nature portfolio

Peer Review File

Drivers of Technology Diffusion Speed in Countries

Corresponding Author: Ms Jenna Greene

This file contains all reviewer reports in order by version, followed by all author rebuttals in order by version.

Version 0:

Reviewer comments:

Reviewer #1

(Remarks to the Author)
Comments:

Low-emission technologies and their rapid diffusion are indeed an important factor in limiting global warming to well below 2 degrees. The paper examines historical diffusion patterns of technologies and identifies technological and country characteristics that may influence the speed of diffusion. This is indeed a very important study with some significant findings for policy makers.

However, I am not convinced that public support for small-scale technologies in general can deliver public benefits in terms of faster global warming mitigation. Firstly, the results presented are not specific to climate change mitigation technologies. Secondly, the study does not take into account the environmental impact of the technologies. In addition to the diffusion of environmentally friendly technologies, the extent to which they reduce emissions is also important for their environmental impact. A low abatement rate with wide diffusion could be equivalent to a high abatement rate with lower diffusion. Thirdly, the study also takes into account relatively small, standardised, etc., but not environmentally friendly and emission reducing technologies, and I do not see why specific policy support is needed here, such as for freezers, mobile phones, tumble dryers, domestic air conditioners, etc. To strengthen the link with the discussion in the paper on climate technologies, the analysis would need to be more focused on them.

As the authors note, there are similarities between different types of technology. But there are also differences (not reflected in the data) between technologies, particularly in terms of the policy requirements for their diffusion. For example, in the case of environmentally friendly technologies, in addition to the positive externalities associated with their development, there are also positive externalities associated with their use. Therefore, the characteristics of this technology usually require more far-reaching policy measures. These policies should have a positive impact on the speed of diffusion. The study does not take into account existing policy measures, which may influence the results and the policy recommendations derived from them. The control variable for state capacity is a poor substitute for this, as policy measures are also related to the type of technology and its characteristics (e.g. environmentally friendly or not) and/or the unobserved policy agenda of the government (e.g. regarding the importance of environmental issues), which does not necessarily depend on state capacity.

Another unaddressed issue refer to network effects potentially arising from the diffusion of a technology. Certain levels of diffusion may make it more likely that the rate of diffusion will increase or, in the case of negative network effects, decrease. For example, the diffusion of electric vehicles accelerates when the density of electric vehicles reaches a certain level. This is (also) because the availability of charging stations improves, making the purchase of an electric vehicle more attractive. Such network effects are unlikely to be fully captured by the "feedstock" variable.

From the description of the estimation techniques used in this paper it is not clear how such issues are addressed. This should be discussed and robustness tests added showing that such issues do not significantly affect the results and consequently the policy discussion.

The characteristics of a country seem to play a minor role in understanding the diffusion pattern. However, certain characteristics that could help to provide a better explanation are missing. The R&D expenditure variable is not significant. It is possible that this is too general a measure of a country's knowledge base. Patent statistics are widely available and it would be interesting to see whether the stock of technological know-how plays a role. Technologies with a broad knowledge base in the country may have a different diffusion pattern than those originating from abroad. Educational indicators, such as the proportion of people with a university degree, should also be widely available and could be important.

Selection issues: The authors note that "technologies with shorter lifetimes grew faster". It is not immediately clear why this is the case. Could it be that firms are more likely to withdraw technologies from the market immediately if they have a short lifespan and do not perform well from the outset, since amortisation period is short? Or are firms more selective in bringing such technologies to market, so that only the most promising are commercialised? This would imply an unobserved pattern of selection that could lead to this result.

Figure 1: The brown line shows the fitted values from the bivariate regression results. The R2 is rather low in most of the figures. Based on visual inspection, it might be that a polynomial approximation would fit the data better. I would suggest adjusting the estimate accordingly. This could also have implications for the interpretation of the results and the policy discussion. Different stages of diffusion could imply different policy responses.

Data: The results are based on an extensive dataset (HATCH) that was used in another publication (Nemet et al. 2023), but was extended to include important information on the technology (e.g. complexity, need for adaptation) and country characteristics. However, it is unclear whether these extended dataset will be available as open source for future studies.

The dataset provides several metrics to measure the diffusion of a technology. These include, for example, annual production, cumulative capacity, total number of units and market share of a technology. It is unclear which metric is used when more than one is available for a technology. Furthermore, the metrics can lead to different results. For example, if I think of a nuclear power plant, the number of units could be very low, the capacity very high and the market share relatively high. Which metric is used to measure technology diffusion and does the chosen metric have an impact on the estimation result? In general, I think it is important to discuss the measurement in more detail because you are looking at many and very different technologies.

Given that the saturation point might be significantly lower than 100% and technology specific, it is unclear how L (in equation 1) is determined? This might effect the steepness parameter and consequently its relationship to the explanatory variables. Please explain.

Measurement of complexity: This is important, but it is not clear from the manuscript why it alone should have an effect (ceteris paribus). Complexity is measured by the number of components. It is unclear how this affects the speed of diffusion. A high number of components (e.g. mobile phones), if they can be processed automatically and sold in a standardised way, may also be positively related to the speed of diffusion, especially if they offer many additional services and thus increase the utility. Therefore, the relationship with customisation - as suggested by Malhotra and Schmidt - is important. From a methodological point of view, it is therefore the interaction of the two components (complexity and customisation) that could better determine the relationship with diffusion speed and improve our understanding of it.

Minor issues:

Supplementary Information:The heading „Interaction of Technology Characteristics“ and the bullet „Type of adopter / granularity are highlighted in yellow. The text appears to be missing.

The following statement is difficult to understand: „While our analysis is focused on a heterogenous set of technologies that do not necessarily mitigate climate change, they exhibit similarities to mitigation technologies.“ Similar in what way? Please be more specific.

(Remarks on code availability)

Reviewer #2

(Remarks to the Author)
The article seeks to systematically analyse drivers of technology diffusion speed, using data on a broad range of heterogeneous technologies from the HATCH dataset (which some of the co-authors published earlier). The authors also have done significant amount of work, identifying and collating diverse explanatory variables. This is the first systematic analysis of drivers of technology diffusion on such a scale. The article uses a meaningful distinction between characteristics of technology and the national context in which the diffusion takes place. It uses a simple but sound methodology – a bivariate analysis followed by a multivariate regression. Some of its conclusions are in line with an earlier publication on technology granularity and simplicity (Wilson et al. 2020). The finding that technology characteristics explain more variation in diffusion speed than national context is noteworthy. However, the paper needs a more careful justification of its metrics, methods and interpretation of the findings, so I would recommend a major revision. If the problems described below are addressed, the article can inform the practice of modelling technologies in mitigation pathways and advance the understanding of technology diffusion.

1. The choice of the growth metric. The article uses K (the growth constant or “steepness parameter”) from the logistic function fitted to growth data as a measure of growth speed. This is equivalent to the approaches where dT or "growth duration" is used (time to get from 10% to 90% of the asymptotic ceiling) (Wilson et al. 2013), since K is inversely proportional to dT. Both these parameters characterise how fast technology growth can approach the ceiling (or the inflection

point on the S-curve), but do not tell anything about how high or low the ceiling is (i.e. what the ultimate technology penetration level or market share is). In other words, a technology can very quickly approach the ceiling (large k or short dT), but the ceiling (ultimate penetration level) can be very low; a growth curve in a similar country growing to a higher penetration level may have a longer dT (hence a smaller K), but still have a similar or a faster growth rate (in units per year). As an example, consider two countries with a similar size of the market and a hypothetical supply technology growing in both countries. In the first country, the technology stabilises at the ceiling of 10% of the total market with the growth duration being 10 years. In the second country, the technology stabilises at the level of 30%, the growth duration being 20 years. With the growth measured by K (the inverse of growth duration), the former country is growing twice as fast as the latter. However, the maximum growth rate (the percentage point of markets added per year) is 1.5 higher for the second country, and the technology is arguably growing faster there. The finding that countries with shorter "duration of transition" dT tend to also have lower ceiling (L) was already discussed in seminal studies of technology transitions with regard to frontrunners vs. latecomers (e.g. Grubler 1998; see Grubler et al. 2016 for a more recent summary). Since the authors frame their study as relevant to the climate mitigation pathways where the ultimate penetration level is as critical as the time to reach it, they should discuss different growth metrics and their respective relevance to global climate mitigation.

Another problem related to using K/dT as the primary measure of growth is that these parameters cannot be reliably measured for technologies with "unfinished growth" (i.e. where no prominent ceiling has been reached) (Cherp et al. 2021). In other words, measuring the same parameters at a later point in time would yield different values (Dixon 1980).

2. The timespan of the analysis. The original HATCH dataset covers a very long time span (the first datapoints are from the 18th century, and there are quite a few technologies for which data from the early 20th century are available). The article does not make it clear which timespan is used for the analysis. First, this should be stated explicitly. Second, if the timespan is more than a few recent decades, it may make sense to take additional steps in the analysis. One possible step is to do separate regression analyses for more and less recent periods (e.g. before and after 1980), hypothesising that not only the year of commercialisation has an effect on growth speed, but the role of different explanatory factors, such as national context, may be different, and this changing role could be one of the article's findings. This could be done alongside the main analysis, or as a sensitivity analysis. It is also important to consider potential systematic time trends of explanatory variables (Fig. 3 shows correlation between the first commercialisation year and some variables – but only a handful of them).

3. One of the most robust effects found by the article is that a technology grows faster if it was commercialised later. The article classifies the year of commercialisation as a feature of technology. Strictly speaking, this may not be a feature of technology as such but a reflection of the "temporal context" in which the technology was first commercialised. It can be argued that a technology first adopted in the 1940s was not only a technology different from those adopted more recently, but a technology adopted in a "different world". The article makes a point to this effect (p. 12): "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." Thus, there may be three, not two categories of variables: features of technology, national context, and the "temporal context" represented by the year of commercialisation in the current analysis. This would be especially useful if, as the authors state, they want to use their findings to inform long-term climate scenarios produced by IAMs. For example, if later commercialised technologies spread faster due to globalisation, one could either assume that globalisation will intensify in the future and thus all future technologies will diffuse even faster or that it will be reversed to some extent, and the technologies will diffuse slower than now.

4. Policy recommendations given by the article are not entirely consistent. The abstract states: "These findings indicate that public support for small technologies may deliver public benefits faster than complex, large technologies, which may require higher levels of policy support and take longer to become adopted", focusing on the public support of more granular technologies. At the same time, the Discussion emphasises the support of lumpy technologies: "Our findings suggest that expensive, large, complex technologies may require regulation and policy support, coupled with bottom-up adoption, to spur faster diffusion speed. There may be some climate technologies that do conform 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."

Overall, specific conclusions regarding policy support could be made only if the authors measured policy support provided to different technologies in the past and studied its effect, but this was not the case.

