffusion speed. Adding a squared term to the model indicates that the most recently commercialized technologies have grown more quickly. An expanded analysis of polynomial approximations is included in Supplementary Information Section B4 and Supplementary Figure 16. This analysis includes technologies commercialized over 268 years: for an analysis more focused on recent dynamics and an extended analysis on heteroskedasticity in this relationship, we include a sensitivity analysis in Supplementary Information Section C6 and Supplementary Figure 28.

Smaller, cheaper technologies that require fewer materials per dollar and a shorter lifetime also grew faster. Granular technologies grew more quickly (n = 1,1169, $p < 0.05$) (Figure 2, panel d), even when only median values of technology growth for each technology is considered (n = 79, $p < 0.05$) (Figure 2, panel c). Technologies with lower material intensity (log of kg per dollar of value) grew more quickly (n = 1,275, $p < 0.05$) (Figure 2, panel f) which is robust when only the median diffusion speed is considered for each technology (n = 87, $p < 0.05$) (Figure 2, panel e). Technologies with shorter lifetimes grew more quickly (n = 1,240, $p < 0.05$) (Figure 2, panel h); this relationship is robust when only median growth speeds for each technology are considered (n = 89, $p < 0.05$) (Figure 2, panel g). Adding a squared term to the model provides a more nuanced understanding of the relationships between granularity and growth speed, as well as material intensity and growth speed. For both characteristics, we find that at a certain level, the relationship flips from negative to positive, indicating that the most expensive and most materially intensive technologies are associated with faster growth speeds than those with slightly lower levels. The model approximation of the relationship between technology lifetime and diffusion speed is not improved with the addition of a squared term. An expanded analysis of the polynomial regression analysis is included in Supplementary Information Section B4 and Supplementary Figure 16.

Complex technologies grew more slowly than simple technologies and design-intensive technologies ($p < 0.05$), which is aligned with our hypothesis (Figure 3, panel a). Customized technologies grew more slowly than standardized and mass-customized technologies ($p < 0.05$), which is also aligned with our hypothesis (Figure 3, panel b). The interaction between complexity and need for customization is not significantly related to growth speed (Supplementary Information Section B2). We also find that technologies grew at different speeds depending on the primary type of adopter. Technologies adopted by individuals grew the fastest ($p < 0.05$) and those adopted by firms grew faster than those adopted by both firms and individuals ($p < 0.05$) (Figure 3, panel c). This is not aligned with our hypothesis that technologies with both firms and individual adopters grew the fastest. Technologies that do not replace an existing technology (but are rather a substantial innovation) grew more quickly than replacing an incumbent technology ($p < 0.05$) (Figure 3, panel d). Finally, technologies that do not require a feedstock grew more quickly than those that do require a feedstock ($p < 0.05$) (Figure 3, panel e). More details of the relationships between each of these variables and growth speed is included in Supplementary Figures 5 – 15 and Supplementary Tables 19 - 31. We also test the interaction of technology characteristics. Based on a typology of low-carbon technologies put forth by Malhotra and Schmidt (2020) wherein technologies are categorized based on complexity and need for customization, we also test the interaction of these two variables[27]. We do not find a significant relationship between the interaction of these variables and technology diffusion speed.

When granularity is held constant, technology diffusion happens more slowly for individuals than firms – changing the direction of the relationship when granularity is not held constant (n = 1,169, $p < 0.05$). We also subdivide the dataset by the primary type of adopter and find that granularity, material intensity, and technology lifetime are not associated with faster growth speeds for technologies that are primarily adopted by firms. We also find that the first year of commercialization is a robust predictor of technology diffusion speed, even when we separately hold granularity, material use, and technology lifetime constant (n = 1,158, n = 1,213, and n = 1,128 (respectively), $p < 0.05$). An extended analysis of the methods and results can be found in Supplementary Information Section B1 and Supplementary Table 32.

Country Characteristics

First, we analyze the relationship between each country characteristic and the speed of diffusion separately through bivariate linear regression analysis (Supplementary Figures 17-24). Spending on research and development has no significant relationship with speed of diffusion, nor does the public acceptance of technology, at the 95% confidence level (described further in section B5 of the Supplementary Information and Supplementary Figures 18 and 19). State capacity and democratic governments are both associated with higher diffusion speeds (Supplementary Figures 20 and 21).

Countries with higher state capacity have faster technology diffusion speeds (n = 1,468, $p < 0.05$). Although the direction of the relationship is significant, numerical state capacity measures only explain 2% of the dispersion of diffusion speeds. We also find that differences in state capacity are not significantly associated with differences in growth speed when we account for the government type of the country (more detailed analysis is included in section B5 of the Supplementary Information and Supplementary Figure 24). This finding suggests that state capacity is not a robust indicator of technology diffusion speed.

We find that technologies in the HATCH dataset grew faster in democracies than in non-democracies ($p < 0.001$). To further investigate this finding, we divide the technologies in the HATCH dataset by their general technology category and compare the growth rates of each category in democracies and non-democracies. While most differences are not significantly different, appliances grew faster in non-democracies (n = 278) than democracies (n = 125, $p > 0.05$) and energy supply technologies grew faster in democracies (n = 189) than in non-democracies (n = 123, $p > 0.05$). However, when we look at individual technologies in each of these categories, the pattern is not robust: in some cases, technologies grow faster in non-democracies than in democracies within these categories and in other cases, there is not enough data in each group to compare the diffusion speed (Supplementary Figures 22 and 23).

These results indicate that the relationship between government type and the speed of technology diffusion is not straightforward, but rather depends on characteristics of specific technologies, further investigated in the multivariate regression analysis.

Combined Effects

After the bivariate analysis with each characteristic and growth speed, we combine these characteristics in multivariate linear regression analysis. We first test the correlation between each numerical explanatory variable and the variance inflation factor of all explanatory variables so that we do not include highly correlated variables in the same multivariate model to avoid multicollinearity (Figure 4).

To build the multivariate regression models, we only include variables that were significant independently in the bivariate regression analysis and avoid adding in more than one categorical variable to avoid overfitting. We do not include GDP per capita and state capacity in the same bivariate because of strong correlation, although both are significant. The reported models in figure 5 show results of combinations of country and technology characteristics.

Year of first commercialization and granularity both remain significant predictors of diffusion speed even when institutional variables are held constant (Figure 5 panels a and b). The time context also remains a robust predictor of technology diffusion speed when granularity, material intensity, and lifetime are held constant separately (Supplementary Information Section B2). When granularity and democracy types are held constant, technologies grow faster in countries with higher state capacity. An increase of one point of the state capacity index is associated with an increase of 0.03 of diffusion speed, when democracy type and granularity are held constant (Figure 5 panel b). Regardless of state capacity, simple technologies grow faster than design-intensive and complex technologies (Figure 4 panel c). When complexity is held constant, an increase of one point of the state capacity index is associated with an increase in 0.04 of diffusion speed (Figure 5 panel c).

The finding that individuals adopt technologies faster than firms, and technologies available in both individual and firm markets grow slower, is robust even when institutional variables are held constant (Figure 5 panel d). Finally, when the size of technologies and institutional variables are held constant, the year of first commercialization remains a significant predictor of diffusion speed (Figure 5 panel e). In these models, R^2 values remain below 32%, meaning that there is still much dispersion of diffusion speeds that cannot be accounted for through these models.

To account for differences in the length of each time series, we also control for the number of points in each time series along with the numerical variables in this analysis (first year of commercialization, granularity, material intensity, technology lifetime, GDP per capita, and state capacity) and find that the relationship for each variable with growth speed stays consistent even when we control for the length of the time series (Supplementary Information Section C4: Supplementary Table 42 and Supplementary Figure 25). This consideration is especially important because of the long span of time that the technologies in HATCH cover.

Discussion

The findings of this study can inform assumptions of technology diffusion used in integrated assessment models, across different scenarios, and for technology forecasts. This can inform the set of technologies that might be most promising to meet temperature goals or suggest technologies that may require additional policy support if they are crucial for these goals. Further, better understanding of the characteristics that are associated with faster and slower growth can help identify the most salient analogous technologies with which to characterize nascent technologies with little of their own empirical data. While the steepness parameter used in this study is not directly used in models, the patterns of temporal, technology, and country characteristics that are associated with relatively faster or slower growth may be further studied and applied to future outlooks of technology diffusion. Assessing the broad and diverse set of technologies in HATCH provides a stronger empirical basis than the more narrow focus on energy technologies we see in previous work. We do find that our energy technology analysis is aligned with previous work. We compare the average annual growth rate in an analysis of the diffusion speed of energy technologies[11] with a subset of HATCH dataset that includes the same technologies. We find that in both data sets, the median average annual growth rate (derived from the logistic steepness parameter calculated for the HATCH dataset) across both datasets is the same, which indicates that the fitting procedure used in this analysis is comparable to other studies (Supplementary Information Section C7).

We find that smaller, cheaper, less materially intensive, shorter-lived technologies diffuse in markets faster than larger, more expensive, materially intensive, long-lived technologies, which is aligned with other studies focused on a smaller set of technologies[28]. We also find that complex technologies and design-intensive technologies grow more slowly, which is also aligned with studies focused on climate technologies[27]. Technologies that are aligned with both of these typologies may have a role in meeting future societal goals, including climate change mitigation.

In addition, we find that more recently commercialized technologies grow more quickly than technologies commercialized earlier. This finding implies that the speed of technology diffusion can be influenced by factors that have changed over time. These may include globalization, increased trade, and knowledge spillovers between countries, although the investigation of these factors is beyond the scope of this analysis.

The adoption context in which a technology diffuses is more complicated. There are specific cases where institutional factors such as the type of government and state capacity may matter, but we do not find robust trends broadly in the dataset. Our analysis focuses on trends over time and cannot analyze specific policy mechanisms for specific technologies. For example, increased state capacity may spur fast diffusion of technologies if policymakers pass policies to eliminate barriers to adoption. On the other hand, regulations can slow the diffusion of technologies if fast growth may threaten other societal goals. Studies that study the impact of specific technologies and their adoption contexts may be able to better capture these nuances.

We generally see that technology characteristics explain more variation than country characteristics. There are many characteristics that may matter for individual technologies but are difficult to get at this level of detail; for example, time between the construction and delivery of products, different financing needs for different technologies, and other economic factors beyond price and GDP. Because the combination of technology characteristics can only explain 32% of dispersion from technology characteristics and even less can be explained when country characteristics are considered, there are likely other factors that matter that are beyond the scope of this analysis and perhaps quite idiosyncratic to adoption contexts in which a particular technology diffuses.

These findings have several implications for climate technologies. First, our findings suggest that more recently commercialized technologies have diffused more quickly than in the past, suggesting that novel climate technologies may benefit from modern systems that have fostered faster technology diffusion. Second, our findings suggest that expensive, large, complex technologies may grow more slowly than cheaper, small, simple technologies. Different climate technologies may have characteristics that align with each of these archetypes. Climate technologies are highly diverse and many technologies with different characteristics will likely still have a role to play in meeting climate targets. For those climate technologies that are expensive, large, and complex, we might expect slower adoption speeds. Therefore, intentional efforts to ready such technologies for market introduction in the near term may facilitate these technologies to reach a climate-relevant level of adoption in the long term. On the other hand, some climate technologies may better align with the characteristics associated with faster growth; such technologies may require robust markets, either for the technology itself or its byproducts, so that demand can increase, and diffusion can occur. These technologies may play an important role in meeting climate targets because of the possibility for faster diffusion. They need a market in which to grow: this may be through niche markets or from demonstration projects in order to spur initial growth, after which fast diffusion may occur. Third, we find a wide range of technology diffusion speeds across countries that are not accounted for by country characteristics broadly. Future research on the role of adoption context and cross-country relationships like trade may elucidate these differences across countries further. Finally, we find that no combination of the characteristics we include in this study explained more than a third of the variation in technology growth rates, which suggests that climate technologies may not follow the patterns of historical technologies, which themselves have diffused differently. Because these characteristics cannot explain the majority of dispersion in growth speed, policy support may play a role in supporting diffusion across different technologies and adoption contexts.

It is important to acknowledge the limitations of this study. There are three main limitations to this study, detailed below: the limitations of focusing on diffusion speed, potential limitations and biases on the data, and limitations of the metrics used to measure technology growth speed and characteristics.

First, the growth speed of climate technologies is one factor that impacts mitigation potential, but not the only factor. For example, if large, complex technologies also have higher potential to reduce emissions or reduce carbon dioxide, then slower growth may have a similar climate impact to faster growth of technologies with lower emission reduction potential. This study does not directly examine climate technology diffusion, but future studies that tie historical technology diffusion to climate technologies should not focus solely on fast growth, but also on the specific mitigation potentials of each climate technologies. Such analyses may also consider the level of market saturation of analogous technologies, while our study focuses on the speed rather than the final extent of technology diffusion.

While the speed of technology diffusion is critical as the climate crisis continues, it is also important to balance fast technology changes with other priorities such as environmental sustainability and equity, as well as costs. Future studies should examine the tensions between these priorities and opportunities for co-benefits of technology adoption.

This analysis focuses on factors that impact technology adoption, which provides insight into historical precedence of technology transitions that may be relevant for increased adoption of novel climate technologies. On the other hand, phasing out fossil fuels is also a key component to meeting climate targets. Recent studies have explored a variety of factors influencing fossil fuel phase out[38]. Future work can focus on pairing the findings in this analysis on technology and country characteristics that impact technology diffusion with those that impact technology phase out to better understand feasibility of both to reach climate targets. We consider technologies independently from one another in this analysis. In practice, the growth of one technology may impact the growth of another. In other analyses and in consideration of climate technology diffusion, this dynamic may be further examined to better understand the role of related technologies on other technologies' diffusion.

Although the HATCH dataset is extensive, there are also limitations associated with the technologies included in the dataset. Historical technologies that we analyze that are included in the HATCH dataset also only include technologies for which we have publicly available adoption data, which biases technologies that were successful in their introduction to market and commercialization. These findings are therefore limited to patterns for technologies that reached this stage, as opposed to examining factors influencing whether a technology was commercialized at all. Because some novel climate technologies are not yet at the commercial stage, these findings do not necessarily indicate whether they will reach that scale. Instead, the patterns we find may provide insights for technology diffusion speeds assuming that these technologies are successful in their commercialization.

The HATCH dataset includes technologies that were commercialized over the span of 268 years. There is a potential bias of older technologies in the dataset also being more complex and radical. This may be because of differences in data collection practices – for example, digitalization and globalization have allowed for more frequent data tracking of recently developed technologies, regardless of how fundamental or complex they are. While we include some analysis of this interaction in Supplementary Information section B3, future studies can explore a subset of the HATCH data further to avoid this potential bias and further test the robustness of our initial insights.

The third set of limitations are related to the metrics used to measure both technology diffusion and the characteristics. In our analysis, we focus on three types of variables that may impact technology adoption: temporal context, technology characteristics, and characteristics of the country in which the technology is adopted. To compare technology adoption speed, we use the steepness parameter of the logistic function fitted onto each technology-country time series. Technology diffusion is a complex process; the number of variables that could be included in such an analysis is vast. We limited variables that either vary by technology or country, but not by both. For example, we do not include patenting activity for each country for the technology sector that matches the technology of interest nor do we gather the solar energy potential in each country specifically for solar PV adoption. Such analyses are useful, but are not feasible for an analysis of this scope with 130 technologies included. In future work, researchers may combine the time series and technology data in the HATCH dataset with variables that vary by both country and technology. Exploring the impact of policy measures on technology diffusion requires gathering data on policies specific to certain technologies that differ by countries that is not feasible at the scale of 5,990 technology-country time series but may be interesting on a smaller scale. Policies play an important role in encouraging technology adoption and regulating its development and future studies may expand our analysis and data to further explore the role of policy changes for different types of technologies, for example.

Further, because our dependent variable is a measure of steepness of the logistic curve, our explanatory variables are time invariant – we cannot measure how changes in a specific technology or country have impacted technology diffusion speed. Time specific dynamics, including the changes in cost of a technology over time, are important to technology diffusion. This is a limitation of our work, but we instead choose to measure the steepness for a direct comparison across a wide range of technologies.

Finally, the diffusion speed metric presents limitations to this analysis. The metric is unitless, which allows for comparability across a wide range of technologies and markets, but is not directly interpretable or usable as a growth rate on its own. Rather, it approximates the steepness of the fitted logistic curve relative to the approximated ceiling of the curve. Deriving a growth rate for a given modelling application requires certain assumptions to be made by the modeler based on the metric used in this, depending on the context represented by the given modelling framework. We include robustness tests and sensitivity analyses of the results based on the measures of technology adoption (Supplementary Information Section C5: Supplementary Figure 26 and 27), the filtering process of the logistic function fits that we include in the analysis (Supplementary Information Section C2-C4), and test an alternative fitting approach using the Gompertz Curve (Supplementary Information Section C1 and Supplementary Tables 33-35). We also include a discussion of other metrics and measures used to study technology diffusion in Supplementary Section D2. In future studies, authors may systematically compare different fitting approaches to measure technology diffusion in the HATCH dataset and examine the patterns associated with those different approaches.