5. The logic of Fig. 3. is unclear. Instead of a single correlation matrix including all variables ("We first test the correlation between _each_ explanatory variable" – lines 234-235), the figure shows 3 different subgroups of variables (panels A-C) with correlations within each group, so the reader does not get to see e.g. correlation of the commercialisation year with GDP per capita. Furthermore, panel C includes something like easier_scitech_Average, leaving it to the reader to figure out what it is (this does not seem any of the independent variables listed in the tables earlier), as no adequate explanation is provided in the caption or surrounding text. Also, in the current form the text in the figure is too small to be readable.

6. Figure 4 and its discussion characterise the size of the effect per unit change in explanatory variables, but these units are never specified. It is not clear whether the regression used variables expressed in their natural units or e.g. variables normalised to mean = 0 and sd =1. Overall, the article should include a summary table reporting range, statistical summaries, the type (continuous, binary, categorical) and units for each independent variable (plus transformations and normalisations, if used).

7. GDP per capita is included as an explanatory variable in Table 1, but then it is not reported among results of bivariate regression in Table 2 and is not used in multivariate regressions reported in Figure 4. Income group is also mentioned among explanatory variables, but never shows up in the results.

8. In the last paragraph in page 10, the text mentions Figure 6, which is absent. Should it be Figure 4?

References

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).

Dixon, R. Hybrid Corn Revisited. Econometrica 48, 1451 (1980)

Grubler, A. Technology and Global Change. Cambridge University Press (1998)

Grubler, 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).

Wilson, C., Grubler, A., Bauer, N., Krey, V. & Riahi, K. Future capacity growth of energy technologies: are scenarios consistent with historical evidence? Climatic Change 118, 381-395 (2013).

Wilson, C. et al. Granular technologies to accelerate decarbonization. Science 368, 36–39 (2020).

(Remarks on code availability)

Reviewer #3

(Remarks to the Author)
Thanks for having the opportunity to review your manuscript. I - as a specialist - gained interesting insights from reading your paper. However, I am not convinced it is worth a publication in Nature Communications. The paper provides a rich correlation analysis between different technologies, their characteristics & country environment and the speed of diffusion. This comprehensive detail may be very valuable when calibrating diffusion curves in a large scale IAM (as you mention) but to me this seems too technical to be relevant for a general interest readership like those of NComms.
Also, many of the insights are not surprising or new, they have just never been documented at such a comprehensive scale which is a contribution.

However, to make the paper stronger, it would be necessary to develop a clearer story about what can be learned from your findings apart from technical insights for model calibration. Technologies are highly heterogeneous & it is also not always clear whether an s curve best captures their shape. What is with diffusion failures or technology replacement curves when the incumbent technological solution is simultaneously taken into account? For the energy transition, not only diffusion matters but especially the phase out of the carbon intensive incumbents while there are many different replacement candidates.

I am also not too convinced of the type of empirical exercise: as mentioned it looks to me like a pure correlation study. A multivariate analysis that also considers policy related variables or time-specific external shocks would be appropriate, especially if your aim is to underline how the study helps in the context of fighting climate change. For example, technology costs change over time & can be changed by policy: just think of oil or emission prices.

Generally, for telling a story about climate technology, I would have expected the empirical analyses to include elements that specifically analyze climate technologies (which are extremely heterogeneous covering probably all dimensions of technology characteristics that you list). Maybe your analysis can be helpful to inform technology selection (at the country level)? For example, choose those tech that diffuse fastest? This might be a direction to develop a paper that leverages the comprehensive descriptive knowledge that you collected.

I hope my comments - despite being harsh - help. Good luck with the article.

Also, the appendix was not self-contained for me. I was missing technical detail about the exact implementation of the curve fitting exercise & I could also not find it in the SM. Also code & data need to be provided.

(Remarks on code availability)

There was no code & data available to review this material. Also, some technical detail about the implementation of the curve fitting exercise was missing in the supplementary material/appendix.

Version 1:

Reviewer comments:

Reviewer #1

(Remarks to the Author)
Review: NCOMMS-24-77209A

First revision: Drivers of Technology Diffusion Speed across Countries

The new version of the manuscript is significantly clearer and more transparent about its limitations. The authors now explain more clearly what they can and cannot do due to limited data availability. For instance, given the time and resource constraints, the decision not to include variables that vary at the country and technology level in the estimates for such a comprehensive analysis of technology diffusion seems reasonable. Additionally, the objective of the paper is now much clearer. In my view, the paper is not concerned with identifying causal patterns, but rather with patterns of relationships between country and technology characteristics, based on a uniquely comprehensive dataset. The results can therefore also be seen as a starting point for more in-depth investigations, such as the effectiveness of specific policy measures.

Comments:

The text now makes it clearer that broad technological coverage also serves the purpose of identifying characteristics that can help climate-friendly technologies spread more quickly. However, in your response, you refer to the “benefit to the public.” But when I look at the list of technologies again, I find technologies such as beer production and oil refining capacities, and I think you should explain this better. It is unclear what public benefit they offer. I believe you are referring to Figure 2 in your response.

The heterogeneity of technologies is very comprehensive, hence it would be good to show some heterogeneity analyses, for instance, if climate mitigation technologies, telecommunication technologies, or agriculture related technologies show a similar pattern. This might also further enrich the discussion. Given the emphasis on climate mitigation technologies in the abstract and introduction, heterogeneity tests for these technologies are in particular relevant. Your explanation for a broader technological focus (lines 178-184) is very useful, however, a test among climate mitigation technologies might still add to it in a significant way.

The findings of the polynomial approximation should also be (briefly) mentioned in the manuscript. It nuances for instance the previous finding that the technology lifetime is negatively related with speed of diffusion. I could only see the reference to the supplementary material in the main text.

The country characteristic is calculated from the first year of adoption for a country-technology pair until the inflection point … Then the values between these two points are averaged. Please describe the rational for this way of calculating the country characteristics and explain why the value at the inflection point is used for „income“?

As explained in the manuscript, the omission of variables can significantly distort the results. Given how comprehensive the study is, I don't think there is much else the authors can do except describe this as a limitation in more detail in the supplementary part to the manuscript.

*Minor issues:

This sentence does not make much sense: The Gompertz function is similar to the logistic function, except it is asymmetrical, with slowing growth after the inflection point until reaching the inflection point (Section C Sensitivity Analyses: lines 1039-1041)

„Former Czechoslovakia has a unique ISO-3 code of CSR, used in this analysis (p. 22, line 328).“ Since Slovakia and the Czech Republic separated in 1993, I do not think it makes sense to combine them in the analyses after 1993. Their economic and technological development has been very different since the separation. I wonder whether it makes sense to remove the country from the analyses. A similar problem could arise in connection with the former Yugoslavia.

B5 Country-specific characteristics: A polynomial approximation could also improve the fit here, at least for some variables. I think it's worth a try.
Supplementary Figure 17 and 18 the R2 values are not visible in the figures.

Supplementary Figure 22: According to the text it should show the relationship between democracy and state capacity, however I see „democracy“ and „not democracy“ on the x-axis and „speed of diffusion“ on the y-axis. Please explain/correct this.

„For each time series, we fit a logistic function to each time series…“. No repetition of „each time series“ is necessary. (line 113)

Similar issue: „…having the fastest growth ($p < 0.05$) and technologies that are adopted by firms adopted more quickly than technologies adopted …“ (lines 306 and 307)

Typo in text below Figure 3: „… withinin box indicates median, …“

(Remarks on code availability)

Reviewer #2

(Remarks to the Author)
I appreciate the changes made to the manuscript, particularly the explicit mentioning of the temporal context, detailed description of independent variables, and more articulated discussion. However, there are few points that I would recommend to address before publishing. I consider one of them (numbered 1 below) critical.

1. The key point from my initial review concerning the growth metric (steepness of the logistic curve, k in the logistic equation) remains essentially unaddressed in the revised version. The entire discussion of the dependent variable in the main text boils down to a single sentence – "For each time series, we fit a logistic function to each time series and use the steepness parameter to represent technology diffusion speed, which is the dependent variable in our analysis" (lines 112-114 in the version with revisions) – which is in a striking contrast with the detailed treatment of independent variables in the revised manuscript.

As explained in detail in my original review, the steepness of the fitted logistic curve (k) reflects only one aspect of growth (speed "relative to the ceiling of the respective S-curve"), and a curve with a greater k may represent slower growth in terms of absolute or normalised units (absolute: e.g. mobile phones or GWh from the electricity source in question; normalised: e.g. mobile phones per person or generation from a source as a proportion of total power generation).

This limits the relevance of the results to "integrated assessment models, across different scenarios, and for technology forecasts" (lines 457-458), because (a) k alone may not adequately represent the growth speed in which modellers and policy-makers are interested; (b) strictly speaking, the steepness parameter is meaningful only in the context of the logistic curve, so it is not directly applicable when a scenario or a forecast does not imply logistic growth (which is often the case).

This concern is not about growth ceiling as such (so it is not addressed by the text added to Discussion, lines 535-536: "while our study focuses on the speed rather than the final extent of technology diffusion"). It is about the limitations of the specific growth metric, which may not capture relevant aspects of technology growth.

As the authors correctly note in their response, the advantage of k is its applicability across different technologies due to its dimensionless nature. This comparability, being essential for this particular study, comes at a price of a limited informativeness and policy relevance.

As a minimum, the introduction of the growth metric as the dependent variable in the main text should be accompanied by a discussion of other growth metrics used in the literature, their advantages, disadvantages, and reasons for choosing the metric used in the article. The results should be properly qualified, given the limitations inherent in the selected growth metric.

2. It would be good to give the reader a more intuitive understanding of what the particular values of the growth metric mean. For example, the article could state that k = 0.25 corresponds to the growth duration (time from 10% to 90% of the ceiling) of 17.6 years*, and the increase of this particular k of by 0.02 would reduce the growth duration by 1.3 years. 0.25 here is just an example, it would make more sense to use a median k across the technology or country-technology sample used in the article. Along the same lines, the phrase "the median diffusion speed has increased from 0.10 to 0.61" (lines 255-256) could be complemented with something like "i.e., growth duration reduced from 44 to 7.2 years", provided the growth duration is defined prior to that.
* Growth duration dT for the logistic curve is calculated as ln(81)/k, according to Wilson (2012).

3. Iyer et al. (2015), using a closely similar metric for global technology growth based on logistic fit, rank ca. 40 technologies from "slow" to "fast" (Table 1 in their paper). It would be important to see if their findings are in line with the profile of fast and slow technologies according to the manuscript.

4. The discussion could benefit from further streamlining.
- In particular, it looks like there is a certain overlap between the messages of the second paragraph (466-476, "lessons for future technology diffusion") and the sixth (503 etc., "implications for climate technologies").
- The point that technologies with "fasted growth profile" may still need policy support can be connected to the point that the factors tested in the article explain only a fraction of the variance in growth speed.
- The sentence "Third, we find a wide range of technology diffusion speeds across countries that are not accounted for by country characteristics broadly" (523-524) seems to merge two different findings of the article – (a) that only a fraction of the variance in growth speed is explained by any variables in the study and (b) that the effect of country characteristics is less pronounced than that of technology characteristics. Perhaps they need to be addressed separately.
- Finally, it would be good to signal explicitly when the Discussion switches to the limitations of the current study.

References

Iyer, G. et al. Diffusion of low-carbon technologies and the feasibility of long-term climate targets. Technol. Forecast. Soc. Chang. 90, 103–118 (2015).
Wilson, C. Up-scaling, formative phases, and learning in the historical diffusion of energy technologies. Energ Policy 50, 81–94 (2012).

(Remarks on code availability)
There's no README file with instruction for running the code, which would be particularly important given that the released code is in two different languages. It should also contain the description of expected results, e.g. names and format of output files. There's no data file in the repository; if the file is released elsewhere, README should contain instruction for obtaining the file and making the code compatible with the file (e.g. in which folder to place the file; where to modify the filename in the code if necessary etc.)

Given the absence of instructions and the data file in the repository, I didn't try to run the code.

Reviewer #4

(Remarks to the Author)
This paper investigates the effects of technology- and country-specific characteristics on the speed of diffusion for 121 technologies across 229 countries. I congratulate the authors for bringing new empirical evidence to an important question—understanding the determinants of technology diffusion—which is also relevant for assessing the feasible dynamics of climate mitigation. The extended dataset, clear documentation, and consistent methodology provide confidence in the results presented.

The paper advances our understanding of innovation diffusion, for example by highlighting how certain characteristics—such as smaller, more granular technologies—are associated with faster diffusion. However, some claims are arguably based on weak evidence, particularly the assertion that the diffusion of technologies has accelerated over time. My recommendation is to accept the article with minor revisions.

Major Comment

My main concern relates to the claim of diffusion acceleration over time. Older technologies might have been more fundamental, complex, and radical (e.g., steam engines), which may explain the greater availability of historical data for such innovations compared to simpler, more recent substitution technologies (e.g., ebook reader). This potential selection bias could produce an artificial appearance of acceleration. At the very least, this issue should be discussed or acknowledged in the paper. For instance, the observed acceleration could be presented as a pattern specific to this sample (albeit a large one), warranting further research to ensure comparisons are made between comparable technologies ("comparing apples with apples").

Furthermore, the empirical evidence supporting the acceleration claim appears weak. Figures 2a and 2b suggest possible heteroscedasticity—i.e., differing error variances over time—and Figure 26 in the Supplementary Information consistently shows zero values for the year of first commercialization.

Title

The title "…Diffusion Speed Across Countries" is somewhat misleading. It suggests a focus on spatial diffusion across countries, whereas in reality, countries are treated as contextual factors influencing diffusion speed. The analysis does not explicitly address whether diffusion increases, decreases, or varies in scope across countries or among latecomers. A minor adjustment could improve accuracy and reader expectations. For instance: "Drivers of Diffusion Speed: Technology and Country Characteristics."

Clarification Needed

Please clarify the metrics used to measure diffusion and extract the parameters, in the main text. It is unclear from the main text whether market share is used alone or in combination with other indicators, and how the relevant market boundaries are defined. A more explicit explanation would improve transparency and replicability.

Minor Comments
• Check the journal's formatting and style guide to avoid having multiple tables with the same numbering (e.g., two Table 1s, 2s, or 3s in the main text).

(Remarks on code availability)

Version 2:

Reviewer comments:

Reviewer #1

(Remarks to the Author)
Review: NCOMMS-24-77209B

Title: Drivers of Technology Diffusion Speed across in Countries

The authors have adequately addressed all my comments and suggestions for improvement. I have no further comments or remarks.

(Remarks on code availability)

Reviewer #2

(Remarks to the Author)
The authors have done a good job revising the paper, having addressed my comments and added proper qualifications. I believe that the article in its current form is worth publishing in Nature Communications. I have a handful of small suggestions regarding the language, but I think that they do not warrant another round of revisions and can be handled during the copyediting process. In any way, my recommendation to publish is not conditional on the authors accepting these suggestions.

p.2 67-68. "technology moves sequentially through distinct phases with feedbacks of knowledge flows to earlier stages" – this reads like technology flows back in time, please clarify (e.g. knowledge spillover from later phases in early adopter countries to earlier phases in other countries).

p. 3, 99. "patterns between technology diffusion speed and technology" – "patterns in the relationship between technology diffusion speed and technology" may be clearer

p. 3, 113-115. "to understand the direction and strength of relationships between technology characteristics, country characteristics, and the combination
of the two on technology diffusion speed." – "to understand the direction and strength of EFFECT OF technology characteristics, country characteristics, and the combination of the two on technology diffusion speed."

p. 3, 138. "It in any case allows for insights to be generated that are relevant, especially about" – "It in any case allows to generate relevant insight, especially about" (streamline).

p. 4, 146. "a growth duration of 27.5 years." – when growth duration is first mentioned, it makes sense to define it and give a reference (Wilson et al. 2013).

p. 15, 435-436. "State capacity and the type of government (democracy or non-democracy) are both associated with higher diffusion speeds." It's either type of government (as a variable) _affects_ diffusion speed, or specific values of that variable (e.g. high level of democracy, democratic type of government) is associated with high diffusion speed.

(Remarks on code availability)
I tested the code available at the Github repo cited in the text.
I got the code running (following the instructions in README) with minor manual modifications, and it produced what looks like the actual results reported in the paper. My recommendations would be:

1. The relationship between the Python and the R parts of the code should be described at the very beginning of README, in Overview (like Python code produces growth speeds based on HATCH dataset, and subsequent analysis of these speeds is done in R. In this repo, the results of running the Python code are available in... so you can copy them to... and run only the R part).

2. Different R files have different expectations regarding working directory (sometimes provided in the form of commented out setwd statements). While it is possible to make it work, this is not a good practice. A better approach would be so set a single working directory once, in the first file to run, or initialization/pipeline script (see below), and make all R scripts use paths relative to that directory.

3. It would be good to create a single workflow/pipeline script for R – a thin wrapper smoothly running all R scripts in the proper order without requiring additional user intervention (optional scripts can be commented out, but when uncommented they should also run smoothly as part of the pipeline). Common initialization – working directory, package loading (it's good to have all necessary packages listed in a single place) – can be handled either at the beginning of the pipeline file or in a separate initialization file to be run first.

4. clean_hatch_data.R is missing a datafile loading statement – I had to add it manually.

5. README contains what seems to be instructions for running R files:
R
- Create R environment
- Run scripts:)
- (list of scripts)

... but then there's a section ## Usage / Workflow, which also lists files to be run (with additional comments/explanations). Consider whether it makes sense to integrate the two sections into one.

6. Instructions for Python code:

Python
- Create environment and install:
- python3

...here list necessary modules (or include requirements.txt in the repo and refer to it).

Reviewer #4

(Remarks to the Author)
I would like to thank the authors for their detailed revisions and am satisfied with the responses provided.

As a suggestion, Supplementary Figure 1 could benefit from the inclusion of a third axis showing the years, which would enhance clarity for readers—this was also noted by the other reviewer.

I therefore strongly recommend the paper for publication.

(Remarks on code availability)

Responses to Reviewers NCOMMS-24-77209-T

Reviewer 1

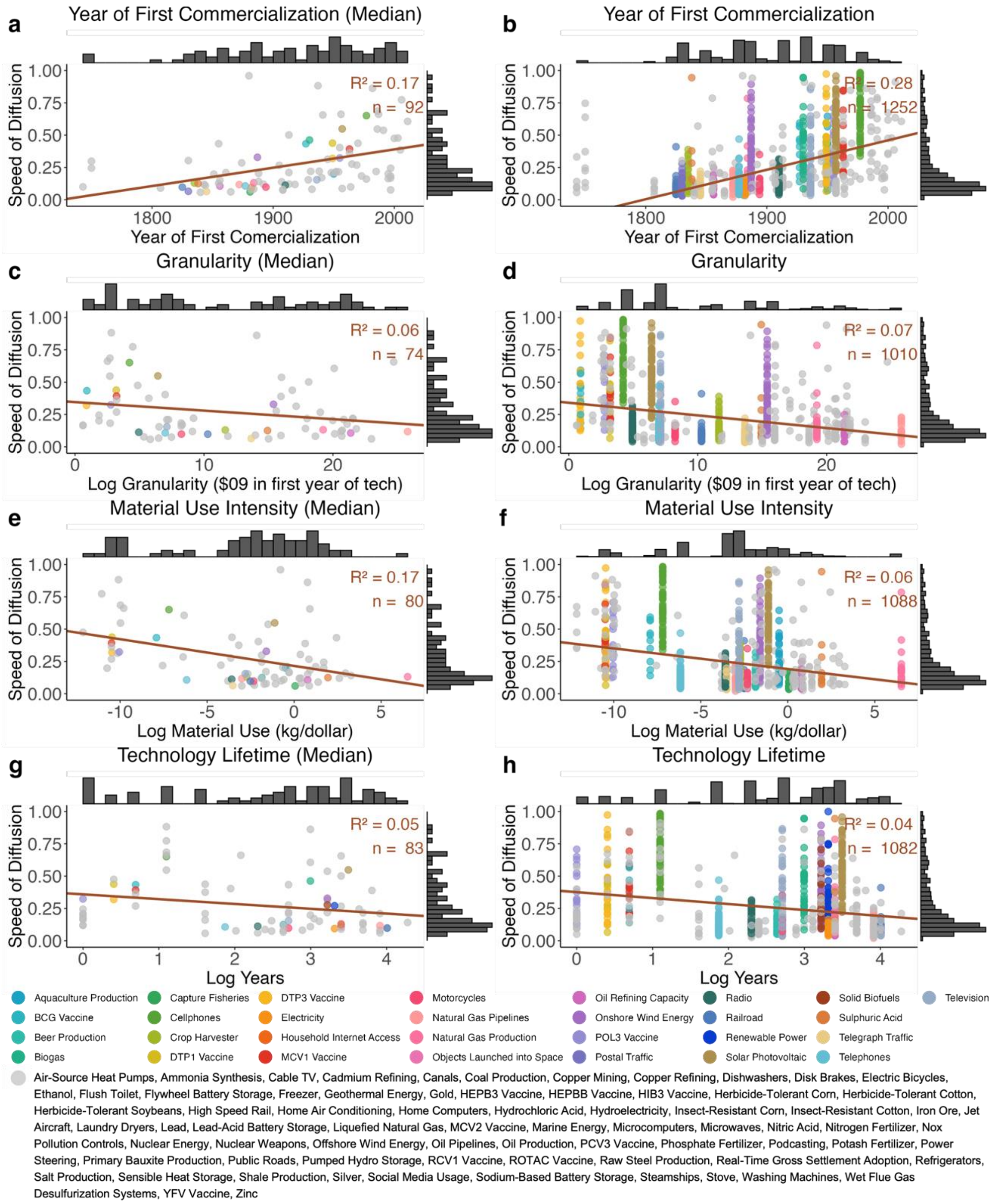
1.1: Low-emission technologies and their rapid diffusion are indeed an important factor in limiting global warming to well below 2 degrees. The paper examines historical diffusion patterns of technologies and identifies technological and country characteristics that may influence the speed of diffusion. This is indeed a very important study with some significant findings for policy makers.