Methods

Data Description

To investigate the inherent characteristics of a technology and characteristics of the market in which the technology is entering, we select indicators aligned with Steg et al's indicators of technological feasibility of mitigation solutions[36]. These include numerical variables (year of first commercialization, granularity, material use, and technology lifetime) and categorical variables (need for customization, complexity, type of adopter, replacement, feedstock requirement, and category). Some of these variables address inherent characteristics of the technology: how they are produced or used (granularity, material use, need for customization, complexity, requirement of a feedstock) and how often adopters make a decision about whether to adopt a technology (technology lifetime). Others describe the market that a technology grows within (type of adopter, replacement, year of first commercialization). Supplementary Table 5 details each variable, hypotheses about the relationship with diffusion speed, metric, source, and a citation for previous research investigating this variable. These data are collected and harmonized by the authors. More details on this data collection are described in Supplementary Section A1 and Supplementary Tables 7-12.

The country characteristics in this analysis are classified into three categories aligned with Steg et al's dimensions of feasibility: economic, institutional, and socio-cultural[36]. The metrics are gathered from publicly available sources. These sources, description of each characteristic, hypotheses on the relationship with growth speed, the metric used to operationalize the variables, and a citation of previous research on the characteristic is included in Supplementary Table 14 and Supplementary Table 15. These metrics cover a different number of countries and range in years of coverage. For our analysis, if multiple metrics are available for measuring the same characteristic, the metric with the most time coverage is selected. These country characteristics vary over time, whereas the response variable of interest in our analysis is time invariant (diffusion speed). To address this, we average the country values from the first year of data until the inflection year for that country-technology pair. For categorical variables, we use the most common value for that same period. Using either the average or mode of a country characteristic gives an indication of that adoption context between the formative and accelerating phase of technology diffusion. More details on this process can be found in Supplementary Information Section A.

For each variable included in our analysis, we provide summary statistics for each in tables 3 and 4. For numerical variables, we report the minimum value, first quartile, median, mean, third quartile, maximum value, and the number of blank values (number of observations with no data on the characteristics). For categorical variables, we report the number of observations per level. The technology characteristics for each technology are reported in Supplementary Table 13.

Measuring Growth

Operationalizing technology diffusion is important to make comparisons between technologies that grew during different time periods, in different markets, and whose data is measured using different metrics. Innovation scholarship in the twentieth century developed a robust finding that new technologies move sequentially through distinct phases in their lifetime: beginning at the time of a technological invention or innovation, followed by a phase of exponential growth until a point at which growth begins to slow until eventual market saturation (this description does not account for technological decline)[17,39]. The movement between these phases and the speed of diffusion results in an s-curve shape to describe technology diffusion[40]. To compare how quickly technologies move between these phases and their eventual market saturation, researchers often fit a logistic function to time series data and extract coefficients of the resulting s-curve (Supplementary Figures 2 and 3)[13,19,20]. The logistic function has been used to measure technology diffusion across sectors, such as in agricultural systems[41], energy technologies[13,42], and industrial systems[16]. Many studies use other functional forms to measure diffusion[43,44], but we use the logistic function because it is the most commonly used across sectors. We also test the robustness of the functional form by adding the Gompertz functional form[23] in the Supplementary Information Section C1.

We assess a growth speed metric for each unique technology-country pair from the time series data in the HATCH dataset. These data vary by the metric (market share, annual production, capacity, and number of units) but the growth metric we use is unitless, allowing us to compare the technology growth to one another. Each technology is only measured using one metric. To assess growth speed from the time series data for each country-technology pair, we fit a logistic function to each time series, which generally approximates the stylized s-curve theorized in innovation literature[17,45]. For each technology-country time series, we fit a logistic function with three free parameters (described in equation 1) using a nonlinear least squares optimization method with specified initial parameters unique to each time series using the curve_fit function in the SciPy Python package[46]. The curve_fit function uses the Levenberg-Marquardt algorithm for the nonlinear least squares optimization. More details on the starting parameters, method, and fitting process are described in Supplementary Information section A2 and Supplementary Tables 16-18. This least squares optimization curve fits generates estimates for three free parameters of the logistic function for each time series, when a fit is successfully found. We specify 5,000 as the maximum number of fit attempts for each time series. More details on the fitting process are described in Supplementary Information section A2. The k parameter found from the fitting process measures the steepness of the logistic function. This is the parameter used to measure speed of diffusion in this analysis.

Other functional forms and growth metrics have been studied, including exponential[15], Gompertz[23], and Bass[43] functions, although none are as extensively studied as the logistic function (further discussed in Supplementary Information Section D2 and Supplementary Table 44).

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

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, which occurs at half of the asymptote's value), and k is the steepness parameter (growth rate for small t).

A successful function fit on a time series does not necessarily imply a good fit or a plausible diffusion speed. To address this, we drop country-technology time series without a good logistic fit following a two-step process. First, after fitting a logistic function on each time series, we measure an R^2 value to quantify the goodness of fit for each time series. We drop any country-technology time series with an R^2 value below 95%[13]. A sensitivity analysis of different filtering levels of R^2 values is included in the Supplementary Information Section C2: Supplementary Tables 36-38. Second, we drop any fit with a k parameter below 0% (as this implies technological decline which is not the focus of this analysis) or above 100% (as this may imply an implausible growth speed). These assumptions are further analyzed in Supplementary Information Section C3: Supplementary Tables 39-41. Through this filtering process, we use 1,555 time series from the total 5,599 time series in the HATCH dataset of national-level technology growth.

The filtering process also attempts to compare time series that follow an s-shaped diffusion pattern, which may not always be the case for technology case. For example, if a technology saturates to one level and then experiences another period of growth and saturation, this might be better approximated through an extended logistic function approximation. Because our study focuses on comparability of technology diffusion, the filtering process allows us to compare technologies with s-curve patterns of diffusion to one another.

We benchmark our extracted k growth parameter with another study that combines 38 technology growth rates[11]. This comparison requires translating the k growth metric to an average annual growth rate through a two-step process, shown in equations 2 and 3. Of the 38 technologies in the growth rate in Iyer et al[11], we find 26 closely related technologies in the HATCH dataset. The median difference in the calculated average annual growth rate between the HATCH dataset and the Iyer et al dataset is 0, which indicates that our approach is not biased faster or slower than other analyses. The median growth speed in the average annual growth rate for both the Iyer et al (2015) data and the selected HATCH data for the matching technologies is the same across both datasets (8%) (see Supplementary Information Section C7: Supplementary Table 43 and Supplementary Figure 29 for full analysis).

$$\Delta T = \ln(81) / k$$

Equation 2. Calculating the number of years to move from 10% to 90% of logistic asymptote5. K is the steepness parameter from the logistic function in equation 1.

$$\text{average annual growth rate} = 219.7/\Delta T$$

Equation 3. Calculating the average annual growth rate based on the number of years it takes for a technology to go from 10 – 90% of the logistic asymptote[15].

One advantage of using the steepness metric derived from a logistic function is that it is unitless, which allows us to compare diffusion speeds across a diverse set of technologies that are measured with different metrics across many different markets. However, inherent in this approach is the assumption that a given technology in a given market follows logistic (or similar) growth, a foundational assumption in the technological diffusion literature[17]. The downside of using a unitless steepness parameter is that the metric itself can be difficult to contextualize, requiring additional interpretation for its application in certain modelling and policy-making contexts. It in any case allows researchers to generate relevant insight, especially about relative growth across different technologies.

Analysis

Our analysis proceeds in two parts. The first is an investigation of the independent relationship between the growth speed of each country-technology time series with each technology and country characteristic. For each numerical technology and country variable, a linear regression tests the predicted relationship between the speed of diffusion and each characteristic (described in equations 4 and 5) and the resulting p-value indicates the significance of that relationship. These results allow us to test the plausibility of the hypotheses described in Supplementary Tables 5 and 15 and the direction of each relationship.

$$\text{speed}_{ij} = \beta_0 + \delta_i x + \varepsilon_{ij}$$

Equation 4. Multivariate regression equation, where i is a country, j is a technology, $\beta_0$is a constant, and δ_i is the value of the country characteristic.

$$\text{speed}_{ij} = \beta_0 + \alpha_j c + \varepsilon_{ij}$$

Equation 5. Multivariate regression equation, where i is a country, j is a technology, $\beta_0$is a constant, and $\alpha_j$is the value of the technology characteristic.

For categorical variables, we use Kruskal-Wallis tests to assess whether there are differences in the mean growth rates of the different categories. If there are more than two categories, we then use a Dunn's Multiple Comparison Test as a post-hoc test to assess which groups have significantly different diffusion speeds from the other.