Response: Thank you for the helpful comments – we agree that understanding patterns of historical technology diffusion is relevant for climate technologies, which is the main motivation of this work, while we also acknowledge that the findings have significance for technologies beyond climate technologies. We appreciate the feedback on the focus of the paper on climate mitigation technologies as well as the comments on metrics and methodology. We have significantly rewritten the manuscript to clarify the purpose and adjust the discussion of the significance of the results, highlighted in our responses below. We have also updated the analysis based on comments.

1.2: However, I am not convinced that public support for small-scale technologies in general can deliver public benefits in terms of faster global warming mitigation. Firstly, the results presented are not specific to climate change mitigation technologies. Secondly, the study does not take into account the environmental impact of the technologies. In addition to the diffusion of environmentally friendly technologies, the extent to which they reduce emissions is also important for their environmental impact. A low abatement rate with wide diffusion could be equivalent to a high abatement rate with lower diffusion. Thirdly, the study also takes into account relatively small, standardised, etc., but not environmentally friendly and emission reducing technologies, and I do not see why specific policy support is needed here, such as for freezers, mobile phones, tumble dryers, domestic air conditioners, etc.To strengthen the link with the discussion in the paper on climate technologies, the analysis would need to be more focused on them.

Response: Thank you for this comment. We agree that the impact of environmental technology diffusion on climate goals depends on their mitigation potential. The analysis does include environmentally friendly technologies, although not only these technologies. For example, it includes renewable energy technologies (solar PV, concentrated solar, onshore and offshore wind energy, nuclear energy), electrification technologies (electric vehicles, air-source heat pumps), and storage technologies. We make this more clear by including all technologies in the legend of figure 1, rather than only those with more than ten countries.

Updated legend to figure 2:



We have rewritten the text in the following ways to address these points:

Abstract – we remove reference to public support:

*"These findings indicate **<u>that</u>** small technologies may deliver public benefits faster than complex, large technologies, which may require higher levels of policy support and take longer to become adopted."*

Note also our use of the word "may," captures some of Reviewer 1's concern. We also do not claim that all of these "public benefits" are directed toward climate change.

Discussion section (lines 403-408):

"First, that if there are societal needs for large, expensive, materially intensive, long-lived technologies, policymakers may plan for longer diffusion timelines for such technologies. Second, even technologies with characteristics aligned with technologies that have grown quickly in the past 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."

Discussion section (lines 454-360):

"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."

1.3: As the authors note, there are similarities between different types of technology. But there are also differences (not reflected in the data) between technologies, particularly in terms of the policy requirements for their diffusion. For example, in the case of environmentally friendly technologies, in addition to the positive externalities associated with their development, there are also positive externalities associated with their use. Therefore, the characteristics of this technology usually require more far-reaching policy measures. These policies should have a positive impact on the speed of diffusion. The study does not take into account existing policy measures, which may influence the results and the policy recommendations derived from them. The control variable for state capacity is a poor substitute for this, as policy measures are also related to the type of technology and its characteristics (e.g. environm entally friendly or not) and/or the unobserved policy agenda of the government (e.g. regarding the importance of environmental issues), which does not necessarily depend on state capacity.

Response: We agree with the reviewer's comment that policy measures are important for the diffusion of technologies. Because of the extensive nature of the technologies and countries we *include in our analysis, we chose to only gather variables that vary on the country or technology level, rather than those that differ by both the country and the technology. Policies that impact technology development fall into the latter category, so we do not include data on specific policies. One reason for this is that it would not be feasible to collapse the entirety of policy mixes, including anticipation and delay, into a single numeric parameter. State capacity, however, could be considered a good proxy, as countries with higher state capacity are better able to anticipate the general public's preferences and identify which policies are supportive of certain technologies*[1]*.*

To discuss this limitation, we add the following paragraph to the discussion section in the main text on pages 20-21, lines 479-495:

> *"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 121 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 5,599 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."*

Regarding state capacity as a variable, we include this variable as a measure of institutional capacity to develop policies or implement a governmental agenda, both of which may impact the ability to pass policies. State capacity does not necessarily indicate the types of policies a government may pass nor does it indicate the political leanings or attitude of a government. Our

[1] Meckling, J. & Nahm, J. Strategic State Capacity: How States Counter Opposition to Climate Policy. *Comparative Political Studies* **55**, 493–523 (2022).

findings do not indicate a straightforward relationship between state capacity and growth speed, which we discuss in the Supplementary Information analysis section.

To highlight this further, we have edited the text in the results section of the main text, page 14 lines 309-313 (added text is underlined):

> *"Countries with higher state capacity have faster technology diffusion speeds (n = 1465, $p < 0.05$). 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 B3 of the Supplementary Information). This finding suggests that state capacity is not a robust indicator of technology diffusion speed."*

1.4: Another unaddressed issue refer to network effects potentially arising from the diffusion of a technology. Certain levels of diffusion may make it more likely that the rate of diffusion will increase or, in the case of negative network effects, decrease. For example, the diffusion of electric vehicles accelerates when the density of electric vehicles reaches a certain level. This is (also) because the availability of charging stations improves, making the purchase of an electric vehicle more attractive. Such network effects are unlikely to be fully captured by the "feedstock" variable. From the description of the estimation techniques used in this paper it is not clear how such issues are addressed. This should be discussed and robustness tests added showing that such issues do not significantly affect the results and consequently the policy discussion.

Response: This is an important dynamic in technology diffusion. On one hand it is captured already in the logistic function, i.e. one reason that the curve becomes steep is that infrastructure and complementary technologies have been built out and enable faster growth. On the other hand we do not explicitly capture the simultaneous development of other technologies. We clarify in the discussion that our analysis considers technologies and their characteristics independently.

Added text in discussion section, page 21 lines 510-514:

> *"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."*

1.5: The characteristics of a country seem to play a minor role in understanding the diffusion pattern. However, certain characteristics that could help to provide a better explanation are missing.The R&D expenditure variable is not significant. It is possible that this is too general a measure of a country's knowledge base. Patent statistics are widely available and it would be interesting to see whether the stock of technological know-how plays a role. Technologies with a broad knowledge base in the country may have a different diffusion pattern than those originating from abroad. Educational indicators, such as the proportion of people with a university degree, should also be widely available and could be important.

Response: Through analyzing both technology and country characteristics, it is difficult to determine a cutoff of how many indicators to consider across the entire group of technologies. We attempted to include one to two variables per indicator from Steg et al (shown in table 1).

We do not include patent data or educational indicators in this analysis for two reasons. First, patent data is available internationally only since 1980. This is already an issue with our R&D indicator, which began reporting to the World Bank in 1996. The lack of historical data on either of these indicators is an issue, but we chose R&D spending as an indicator of a country's ability to devote resources to technology development rather than the innovative activity within a country. Second, we do not include educational attainment because of the wide range of technologies and lack of a strong hypothetical basis for the relationship between broad technology diffusion and education. Similarly, it would be extremely challenging to map patent classifications to individual technologies in the data set. It certainly would not be feasible for over 200 technologies and even for one technology there are patents that are clearly related to the technology and others that are more distantly related, requiring many subjective judgement calls on inclusion.

The question that the reviewer brings up about knowledge stock for each type of technology in each country is an interesting issue, however it is a variable that varies both by technology and country, and would therefore need to be gathered on both axes. We sought to gather technology characteristics specific to each technology but not varying by country and country characteristics that only take into account the technology-specific time period but no other technology-specific elements. This could be an interesting area for future analyses focused on a specific type of technologies, though.

We add a paragraph on future work and limitations in lines 479- 495 on pp. 20-21 of the main text, (reference to patent activity is bolded for clarification):

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 121 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. For example, 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 5,599 technology-country time series but may be interesting on a smaller scale.*

1.6: Selection issues: The authors note that "technologies with shorter lifetimes grew faster". It is not immediately clear why this is the case. Could it be that firms are more likely to withdraw technologies from the market immediately if they have a short lifespan and do not perform well from the outset, since amortisation period is short? Or are firms more selective in bringing such technologies to market, so that only the most promising are commercialised? This would imply an unobserved pattern of selection that could lead to this result.

Response: Our hypothesis is based on the relationship between technology lifetime and technology lock-in, which can be a function of both technology cost and the ability for a firm to implement technological improvements through iteration (Wilson et al 2020[2]).

We added text to table 2, where we describe each technology variable, in the row describing technology lifetime:

> *"Shorter lifetimes allow for faster turnaround for technological improvements, leading to faster adoption."*

The reviewer also brings up a selection pattern that may be present in our data which we agree with – it is a common theme in empirical technology diffusion research that the technologies for which we have data are those that have diffused 'successfully', meaning the technology was successfully brought to market, commercialized, and demonstrated some growth in a market. This pattern comes in part because these are the technologies with publicly available data. Technologies that did not make it past the lab scale or demonstration scale, for example, will not necessarily have adoption data that is publicly available, especially older technologies, because of a lack of infrastructure for data collection.

To address this concern, we add the following paragraph to the main text (page 20, lines 464-472):

> *"Historical technologies that we analyse 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*

[2] Wilson, C. *et al.* Granular technologies to accelerate decarbonization. *Science* **368**, 36–39 (2020).

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."

1.7: Fitting Methodology: Figure 1: The brown line shows the fitted values from the bivariate regression results. The R2 is rather low in most of the figures. Based on visual inspection, it might be that a polynomial approximation would fit the data better. I would suggest adjusting the estimate accordingly. This could also have implications for the interpretation of the results and the policy discussion. Different stages of diffusion could imply different policy responses.

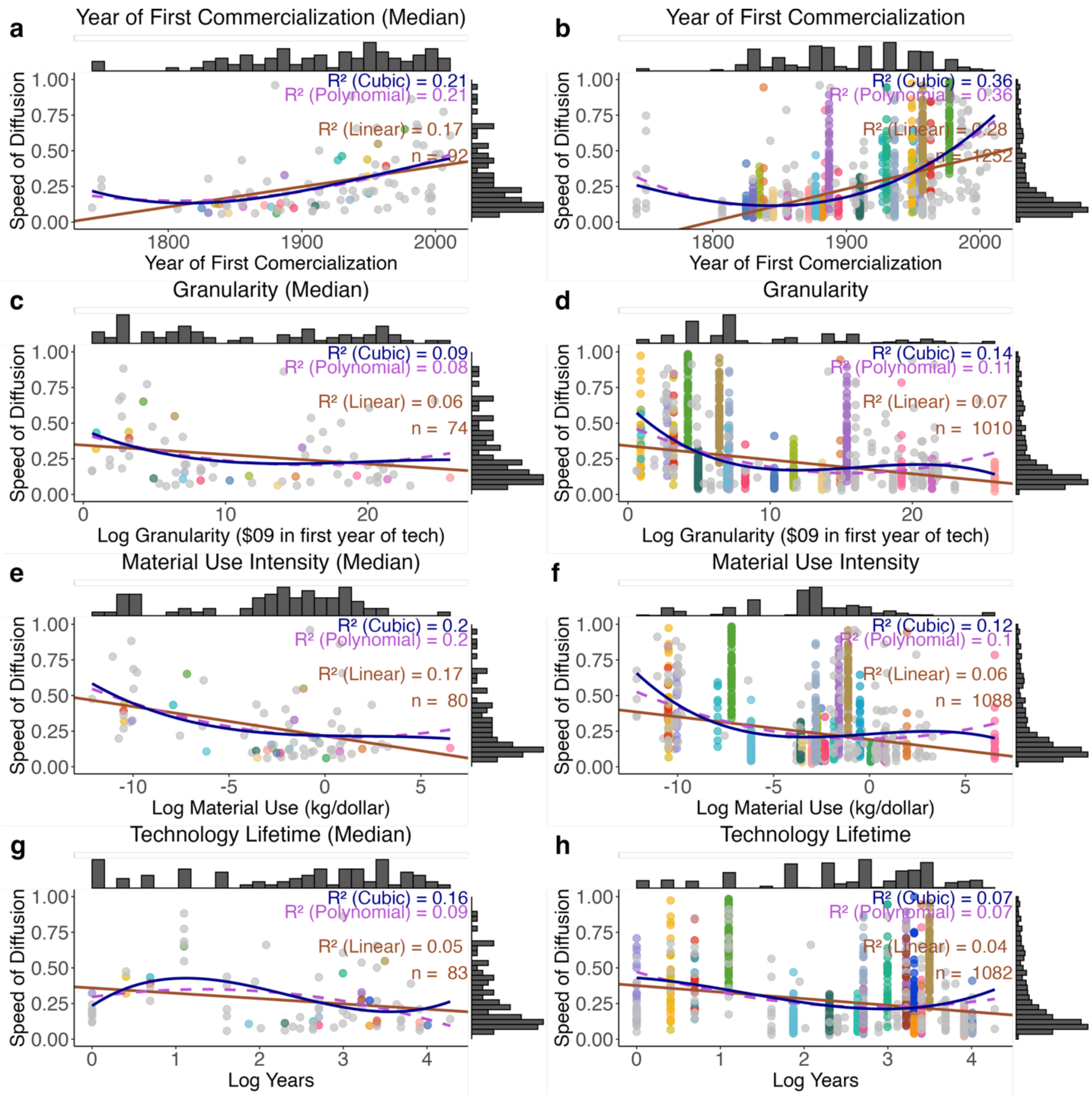
Response: The R2 values of the linear regressions for the numerical technology characteristics (shown in figure 2) are indeed low. We test a polynomial approximation for these four variables into the Supplementary Information Section B4 and add a reference to this section in the main text, page 11 lines 253-255:

"We also test the relationship with each of these characteristics with diffusion speed using a polynomial regression in Supplementary Information section B2."

Each of the squared terms of the polynomial regression are significantly related to the growth rate, but the R2 values are only marginally higher.

We add the following figure and discussion to the Supplementary Information section B4 pages 37-38 lines 537 – 560:

"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 1. The R^2 values for the polynomial regression approximation are higher across all technology characteristics, although still only explain 36% of dispersion for year of first commercialization, 11% of dispersion for granularity, 10% of dispersion for material intensity, and 7% for technology lifetime.



Supplementary Figure 1. Technology Characteristics and Diffusion Speeds with Polynomial Regression Approximations. 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.

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. We do not find a difference in the R2 value between the two polynomial approximations for the year of first commercialization or technology lifetime, and only a slight increase in granularity and material use intensity. None of the terms are significant for the year of first commercialization using this approximation. For granularity, we find 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. We find a similar pattern for material use intensity. For average lifetime, we find that the cubic term is significant and positive, which that the technologies with the longest lifetime in the dataset have grown quickly."

1.8: Data: The results are based on an extensive dataset (HATCH) that was used in another publication (Nemet et al. 2023), but was extended to include important information on the technology (e.g. complexity, need for adaptation) and country characteristics. However, it is unclear whether these extended dataset will be available as open source for future studies.

Response: The extended HATCH dataset (including more technology-country time series) and the technology characteristics will be made publicly available. We have clarified in text that this data will be made publicly available and we include the data as a supplementary file to this revision.

Main text page 4, lines 127 – 128:

> *"The dataset is publicly available for future studies on technology diffusion speed and technology characteristics (see Supplementary Materials)."*

Added a data availability statement in Methods text lines 118-119:

> *" The data used in this analysis is available at {Will insert Zenodo link at time of publication}. The Extended HATCH Data is publicly available at {Will insert Zenodo link at time of publication}."*

1.9: The dataset provides several metrics to measure the diffusion of a technology. These include, for example, annual production, cumulative capacity, total number of units and market share of a technology. It is unclear which metric is used when more than one is available for a technology. Furthermore, the metrics can lead to different results. For example, if I think of a nuclear power plant, the number of units could be very low, the capacity very high and the market share relatively high. Which metric is used to measure technology diffusion and does the chosen metric have an impact on the estimation result? In general, I think it is important to discuss the measurement in more detail because you are looking at many and very different technologies.

Response: We agree with the reviewer about the importance of thinking about the metrics used to measure technology diffusion. Indeed, it is a question we have considered extensively. Many diffusion studies use market share as the metric, others generalize to include cumulative adoption (Rao and Kishore 2010)[3], and others use cumulative capacity when focused on energy technologies (C. Wilson et al. 2013)[4]. When we gathered the data for the HATCH dataset, we struggled with the question about converting time series data measured in annual production or number of units into data on market share. For example, when measuring the diffusion of bicycles, would the market be the population of a country? That may not account for people who own multiple bicycles, in this example. Because of the struggle to identify a market appropriate for each technology, we elected not to convert metrics into market share.

We ensured that the data measured in number of units was only converted to cumulative number of units if the original dataset was focused on the number of added units per year, rather than the total in the economy. The results do not shift, but the number of observations have changed such that we have updated the analysis to reflect the new number of observations.

We clarify in lines 43 – 45 of the methods text that technologies are measured using different metrics. Because the k parameter is unitless, we can compare the speed of adoption.

> *"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."*

---

[3] Rao, K. U. & Kishore, V. V. N. A review of technology diffusion models with special reference to renewable energy technologies. *Renewable and Sustainable Energy Reviews* **14**, 1070–1078 (2010).

[4] Wilson, C., Grubler, A., Bauer, N., Krey, V. & Riahi, K. Future capacity growth of energy technologies: are scenarios consistent with historical evidence? *Climatic Change* **118**, 381–395 (2013).

We have clarified in the paper, both in the methods section (line 45) and the Supplementary Information section A1, that we only measure technology diffusion with one metric per technology.

> *"Each technology is only measured using one metric."*

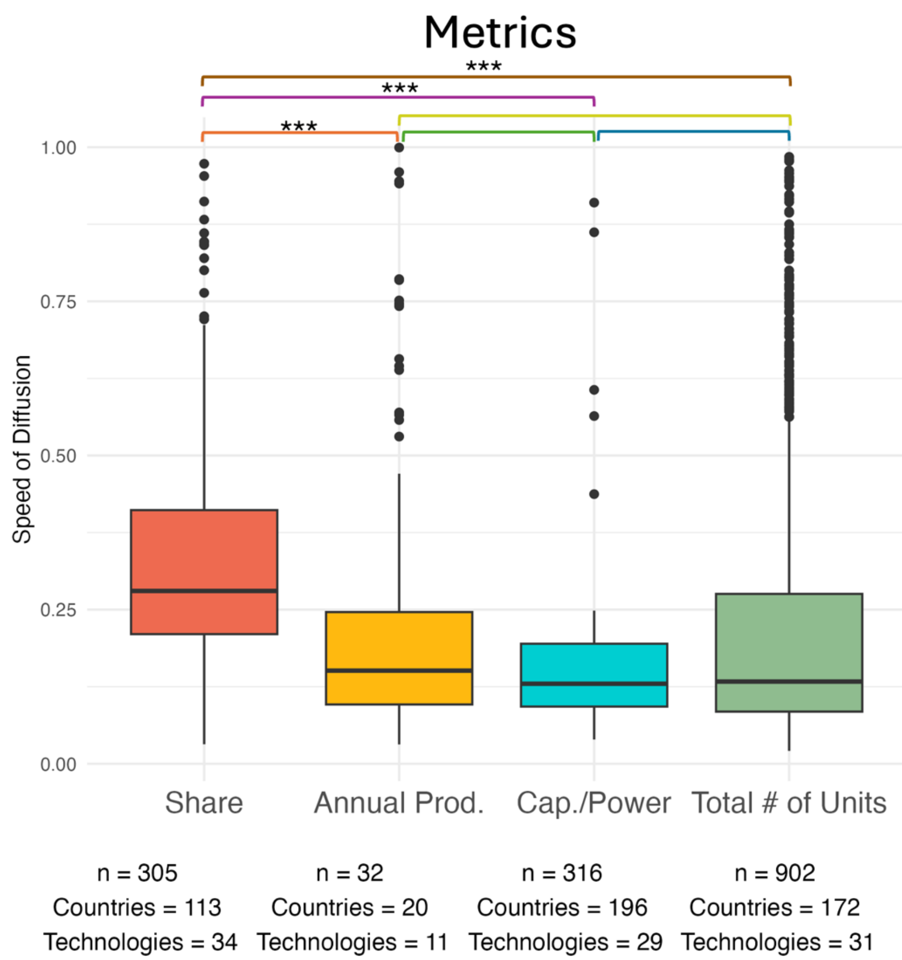
We select cumulative rated power for storage technologies rather than cumulative rated capacity (already specified in lines 58 – 60 of the Supplementary Information section A1). There is one other case of a technology with two metrics – home air conditioning in the USA – which is measured both in terms of number of units and market share. Because all other countries included in the analysis are measured in number of units, we drop the home air conditioning market share metric. We clarify this in text, lines 50 – 52 of Supplementary Information section A1).

> *"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."*

We also add a robustness test to our supplementary results on the metric used. We include a comparison of growth rates across technology metrics as well as a bivariate analysis for each cross section of the data, found in Supplementary Information section C5.