The second part focuses on combining different technology characteristics, country characteristics, and a combination of the two to test the robustness of relationships and the predictive power of multiple variables on growth speed. We assess the relationship between these variables through multivariate linear regression described in equation 6.

$$\text{speed}_{ij} = \beta_0 + \delta_i x + \alpha_j c + \varepsilon_{ij}$$

Equation 6. Multivariate regression equation, where i is a country, j is a technology, $\beta_0$is a constant, δ_i is the value of the country characteristic, and $\alpha_j$is the value of the technology characteristic for the country-technology time series.

Data Availability

The extended HATCH 1.5 dataset used in this study are available in the Zenodo database under accession code https://doi.org/10.5281/zenodo.10231865.

Code Availability

Code used to develop this analysis is available at https://github.com/jennagreene22/National_Technology_Diffusion.

References

1. Summary for Policymakers. in *Climate Change 2022 - Mitigation of Climate Change* (ed. Intergovernmental Panel On Climate Change) 3–48 (Cambridge University Press, 2023). doi:10.1017/9781009157926.001.
2. Geels, F. W. From sectoral systems of innovation to socio-technical systems. *Res. Policy* **33**, 897–920 (2004).
3. Grübler, A., Wilson, C. & Nemet, G. Apples, oranges, and consistent comparisons of the temporal dynamics of energy transitions. *Energy Res. Soc. Sci.* **22**, 18–25 (2016).
4. Smil, V. Examining energy transitions: A dozen insights based on performance. *Energy Res. Soc. Sci.* **22**, 194–197 (2016).
5. Sovacool, B. K. How long will it take? Conceptualizing the temporal dynamics of energy transitions. *Energy Res. Soc. Sci.* **13**, 202–215 (2016).
6. Grübler, A. Diffusion: Long-term patterns and discontinuities. *Technol. Forecast. Soc. Change* **39**, 159–180 (1991).
7. Lamboll, R. D. *et al.* Assessing the size and uncertainty of remaining carbon budgets. *Nat. Clim. Change* **13**, 1360–1367 (2023).
8. Grübler, A. Energy transitions research: Insights and cautionary tales. *Energy Policy* **50**, 8–16 (2012).

9. Jaxa-Rozen, M. & Trutnevyte, E. Sources of uncertainty in long-term global scenarios of solar photovoltaic technology. *Nat. Clim. Change* **11**, 266–273 (2021).
10. Creutzig, F. *et al.* The underestimated potential of solar energy to mitigate climate change. *Nat. Energy* **2**, 17140 (2017).
11. Iyer, G. *et al.* Diffusion of low-carbon technologies and the feasibility of long-term climate targets. *Technol. Forecast. Soc. Change* **90**, 103–118 (2015).
12. Kazlou, T., Cherp, A. & Jewell, J. Feasible deployment of carbon capture and storage and the requirements of climate targets. *Nat. Clim. Change* **14**, 1047–1055 (2024).
13. Wilson, C., Grubler, A., Bauer, N., Krey, V. & Riahi, K. Future capacity growth of energy technologies: are scenarios consistent with historical evidence? *Clim. Change* **118**, 381–395 (2013).
14. Hanna, R., Abdulla, A., Xu, Y. & Victor, D. G. Emergency deployment of direct air capture as a response to the climate crisis. *Nat. Commun.* **12**, 368 (2021).
15. Odenweller, A., Ueckerdt, F., Nemet, G. F., Jensterle, M. & Luderer, G. Probabilistic feasibility space of scaling up green hydrogen supply. *Nat. Energy* **7**, 854–865 (2022).
16. Van Ewijk, S. & McDowall, W. Diffusion of flue gas desulfurization reveals barriers and opportunities for carbon capture and storage. *Nat. Commun.* **11**, 4298 (2020).
17. Rogers, E. M. *Diffusion of Innovations*. (Free Press of Glencoe, New York, 1962).
18. Bento, N., Wilson, C. & Anadon, L. D. Time to get ready: Conceptualizing the temporal and spatial dynamics of formative phases for energy technologies. *Energy Policy* **119**, 282–293 (2018).
19. Bento, N. & Wilson, C. Measuring the duration of formative phases for energy technologies. *Environ. Innov. Soc. Transit.* **21**, 95–112 (2016).
20. Wilson, C. Up-scaling, formative phases, and learning in the historical diffusion of energy technologies. *Energy Policy* **50**, 81–94 (2012).

21. Grübler, A. *Technology and Global Change*. (Cambridge University Press, 1998). doi:10.1017/CBO9781316036471.
22. Keller, W. International Technology Diffusion. (2001).
23. Cherp, A., Vinichenko, V., Tosun, J., Gordon, J. A. & Jewell, J. National growth dynamics of wind and solar power compared to the growth required for global climate targets. *Nat. Energy* **6**, 742–754 (2021).
24. Rubin, E. S., Azevedo, I. M. L., Jaramillo, P. & Yeh, S. A review of learning rates for electricity supply technologies. *Energy Policy* **86**, 198–218 (2015).
25. Batz, F.-J., Peters, K. j. & Janssen, W. The influence of technology characteristics on the rate and speed of adoption. *Agric. Econ.* **21**, 121–130 (1999).
26. Comin, D. & Hobijn, B. Cross-country technology adoption: making the theories face the facts. *J. Monet. Econ.* **51**, 39–83 (2004).
27. Malhotra, A. & Schmidt, T. S. Accelerating Low-Carbon Innovation. *Joule* **4**, 2259–2267 (2020).
28. Wilson, C. *et al.* Granular technologies to accelerate decarbonization. *Science* **368**, 36–39 (2020).
29. Brutschin, E., Cherp, A. & Jewell, J. Failing the formative phase: The global diffusion of nuclear power is limited by national markets. *Energy Res. Soc. Sci.* **80**, 102221 (2021).
30. Vinichenko, V., Jewell, J., Jacobsson, J. & Cherp, A. Historical diffusion of nuclear, wind and solar power in different national contexts: implications for climate mitigation pathways. *Environ. Res. Lett.* **18**, 094066 (2023).
31. Wüstenhagen, R., Wolsink, M. & Burer, M. J. Social Acceptance of Renewable Energy Innovation: An Introduction to the Concept. *Energy Policy* 2683–2691 (2007) doi:10.1016/j.enpol.2006.12.001.

32. Caselli, F. & Coleman, W. J. Cross-Country Technology Diffusion: The Case of Computers. *Am. Econ. Rev.* **91**, 328–335 (2001).
33. Comin, D. & Hobijn, B. An Exploration of Technology Diffusion. *Am. Econ. Rev.* **100**, 2031–2059 (2010).
34. Nemet, G., Greene, J., Zaiser, A. & Hammersmith, A. Historical Adoption of Technologies (HATCH) Dataset. Zenodo https://doi.org/10.5281/zenodo.10231865 (2023).
35. Comin, D. & Hobijn, B. *The CHAT Dataset*. w15319 http://www.nber.org/papers/w15319.pdf (2009) doi:10.3386/w15319.
36. Steg, L. *et al.* A method to identify barriers to and enablers of implementing climate change mitigation options. *One Earth* **5**, 1216–1227 (2022).
37. Roberts, C. & Nemet, G. Lessons for scaling direct air capture from the history of ammonia synthesis. *Energy Res. Soc. Sci.* **117**, 103696 (2024).
38. Xie, J. J., Brutschin, E., Rogelj, J. & Staffell, I. Past socio-political transitions away from coal and gas show challenges and opportunities ahead. *Environ. Res. Lett.* https://doi.org/10.1088/1748-9326/add0c6 (2025) doi:10.1088/1748-9326/add0c6.
39. Rogers, E. M. Categorizing the adopters of agricultural practices. *Rural Sociol.* **23**, 345–354 (1958).
40. Geroski, P. A. Models of technology diffusion. *Res. Policy* **29**, 603–625 (2000).
41. Griliches, Z. Hybrid Corn: An Exploration in the Economics of Technological Change. *Econometrica* **25**, 501–522 (1957).
42. van Vuuren, D. P. *et al.* Alternative pathways to the 1.5 °C target reduce the need for negative emission technologies. *Nat. Clim. Change* **8**, 391–397 (2018).
43. Zielonka, N., Wen, X. & Trutnevyte, E. Probabilistic projections of granular energy technology diffusion at subnational level. *PNAS Nexus* **2**, pgad321 (2023).