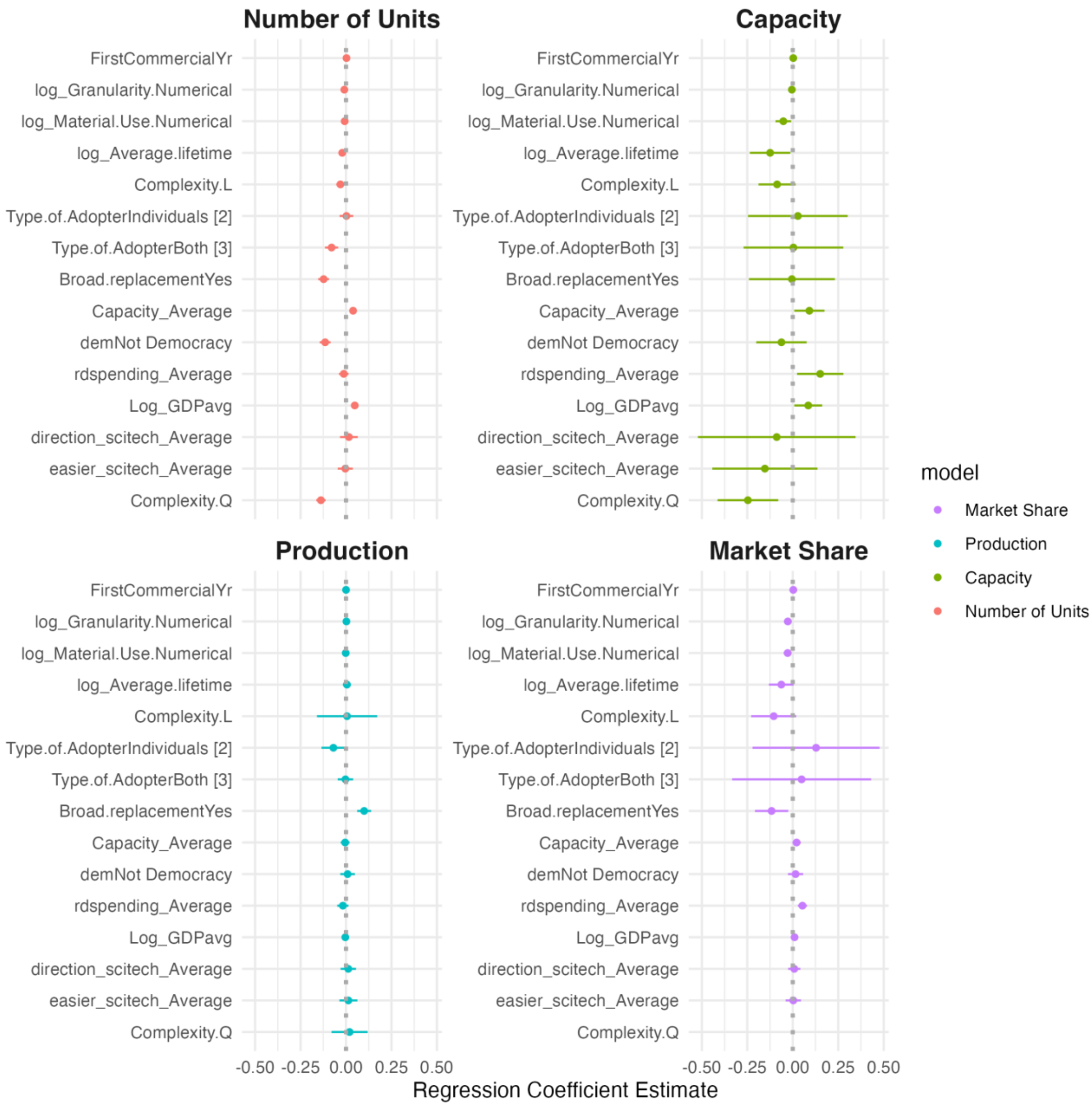
Text added to page 58, lines 819 – 836 of Supplementary Information:

> *"C6. 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 2). The others are not significantly different from one another The greatest number of technologies are measured in terms of market share (n = 34) but the number of observations is highest for total number of units (n = 902) and capacity/power (n = 316).*



Supplementary Figure 2. Relationship between Type of Metric and Diffusion Speed of Technologies.

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 ($n = 1220$, $p = 0.5$). Bivariates for each metric and each variable are included in Supplementary Figure 3."



Supplementary Figure 3. Bivariate of each metric and each variable in the analysis. Plots show the coefficient for each individual bivariate regression. Dots show the coefficient estimate, with whiskers on either end showing the 95% confidence interval. If whiskers extend past the dotted line (shown at 0) then the estimate is not significant at the 95% confidence level.

1.10: Given that the saturation point might be significantly lower than 100% and technology specific, it is unclear how L (in equation 1) is determined? This might effect the steepness parameter and consequently its relationship to the explanatory variables. Please explain.

Response: We agree with the reviewer that the saturation point for some technologies may be lower than the theoretical market size (for market share, this would be 100% of the market, *although the majority of technologies are not measured in terms of market share). The L parameter, which represents the diffusion ceiling, is one of three free parameters in the logistic function. We include additional details on the curve fitting process in the methods section and in the Supplementary Information section A2.*

Updated methods section (underlined text shows the added text):

> *"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(Virtanen et al. 2020). 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. 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. 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."*

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

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).

In the Supplementary Information section A2, we make the following changes (underlined the added text):

> *"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(Virtanen et al. 2020). The nonlinear least squares method implements the Levenberg-Marquardt algorithm to attempt a fit on the time series data. We specify 5,000 function calls to attempt a fit. The parameters are not bounded during the fitting process. The fitting results in an estimate of the three free parameters in the logistic function which is the result of the implemented Levenberg-Marquardt algorithm of least squares optimization. The initial parameters used in function fitting are based on Cherp et al shown in table supplementary table 13 below, calculated for each time series(Cherp et al. 2021)."*

1.11: Measurement of complexity: This is important, but it is not clear from the manuscript why it alone should have an effect (ceteris paribus). Complexity is measured by the number of components. It is unclear how this affects the speed of diffusion. A high number of components (e.g. mobile phones), if they can be processed automatically and sold in a standardised way, may also be positively related to the speed of diffusion, especially if they offer many additional services and thus increase the utility. Therefore, the relationship with customisation - as suggested by Malhotra and Schmidt - is important. From a methodological point of view, it is therefore the interaction of the two components (complexity and customisation) that could better determine the relationship with diffusion speed and improve our understanding of it.

Response: We appreciate this suggestion. We add the interaction of complexity and need for customization to the analysis, both in the main text and the supplementary analysis (shown below).

We added the following line to the main text (pp. 13-14, lines 284-288):

> *"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. We do not find a significant relationship between the interaction of these variables and technology diffusion speed."*

We also added more detail in the Supplementary Information on the interactions (page 36, lines 524 – 534).

> *"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(Malhotra and Schmidt 2020). 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 = 0.25). We therefore do not find empirical support for this typology related to technology diffusion speed."*

Regarding complexity as a variable separately, we keep complexity as a separate variable as well as adding the interaction with customization. Wilson et al (2020)[5] *finds that complexity (measured in component parts just as we measure complexity) is significantly related to*

[5] Wilson, C. *et al.* Granular technologies to accelerate decarbonization. *Science* **368**, 36–39 (2020).

technology granularity. In their analysis, authors specify that innovation cycles may move quickly because simpler technologies have fewer coordination challenges. This may lead to rapid learning and iterations at early stages of simpler technologies, leading to faster diffusion.

We add more description to Table 2 of the main text, where we describe each technology characteristic variable (page 7, table 2):

> *"Simple technologies allow for faster diffusion speeds through faster learning cycles -- faster production times, faster improvements, and fewer coordination hurdles allow for more iterations to improve a technology."*

1.12: Supplementary Information: The heading „Interaction of Technology Characteristics" and the bullet „Type of adopter / granularity are highlighted in yellow. The text appears to be missing.

Response: *Thank you for pointing this out!*

We have added text in this section in the Supplementary Information page 36:

> *"Beyond individual bivariate analyses of technology characteristics and technology growth speeds, we also test the interaction of technology characteristics on growth speed. 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 ($n = 435$, $p < 0.05$). 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 ($n = 309$, $p < 0.05$). However, for technologies primarily adopted by firms, we do not find a significant relationship between granularity and growth speed ($n = 266$, $p = 0.67$). 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 ($n = 305$, $p < 0.05$) and longer lived technologies are associated with faster growth speeds ($n = 283$, $p < 0.05$).*

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(Malhotra and Schmidt 2020). 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 ($p = 0.25$). We therefore do not find empirical support for this typology related to technology diffusion speed."

1.13: The following statement is difficult to understand: „While our analysis is focused on a heterogenous set of technologies that do not necessarily mitigate climate change, they exhibit similarities to mitigation technologies." Similar in what way? Please be more specific.

Response: We have changed the sentence to clarify the purpose of our analysis and the link between a wide range of historical technologies in the HATCH dataset and mitigation technologies (lines 164 – 171):

"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 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."

Reviewer 2

2.1: The article seeks to systematically analyse drivers of technology diffusion speed, using data on a broad range of heterogeneous technologies from the HATCH dataset (which some of the co-authors published earlier). The authors also have done significant amount of work, identifying and collating diverse explanatory variables. This is the first systematic analysis of drivers of technology diffusion on such a scale. The article uses a meaningful distinction between characteristics of technology and the national context in which the diffusion takes place. It uses a simple but sound methodology – a bivariate analysis followed by a multivariate regression. Some of its conclusions are in line with an earlier publication on technology granularity and simplicity (Wilson et al. 2020). The finding that technology characteristics explain more variation in diffusion speed than national context is noteworthy.

Response: Thank you for the helpful, thorough comments and feedback to strengthen the analysis. We have adjusted the text to highlight two novel parts of the analysis: the gathering of a large set of technology characteristics and the scale of the analysis (number of technologies and countries included).

Page 2, lines 46 – 48:

> *"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."*

2.2: However, the paper needs a more careful justification of its metrics, methods and interpretation of the findings, so I would recommend a major revision. If the problems described below are addressed, the article can inform the practice of modelling technologies in mitigation pathways and advance the understanding of technology diffusion.

Response: Thank you for the very thorough comments. We agree that this analysis can inform both the modelling of technologies in mitigation pathways and enhance our general understanding of technology diffusion. We have addressed each comment, which we believe has made the analysis stronger and the message more precise. We look forward to your feedback on the revised manuscript.

2.3: The choice of the growth metric. The article uses K (the growth constant or "steepness parameter") from the logistic function fitted to growth data as a measure of growth speed. This is equivalent to the approaches where dT or "growth duration" is used (time to get from 10% to 90% of the asymptotic ceiling) (Wilson et al. 2013), since K is inversely proportional to dT. Both these parameters characterise how fast technology growth can approach the ceiling (or the inflection point on the S-curve), but do not tell anything about how high or low the ceiling is (i.e. what the ultimate technology penetration level or market share is). In other words, a technology can very quickly approach the ceiling (large k or short dT), but the ceiling (ultimate penetration level) can be very low; a growth curve in a similar country growing to a higher penetration level may have a longer dT (hence a smaller K), but still have a similar or a faster growth rate (in units per year). As an example, consider two countries with a similar size of the market and a hypothetical supply technology growing in both countries. In the first country, the technology stabilises at the ceiling of 10% of the total market with the growth duration being 10 years. In the second country, the technology stabilises at the level of 30%, the growth duration being 20 years. With the growth measured by K (the inverse of growth duration), the former country is growing twice as fast as the latter. However, the maximum growth rate (the percentage point of markets added per year) is 1.5 higher for the second country, and the technology is arguably growing faster there. The finding that countries with shorter "duration of transition" dT tend to also have lower ceiling (L) was already discussed in seminal studies of technology transitions with regard to frontrunners vs. latecomers (e.g. Grubler 1998; see Grubler et al. 2016 for a more recent summary). Since the authors frame their study as relevant to the climate mitigation pathways where the ultimate penetration level is as critical as the time to reach it, they should discuss different growth metrics and their respective relevance to global climate mitigation.

Response: We thank the reviewer for this detailed comment. Our analysis does focus on the 'k' metric in part because it allows for comparison across technologies and market as it is unitless. Because of the various units for the technologies in our analysis and the differences in market size, a comparison of the saturation level for these data is not meaningful because of the differences in units across technologies and differences in market sizes by countries. While our analysis does not focus on the drivers of saturation/ceiling differences, we add a paragraph to the discussion section about the application of our results to climate technologies that would consider both speed and extent of diffusion to address this issue.

Added text page 20 of main text, lines 454-462:

> *"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 remove 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."*

2.4: Another problem related to using K/dT as the primary measure of growth is that these parameters cannot be reliably measured for technologies with "unfinished growth" (i.e. where no prominent ceiling has been reached) (Cherp et al. 2021). In other words, measuring the same parameters at a later point in time would yield different values (Dixon 1980).

Response: We appreciate the attention that the reviewer pays to the measure of growth – we agree it is important because it is the basis of our analysis. It is why we filter the time series to only include those with an R2 value of above 95% for the logistic function and filter out implausible growth parameters (above 1 and below 0). Both of these robustness measures are included in Supplementary Information section C.

We reference these robustness tests in the methods section in lines 73-74:

> *"These assumptions are further analyzed in Supplementary Information Section C2 and C3."*

To assess whether our findings change depending on the length of the time series, we also include a robustness test in Supplementary Section C4 by including the number of points in the time series in multivariate analyses with each other variable and find the same relationships with numerical variables when we account for the number of points.

We further describe this finding and add reference to these supplementary analyses to the main text in lines 373-379:

> *"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). This consideration is especially important because of the long span of time that the technologies in HATCH cover. "*

We do not filter the time series to only include technologies with finished growth because doing so would bias our analysis to only include older technologies. Because we are interested in how technology diffusion has changed over time, this filtering is unrealistic for our analysis. We are interested in the lessons of historical technology diffusion for current novel technologies, so knowledge about more recent technologies is especially relevant to understand diffusion in today's world. This is particularly noteworthy because of our robust finding that more recently commercialized technologies have grown more quickly, indicating that technology diffusion has changed over time.

2.5: The timespan of the analysis. The original HATCH dataset covers a very long time span (the first datapoints are from the 18th century, and there are quite a few technologies for which data from the early 20th century are available). The article does not make it clear which timespan is used for the analysis. First, this should be stated explicitly.

Second, if the timespan is more than a few recent decades, it may make sense to take additional steps in the analysis. One possible step is to do separate regression analyses for more and less recent periods (e.g. before and after 1980), hypothesising that not only the year of commercialisation has an effect on growth speed, but the role of different explanatory factors, such as national context, may be different, and this changing role could be one of the article's findings. This could be done alongside the main analysis, or as a sensitivity analysis. It is also important to consider potential systematic time trends of explanatory variables (Fig. 3 shows correlation between the first commercialisation year and some variables – but only a handful of them).

Response: We agree with the reviewer's point that the HATCH dataset covers a very large timespan. We see this as a strength of the dataset, as the purpose of the analysis is to study technology diffusion over a large period of history to understand trends and to contextualize the growth required of climate mitigation technologies to reach temperature targets. To clarify the role of time in this analysis, we make four main changes: add a sentence in the text explicitly on the span of the HATCH dataset, adding summary statistics for each variable (including first year of commercialization) in the variable table in Methods section, adding a sensitivity analysis in the supplementary information section on the role of technology and country characteristics for technologies commercialized before 1975 and after 1975, and we reference to interaction of technology characteristics, including year of first commercialization in the main text. These changes are described below.

Added sentence in main text (lines 241 – 243):

> *"This analysis includes technologies commercialized over 268 years: for an analysis more focused on recent dynamics, we include a sensitivity analysis in Supplementary Information section C5."*

Added sentence on the importance of year of first commercialization in the main text with reference to Supplementary Information Text (page 17, lines 354-357):

> *"Year of first commercialization and granularity both remain significant predictors of diffusion speed even when institutional variables are held constant (**Error! Reference source not found.** 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)."*

Added text in Supplementary Information section C6, pp. 60-61 lines 838 – 881:

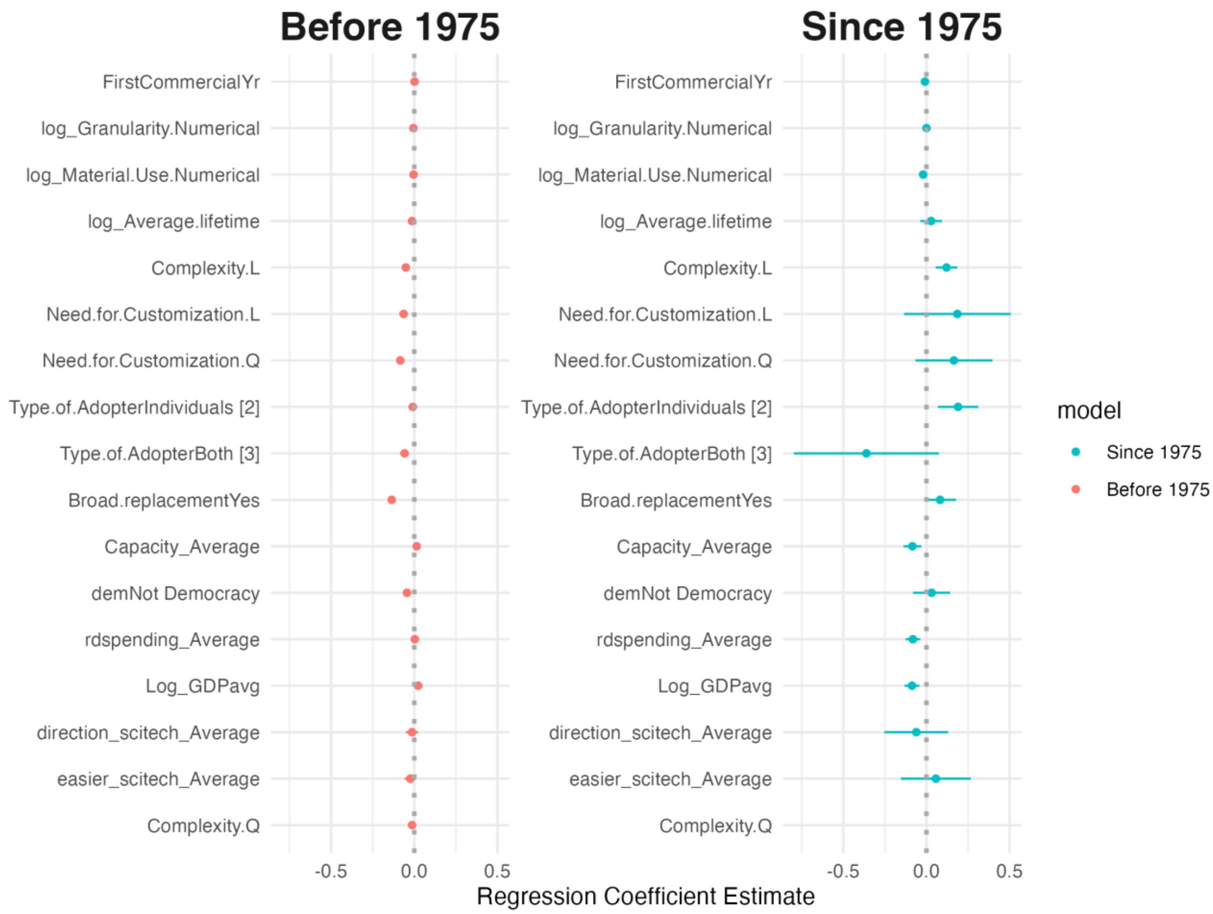
> *"The HATCH dataset includes technologies from a wide range of time. The earliest technology in the filtered dataset used in this analysis was first commercialized in 1743 (zinc production) and the most recent was first commercialized in 2011 (flywheel battery storage). The year a technology was first 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 1,133 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 XYZ. 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, n = 70) have grown more quickly in the past 50 years than simple technologies (n = 30). 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 22. Bivariate regression coefficients across time periods. Dots and whiskers that intersect with 0 (shown in a gray dotted line) are not significantly associated with growth speed at a 95% confidence interval.

2.6: One of the most robust effects found by the article is that a technology grows faster if it was commercialised later. The article classifies the year of commercialisation as a feature of technology. Strictly speaking, this may not be a feature of technology as such but a reflection of the "temporal context" in which the technology was first commercialised. It can be argued that a technology first adopted in the 1940s was not only a technology different from those adopted more recently, but a technology adopted in a "different world". The article makes a point to this effect (p. 12): "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." Thus, there may be three, not two categories of variables: features of technology, national context, and the "temporal context" represented by the year of commercialisation in the current analysis. This would be especially useful if, as the authors state, they want to use their findings to inform long-term climate scenarios produced by IAMs. For example, if later commercialised technologies spread faster due to globalisation, one could either assume that globalisation will intensify in the future and thus all future technologies will diffuse even faster or that it will be reversed to some extent, and the technologies will diffuse slower than now.

Response: We agree that the year of commercialization is a different category than a technology characteristic and appreciate the reviewer's suggestion to treat it as a 'temporal context' rather than a national or technology context.

We have adjusted table 1 to reflect this shift as well as the following text changes (lines 178 – 182):

> *"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."*

Lines 102-104:

> *In this study, we describe the impact of <u>temporal,</u> technology, and country characteristics on technology diffusion through bivariate analyses and linear regression models for each unique technology-country time series.*

Lines 121 – 122:

> *"Second, we combine the <u>temporal context</u>, technology characteristics and country characteristics as indicators of diffusion speed."*

2.7: Policy recommendations given by the article are not entirely consistent. The abstract states: "These findings indicate that public support for small technologies may deliver public benefits faster than complex, large technologies, which may require higher levels of policy support and take longer to become adopted", focusing on the public support of more granular technologies. At the same time, the Discussion emphasises the support of lumpy technologies: "Our findings suggest that expensive, large, complex technologies may require regulation and policy support, coupled with bottom-up adoption, to spur faster diffusion speed. There may be some climate technologies that do conform 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."