44. Nemet, G., Greene, J., Müller-Hansen, F. & Minx, J. C. Dataset on the adoption of historical technologies informs the scale-up of emerging carbon dioxide removal measures. *Commun. Earth Environ.* https://doi.org/10.1038/s43247-023-01056-1 (2023) doi:10.1038/s43247-023-01056-1.
45. Grübler, A., Nakićenović, N. & Victor, D. G. Dynamics of energy technologies and global change. *Energy Policy* **27**, 247–280 (1999).
46. Virtanen, P. *et al.* SciPy 1.0: fundamental algorithms for scientific computing in Python. *Nat. Methods* **17**, 261–272 (2020).
47. Akinwande, M. O., Dikko, H. G. & Samson, A. Variance Inflation Factor: As a Condition for the Inclusion of Suppressor Variable(s) in Regression Analysis. *Open J. Stat.* **05**, 754 (2015).

Funding

This work received funding from the European Union’s Horizon 2020 research and innovation programme under the European Research Council (ERC) Grant Agreement No. 951542-GENIE-ERC-2020-SyG,“GeoEngineering and NegatIve Emissions pathways in Europe” (GENIE) (J.H.G., M.J.G., E.B., G.F.N.). This work was developed through the 2023 Young Scientists Summer Program, with financial support from the National Academies of Sciences and funding for continued collaboration between University of Wisconsin – Madison and IIASA from Wes and Anke Foell (J.H.G).

Author Contributions

J.H.G.: conceptualization; methodology; analysis; data curation; software; visualization; writing – original draft; writing – review and editing
M.J.G.: conceptualization; writing – review and editing; supervision
E.B.: conceptualization; writing – review and editing; supervision
G.F.N.: conceptualization; methodology; writing – review and editing; supervision; funding acquisition

Competing Interests

The authors declare no competing interests.

Tables

Type	Dimension	Indicators (from Steg et al 2022)	Variables
Technology Characteristics	Technological	Simplicity	• Complexity • Need for customization • Granularity
		Scalability	• Material use • Technological lifetime • Replacement • Feedstock • Type of adopter
Temporal Context		Maturity and technology readiness	• First year of commercialization
Country Characteristics	Economic	Economic development	• Income group • Log GDP per capita
		Spending on technology development	R&D spending as % of GDP
	Institutional	Institutional Capacity	State capacity
		Governance Structures	Polity index (dem, not dem)
	Socio-cultural	Public acceptance	Responses to World Value Survey: • Science/Technology making life better • Science/Technology making life easier

Table 1. Dimensions of Feasibility. Includes the metrics used in this analysis used to operationalize feasibility indicators in the HATCH dataset.

Characteristic Type	Variable	Hypothesis	Expected direction	Direction found
Temporal	First year of commercialization	Later years of first commercialization will be associated with faster growth than earlier.	Positive	Positive
Technology	Technological Lifetime	Shorter technological lifetimes will be associated with faster growth than longer lifetimes.	Negative	Negative
	Material Use	Low material intensity will be associated with faster growth than high material intensity.	Negative	Negative
	Granularity	Lower price and size (highly granular) will be associated with faster growth.	Negative	Negative
	Complexity	Simple will be associated with faster growth than more complex.	Negative	Negative*
	Need for Customization	Less need for customization will be associated with faster growth than more.	Negative	Negative*
	Type of Adopter	Individuals will adopt more quickly than firms, but technologies available to both firms and individuals will benefit from multiple markets.	Positive	Negative/ Mixed
	Requires Feedstock	No feedstock requirement will allow for faster growth.	Negative	Negative
	Replacement	Replacing an existing technology will allow for faster growth.	Positive	Negative
	Category	Control variable.	--	--
Country	Economic development	Countries with higher income per capita are associated with faster technology adoption through more available resources.	Positive	Positive
	Spending on technology development	More spending on technological R&D associated with faster technology adoption.	Positive	Not significant
	Type of government	Democracies allow for faster growth of technologies, whereas non-democracies experience slower technology adoption.	Positive	Positive
	Institutional capacity to pass, support, coordinate policies	For large, non-industrial technologies, higher state capacity is associated with faster growth.	Positive	Positive
	Public acceptance of technology	Higher public acceptance for science and technologies allows for faster technology adoption.	Positive	Not significant

*Table 2. Findings of Bivariate Regressions with Technology and Country Characteristics. Direction of the relationship between each variable and the growth speed found through bivariate regression compared to the hypothesis and expected direction from that hypothesis. *While the results for these categorical variables have mixed statistical significance, the direction between the first and last level are significant and used to determine the direction found.*

Type	Variable	Min	First Quartile	Median	Mean	Third Quartile	Max	NA Values
Technology	Year of first commercialization	1743	1877	1887	1900	1936	2011	N = 331
	Granularity (log)	0.62	5.72	7.12	9.90	13.66	25.76	N = 581
	Material use (log)	-12.13	-3.59	-3.01	-3.24	-1.59	6.52	N = 475
	Lifetime (log)	-2.08	1.87	2.71	2.36	3.31	4.28	N = 510
Country	R&D Spending	0.01	0.27	0.63	0.99	1.59	4.31	N = 955
	WVS Response: “Technology makes life better”	3.8	6.28	6.82	6.72	7.3	8.84	N = 1,354
	WVS Response: “Technology makes life easier”	1.97	6.64	6.99	7.03	7.59	8.91	N = 1,354
	State capacity	-1.40	-0.19	0.41	0.54	1.30	2.89	N = 282
	GDP per capita (log)	6.34	7.94	8.8	8.8	9.59	11.21	N = 158

Table 3. Summary statistics for temporal context and technology characteristics.

Type	Variable	Level	Count	Min	First Quartile	Median	Mean	Third Quartile	Max
Technology	Need for Customization	Standardized	1,011	0.03	0.11	0.19	0.26	0.35	0.98
		Mass-Customized	221	0.03	0.11	0.19	0.26	0.34	0.96
		Customized	505	0.02	0.07	0.11	0.16	0.19	1.00
		NA	13	--	--	--	--	--	--
	Complexity	Simple	779	0.02	0.12	0.19	0.26	0.33	0.97
		Design-Intensive	472	0.03	0.10	0.15	0.25	0.34	0.98
		Complex	499	0.03	0.07	0.12	0.18	0.21	1.00
	Type of Adopter	Firms	472	0.02	0.10	0.16	0.23	0.28	0.96
		Individuals	659	0.03	0.13	0.22	0.29	0.38	0.98
		Both	619	0.03	0.08	0.12	0.18	0.19	1.00
	Replacement	Yes	914	0.02	0.09	0.13	0.19	0.20	1.00
		No	836	0.03	0.12	0.22	0.28	0.38	0.97
	Feedstock	Yes	487	0.03	0.09	0.12	0.17	0.18	0.95
		No	983	0.03	0.10	0.17	0.26	0.36	1.00
		NA	280	--	--	--	--	--	--
	Category	Appliances	436	0.03	0.09	0.13	0.22	0.22	0.98
		Chemicals and Industrial	45	0.06	0.11	0.15	0.18	0.20	0.94
		Digitalization	197	0.11	0.21	0.26	0.29	0.35	0.95
		Energy Supply	341	0.03	0.13	0.26	0.33	0.47	1.00
		Food and Health	224	0.03	0.12	0.20	0.29	0.40	0.97
		Infrastructure	213	0.02	0.05	0.08	0.09	0.11	0.41
		Materials	35	0.06	0.09	0.16	0.26	0.29	0.96
		Sea and Water	61	0.03	0.11	0.17	0.20	0.24	0.65
		Space and Defense	23	0.05	0.06	0.09	0.12	0.13	0.36
		Storage Technology	11	0.08	0.13	0.16	0.28	0.32	0.86
		Transportation	164	0.04	0.09	0.12	0.15	0.16	0.66
Country	Economic Level	High	978	0.03	0.10	0.18	0.25	0.35	1.0
		Low	490	0.03	0.10	0.15	0.21	0.24	0.98
		NA	282	--	--	--	--	--	--
	Government Type	Democracy	606	0.03	0.1	0.21	0.28	0.39	0.98
		Non-Democracy	935	0.03	0.10	0.14	0.20	0.24	1.0
		NA	209	--	--	--	--	--	--

Table 4. Summary statistics for categorical technology and country variables.

Figure Legends

Figure 1. Histograms of the frequency of countries and technologies in the HATCH dataset. Panel a shows the number of countries for each technology in the HATCH dataset and panel b shows the number of technologies for each country in the HATCH dataset.

Figure 2. Numerical Technology Characteristics and Diffusion Speed of Technologies. Panels b, d, f, and h show the association between each technology characteristic and the diffusion speed, with the distributions shown on the outside of the scatter plot as histograms (p-values for the association between each variable and growth speed are 0.002, -0.010, -0.017, and -0.039, respectively). Panels a, c, e, and g display the median growth speed of each technology across all countries in the dataset for that technology, which tests whether the bivariate results are biased toward technologies with more country observations (p-values for the association between each variable and growth speed are 0.001, -0.007, -0.021, and -0.031, respectively). Gray points display technologies with fewer than ten countries, whereas non-gray points are technologies with more than ten countries (shown in the legend). The solid brown line displays the predicted values given from the bivariate regression results. Text in each panel shows the R^2 *value of that fit and the number of observations.*

*Figure 3. Categorical Technology Characteristics and Diffusion Speed of Technologies. Panels a-e show boxplots of diffusion speed across categorical technology characteristics. Each boxplot compares the distribution of the speed of technology diffusion between the categories. Panel a shows levels of complexity, panel b shows levels of customization needs, panel c shows types of adopters, panel d shows the classification of technology replacement, and panel e shows whether the technology requires a feedstock. 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. All box plots in this analysis use the same ranges for display. Text below each box display the number of observations, the number of unique countries, and the number of unique technologies for each category. Statistical significance is determined through a two-sided Dunn test that compares the distribution of diffusion speeds between the categories (shown above brackets if significant; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; blank indicates these groups are not significantly different). More details on the analysis, including exact p-values, are included in Supplementary Tables 19, 21, 24, 26, and 29.*

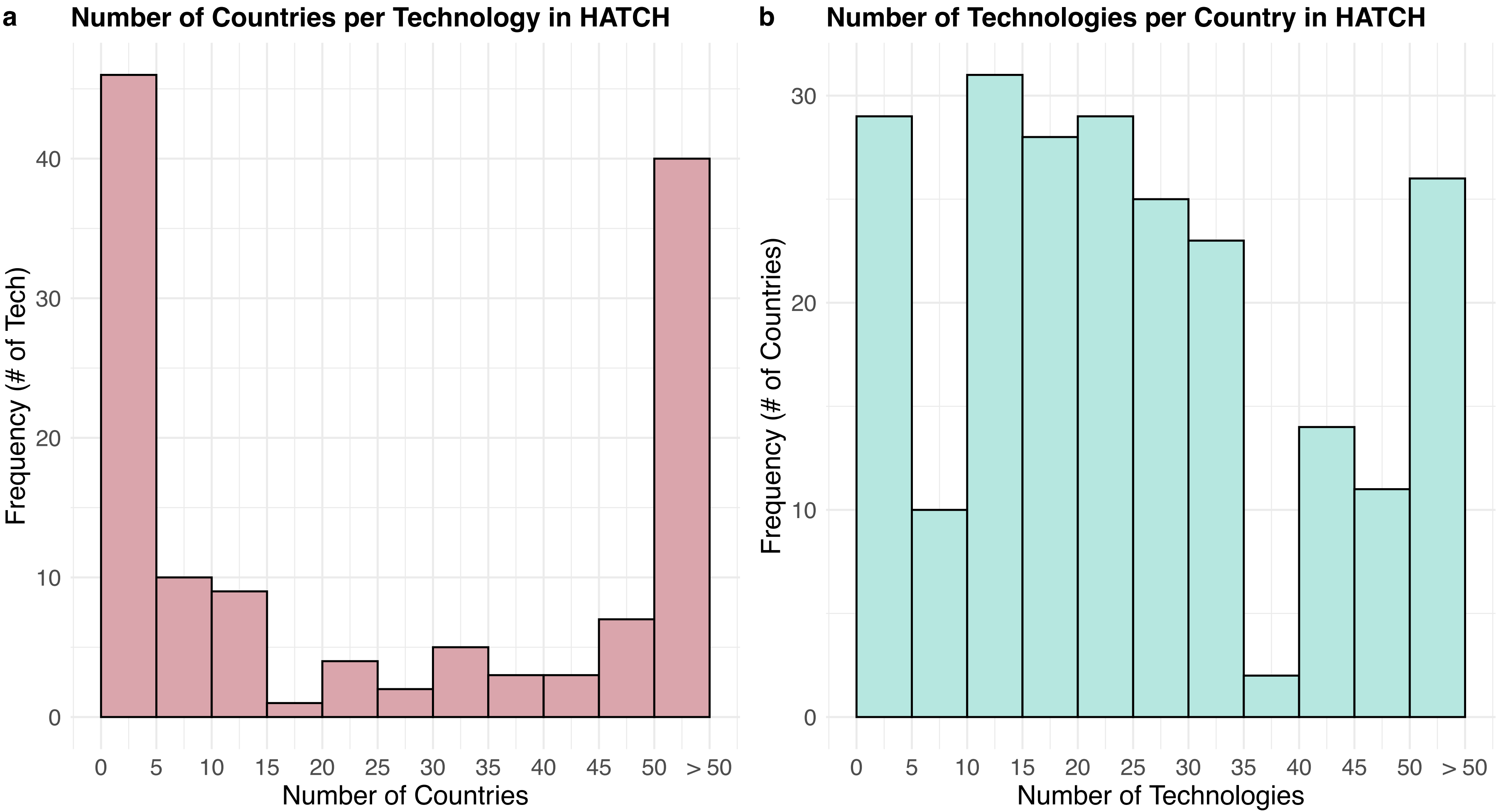
Figure 4. Independent variable correlation plots. In panel a, more saturated colors indicate higher correlation between explanatory variables and the Pearson correlation coefficient between each set of explanatory variables is reported in each square. Shades of red indicate a negative association and shades of blue indicate a positive association between variables. Variables with greater than 0.7 are considered at risk of introducing multicollinearity and are thus not included in the same model. In panel b, the Variance Inflation Factor is reported for each variable as a measure of multicollinearity between variables when all are used in a model. A VIF between 5 and 10 indicates high correlation with other predictors and above 10 is not used in a model to avoid multicollienarity[47]*.*

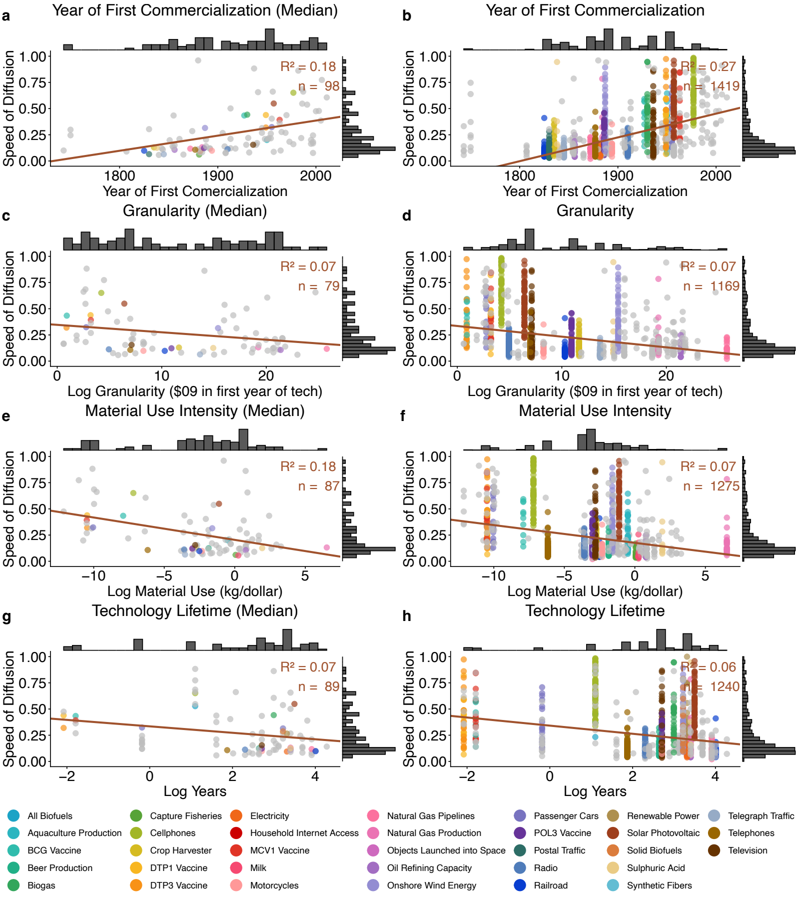
Figure 5. Multivariate linear regression coefficients for growth speed. Each panel shows the regression coefficients of the estimated effect of each independent variable on growth speed in a multivariate linear regression model. For all panels, the following specifications apply. Dots and whiskers shown in blue display country characteristics and pink shows temporal or technology characteristics. 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 ($p < 0.05$). Panels a, b, and d display the results of multivariate linear regression models that include the estimated effect of one technology or temporal characteristic (year of first commercialization, granularity, and type of adopter, respectively) as well as state capacity and type of government on growth speed. Panel c shows the estimated effect of technological complexity and state capacity on growth speed. Panel e shows the estimated effect of year of first commercialization, granularity, state capacity, and type of government on growth speed.

Editorial Summary

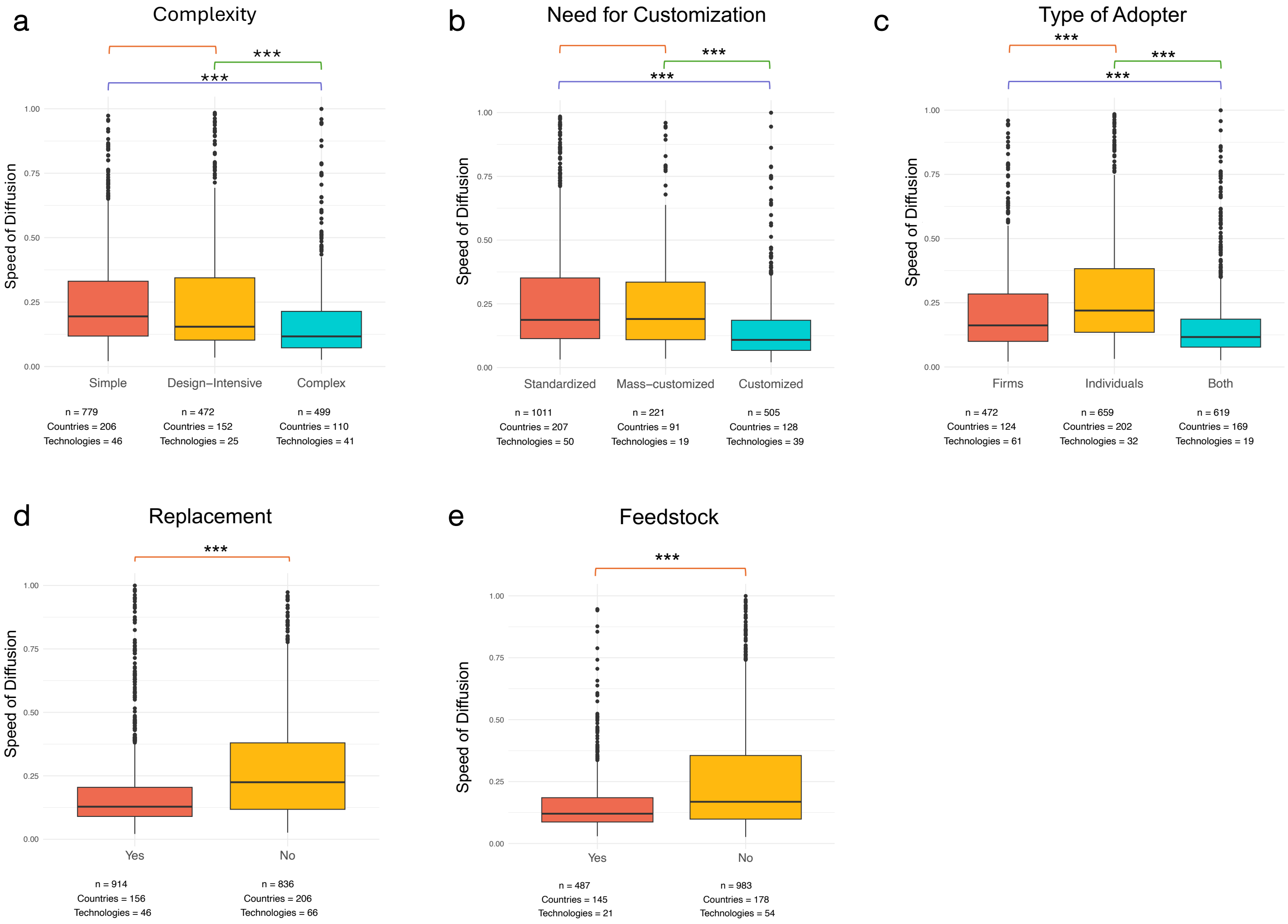
National-level technology diffusion rates vary substantially across 130 technologies and 5,990 time series. Newer technologies, as well as smaller, less materially intensive, and shorter-lived technologies, tend to be adopted more quickly.

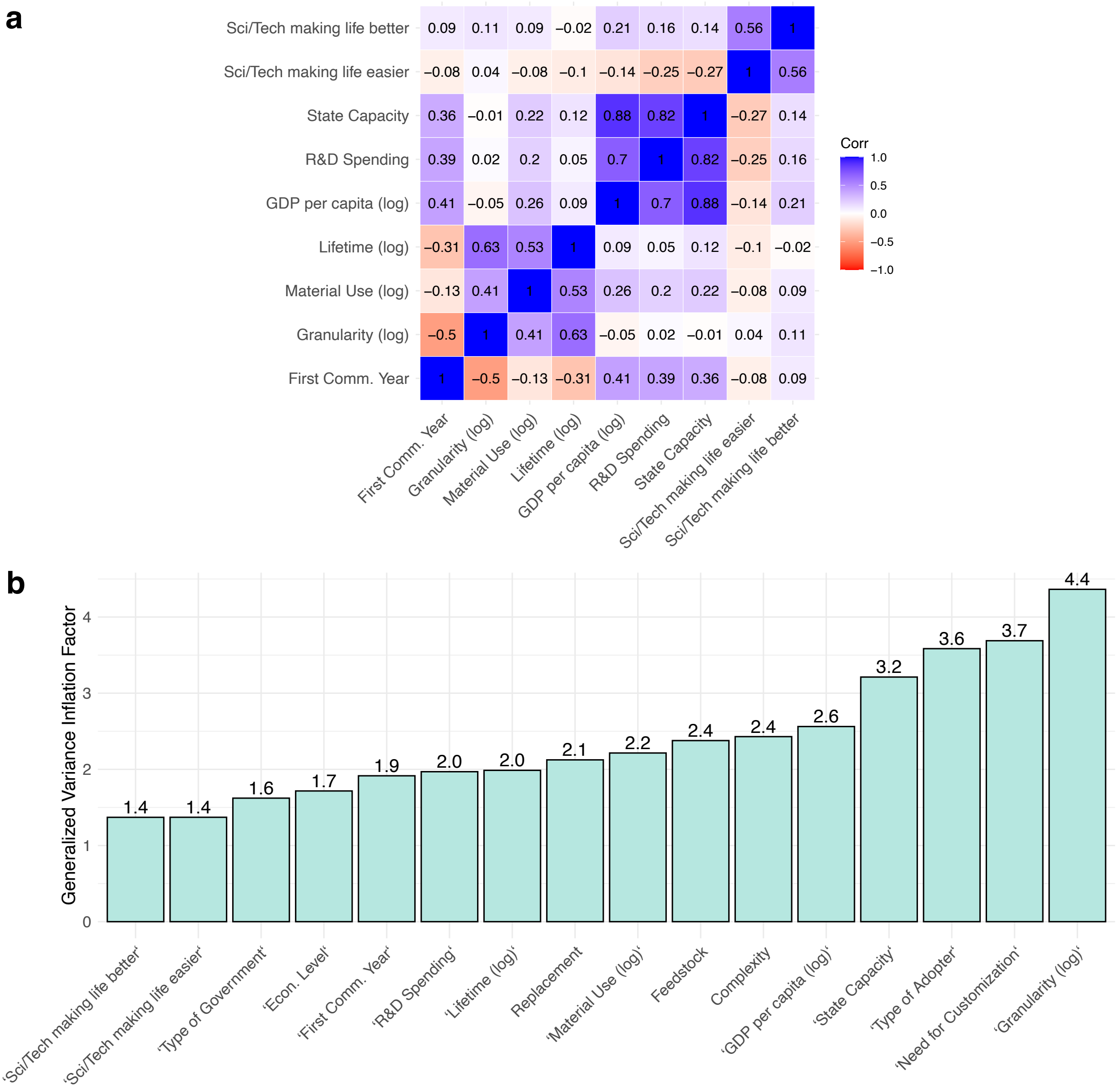
Peer Review Information: *Nature Communications* thanks Nuno Bento and the other, anonymous, reviewer(s) for their contribution to the peer review of this work. A peer review file is available.


a
Number of Countries per Technology in HATCH
Frequency (# of Tech)
0
10
20
30
40
0
5
10
15
20
25
30
35
40
45
50
> 50
Number of Countries
b
Number of Technologies per Country in HATCH
Frequency (# of Countries)
0
10
20
30
0
5
10
15
20
25
30
35
40
45
50
> 50
Number of Technologies

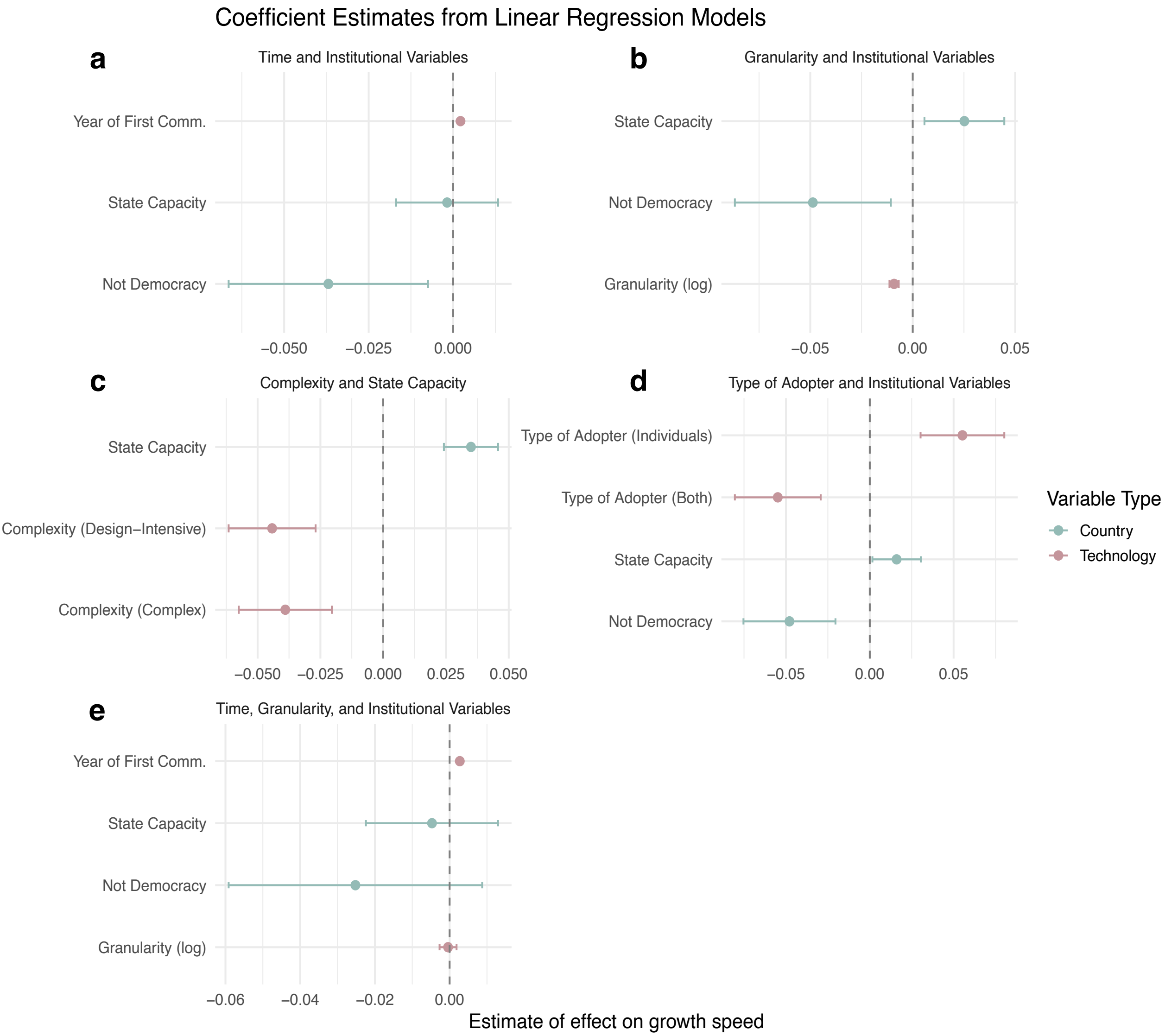


● Ammonia Synthesis, Cable TV, Cadmium Refining, Canals, Cane Sugar, Coal Production, Copper Mining, Copper Refining, Crude Oil, Dishwashers, Disk Brakes, Electric Bicycles, Ethanol, Flush Toilet, Flywheel Battery Storage, Freezer, Geothermal Energy, Gold, Ground Source Heat Pumps, HEPB3 Vaccine, HEPBB Vaccine, HIB3 Vaccine, Herbicide-Tolerant Corn, Herbicide-Tolerant Cotton, Herbicide-Tolerant Soybeans, High Speed Rail, Home Air Conditioning, Home Computers, Hydrochloric Acid, Hydroelectricity, Insect-Resistant Corn, Insect-Resistant Cotton, Iron Ore, Jet Aircraft, Laundry Dryers, Lead, Lead-Acid Battery Storage, Liquefied Natural Gas, MCV2 Vaccine, Marine Energy, Microcomputers, Microwaves, Nickel, Nitric Acid, Nitrogen Fertilizer, Nox Pollution Controls (Boilers), Nuclear Energy, Nuclear Weapons, Offshore Wind Energy, Oil Pipelines, Oil Production, PCV3 Vaccine, Phosphate Fertilizer, Podcasting, Potash Fertilizer, Power Steering, Primary Aluminum Production, Primary Bauxite Production, Public Roads, Pumped Hydro Storage, RCV1 Vaccine, ROTAC Vaccine, Raw Steel Production, Real-Time Gross Settlement Adoption, Refrigerators, Salt Production, Sensible Heat Storage, Shale Production, Silver, Social Media Usage, Sodium-Based Battery Storage, Steamships, Stove, Washing Machines, Wet Flue Gas Desulfurization Systems, YFV Vaccine, Zinc


a
Complexity
***
***
Speed of Diffusion
1.00
0.75
0.50
0.25
0.00
Simple
Design−Intensive
Complex
n = 779
Countries = 206
Technologies = 46
n = 472
Countries = 152
Technologies = 25
n = 499
Countries = 110
Technologies = 41
b
Need for Customization
***
***
Speed of Diffusion
1.00
0.75
0.50
0.25
0.00
Standardized
Mass−customized
Customized
n = 1011
Countries = 207
Technologies = 50
n = 221
Countries = 91
Technologies = 19
n = 505
Countries = 128
Technologies = 39
c
Type of Adopter
***
***
***
Speed of Diffusion
1.00
0.75
0.50
0.25
0.00
Firms
Individuals
Both
n = 472
Countries = 124
Technologies = 61
n = 659
Countries = 202
Technologies = 32
n = 619
Countries = 169
Technologies = 19
d
Replacement
***
Speed of Diffusion
1.00
0.75
0.50
0.25
0.00
Yes
No
n = 914
Countries = 156
Technologies = 46
n = 836
Countries = 206
Technologies = 66
e
Feedstock
***
Speed of Diffusion
1.00
0.75
0.50
0.25
0.00
Yes
No
n = 487
Countries = 145
Technologies = 21
n = 983
Countries = 178
Technologies = 54



	First Comm. Year	Granularity (log)	Material Use (log)	Lifetime (log)	GDP per capita (log)	R&D Spending	State Capacity	Sci/Tech making life easier	Sci/Tech making life better
Sci/Tech making life better	0.09	0.11	0.09	−0.02	0.21	0.16	0.14	0.56	1
Sci/Tech making life easier	−0.08	0.04	−0.08	−0.1	−0.14	−0.25	−0.27	1	0.56
State Capacity	0.36	−0.01	0.22	0.12	0.88	0.82	1	−0.27	0.14
R&D Spending	0.39	0.02	0.2	0.05	0.7	1	0.82	−0.25	0.16
GDP per capita (log)	0.41	−0.05	0.26	0.09	1	0.7	0.88	−0.14	0.21
Lifetime (log)	−0.31	0.63	0.53	1	0.09	0.05	0.12	−0.1	−0.02
Material Use (log)	−0.13	0.41	1	0.53	0.26	0.2	0.22	−0.08	0.09
Granularity (log)	−0.5	1	0.41	0.63	−0.05	0.02	−0.01	0.04	0.11
First Comm. Year	1	−0.5	−0.13	−0.31	0.41	0.39	0.36	−0.08	0.09


Coefficient Estimates from Linear Regression Models
a
Time and Institutional Variables
Year of First Comm.
State Capacity
Not Democracy
−0.050
−0.025
0.000
b
Granularity and Institutional Variables
State Capacity
Not Democracy
Granularity (log)
−0.05
0.00
0.05
c
Complexity and State Capacity
State Capacity
Complexity (Design−Intensive)
Complexity (Complex)
−0.050
−0.025
0.000
0.025
0.050
d
Type of Adopter and Institutional Variables
Type of Adopter (Individuals)
Type of Adopter (Both)
State Capacity
Not Democracy
−0.05
0.00
0.05
Variable Type
Country
Technology
e
Time, Granularity, and Institutional Variables
Year of First Comm.
State Capacity
Not Democracy
Granularity (log)
−0.06
−0.04
−0.02
0.00
Estimate of effect on growth speed