Overall, specific conclusions regarding policy support could be made only if the authors measured policy support provided to different technologies in the past and studied its effect, but this was not the case.

Response: We have updated the text to better reflect the findings of this analysis., both in the abstract and discussion section.

In the abstract, lines 20-22:

“These findings indicate that small technologies may deliver public benefits faster than complex, large technologies, which may take longer to become adopted.”

Updated discussion text, page 19 lines 401-406:

“This finding implies two lessons for future technology diffusion. First, that if there are societal needs for large, expensive, materially intensive, long-lived technologies, policymakers may plan for longer diffusion timelines for such technologies. Second, even technologies with characteristics aligned with technologies that have grown quickly in the past 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.”

In the discussion section pp. 19-20, lines 433-450:

“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 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. 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.”

2.8: The logic of Fig. 3. is unclear. Instead of a single correlation matrix including all variables ("We first test the correlation between _each_ explanatory variable" – lines 234-235), the figure shows 3 different subgroups of variables (panels A-C) with correlations within each group, so the reader does not get to see e.g. correlation of the commercialisation year with GDP per capita. Furthermore, panel C includes something like easier_scitech_Average, leaving it to the reader to figure out what it is (this does not seem any of the independent variables listed in the tables earlier), as no adequate explanation is provided in the caption or surrounding text. Also, in the current form the text in the figure is too small to be readable.

Response: Thank you for the comment on the correlation analysis. We have now grouped all numerical variables into a correlation matrix. Because many of the categorical variables in the analysis are not binary, we do not calculate Pearsons coefficient and therefore do not include any categorical variables in the correlation matrix. However, we have expanded the variance inflation factor analysis to include all explanatory and control variables. We use the generalized variance inflation factor to account for both categorical (binary, ordinal, and unordered) and numerical variables. These changes are made to figure 4, the caption, and the text.

Added text (lines 335 – 338):

> *"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)"*

Updated figure 4:

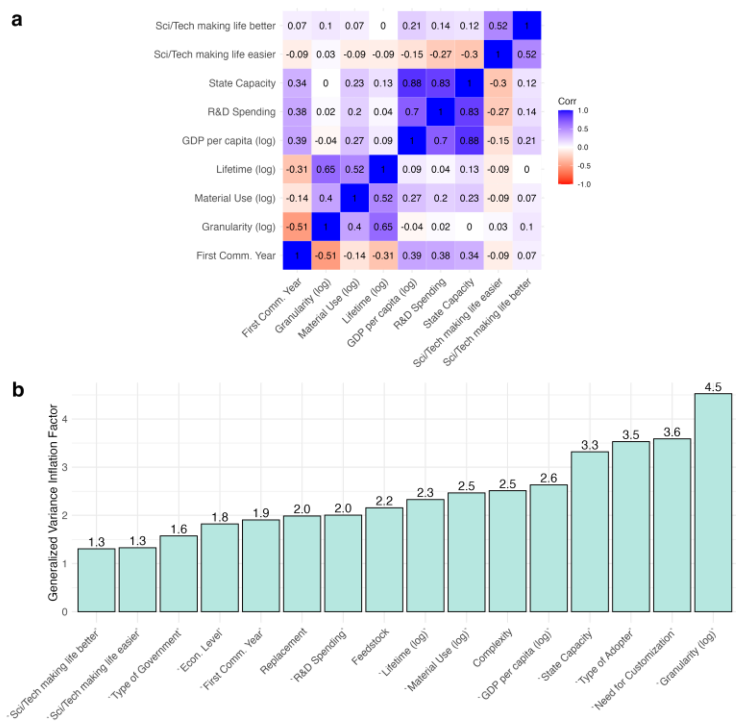


Figure 1. Correlation plots. In panel A, more saturated colors indicate higher correlation between explanatory variables and the Pearson correlation coefficient between each set of explanatory variables is reported in the middle square. Variables with greater than 0.7 are considered at risk of introducing multicollinearity and are thus not included in the same model. In panel B, Variance Inflation Factor 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[51].

We also adjust table 1 to include the names of each variable we use in the analysis so that the labels in the resulting figures are clearly associated with each variable. We have also made the text size bigger to be readable.

From table 1:

Public acceptance	Responses to World Value Survey: • Science/Technology making life better • Science/Technology making life easier

2.9: Figure 4 and its discussion characterise the size of the effect per unit change in explanatory variables, but these units are never specified. It is not clear whether the regression used variables expressed in their natural units or e.g. variables normalised to mean = 0 and sd =1. Overall, the article should include a summary table reporting range, statistical summaries, the type (continuous, binary, categorical) and units for each independent variable (plus transformations and normalisations, if used).

Response: We do not normalize the explanatory variables in the analysis, but we agree that a summary table would be a helpful addition. We moved two tables from the Methods section to the main text along with added details about each variable. The two tables are shown below.

Table 2:

Variable	Description and hypothesis	Example	Type	Transformations	Source	Citation
First year of commercialization	Modern systems have enabled more recently developed technologies to grow faster.	Digitalization and globalization allow for faster growth through more trade and communication	Numerical	Unit: Year	Author historical and archival research	Comin & Hobijn 2010(Comin and Hobijn 2010)
Technological Lifetime	Shorter technological lifetimes are associated with faster adoption speed.	Shorter lifetimes allow for faster turnaround for technological improvements, leading to faster adoption	Numerical	Unit: Number of years Transformation: log	Author historical and archival research	Wilson et al 2020(C. Wilson et al. 2020)
Material Use	Technologies with lower material intensity per dollar of value allow for faster growth.	The covid vaccine involves a small amount of materials per dollar of value. Because there are fewer materials per	Numerical	Unit: kilogram per dollar (2009)	Author historical and archival research	--

		dollar of value, fast improvements can be made thus allowing for faster growth.		Transformation: log		
Granularity	Granular (cheaper, smaller) technologies are more easily replaced and produced, enabling more rapid growth.	More granular technologies benefit from faster production, which allows for technology improvements and learning to happen faster, avoiding lock-in.	Numerical	Unit: 2009 US dollars Transformation: log	Author historical and archival research	Wilson et al 2020(C. Wilson et al. 2020) Sweerts et al 2020(Sweerts, Detz, and van der Zwaan 2020)
Complexity	The number of design elements in a technology, as well as their interactions, impacts the speed of technology growth.	Simple technologies allow for faster learning because of faster production times, faster improvements, and fewer coordination hurdles.	Categorical	Unit: Number of components Levels: Simple, Design-Intensive, Complex	Gathered through expert review.	Malhotra and Schmidt 2020(Malhotra and Schmidt 2020)
Need for Customization	The greater need to customize a technology in its installation or adoption will slow growth.	Highly customized technologies may require long, site-specific design stages, which slows technology adoption speed.	Categorical	Unit: Design Specification Level: Standardized, Mass-Customized, Customized	Gathered through expert review.	Malhotra and Schmidt 2020(Malhotra and Schmidt 2020)
Type of Adopter	Technologies adopted by both individuals and firms may benefit from more markets for growth, thus enabling faster diffusion.	Technology learning can transfer between markets within countries, leading to faster growth as improvements occur.	Categorical	Level: Individuals, Firms, Both	Gathered through expert review.	--

Requires Feedstock	Requirement of fuel may be associated with slower growth if additional trade and economic sectors are involved in production.		Binary	Level: Yes, No	Author categorization.	Skare, Riberio, Soriano 2021(Skare and Riberio Soriano 2021)
Replacement	If a technology is replacing another technology, then the infrastructure may already exist to support its growth, therefore leading to faster growth.	If a technology is replacing a similar technology with large support networks and systems, that replacement technology benefits from past learning and can grow more quickly.	Binary	Level: Yes, No	Author categorization.	Grübler and Nakićenović 1991(Grübler and Nakićenović 1991)
Category	Allows for interactions with other characteristics (control variable).	See other examples.	Categorical	Type: Categorical	Author categorization.	Comin & Hobijn 2010(Comin and Hobijn 2009)

Table 3:

Variable	Description and hypothesis	Example	Type	Metric and Transformation	Metric and Source	Citation
Country income level	Countries with higher wealth can allow for faster adoption of technologies because of resources available to build out systems quickly.	Countries with higher income may have resources to spend beyond meeting basic needs, for example on technology adoption.	Metric 1: Numerical Metric 2: Categorical	Metric 1: GDP per capita, Transformation: mean value in sample, logged. Metric 2: Income Group, Level: Low, High Transformation: Most common value in sample	Metric 1: Log GDP per capita, Bolt & Van Zanden, 2024(Bolt and Luiten van Zanden, n.d.) Metric 2: Income group, Fantom & Serajuddin, 2016(Fantom and Serajuddin 2016)	Comin & Hobjin, 2010(Comin and Hobijn 2010)

Spending on tech development	Spending on technology research and development may be associated with faster technology adoption.	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.	Numerical	Metric: Spending as percent of GDP Transformation: Mean value in sample	R&D spending as % of GDP, World Bank 2024(“Research and Development Expenditure (% of GDP) | Data,” n.d.) 6/4/2025 2:01:00 PM	Assiotis et al, 2015(Assiotis, Zachariadis, and Savvides 2015); Miremadi et al, 2019(Miremadi, Saboohi, and Arasti 2019)
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.	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.	Categorical	Metric: Democracy or non-democracy Transformation: Derived from polity score	Polity index (democracy, not democracy), Marshall & Jaggers, 2007(Marshall and Jaggers 2007)	Comin & Hobjin, 2010(Comin and Hobijn 2010); Okada & Samreth, 2023(Okada and Samreth 2023)
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.	States with stronger ability to pass policy may allow for fast adoption of technologies with high costs but with societal benefits.	Numerical	Metric: State Capacity Index Transformation: Mean value in sample. High/low derived from state capacity index.	State capacity, Hanson & Sigman, 2021(Hanson and Sigman 2021)	Brutschin et al, 2021(Brutschin, Cherp, and Jewell 2021)
Public acceptance of technology	Higher public acceptance for technology and science allows for faster technology adoption.	Attitudes about technologies influence individual’s and, collectively, organization’	Numerical	Measured with responses to two questions from World Value Survey on scale of 1 to 10.	Responses to World Value Survey, Haerpfer et al, 2022(Haerpfer et al. 2022)	Davis, 1989(Davis 1989)

		s intention to adopt technologies.		Transformation: Mean value in sample		

We also add summary tables to the methods section to describe each variable in the analysis.

Summary Tables (Methods section, pp 1-3):

	Year of first commercialization	Granularity (log)	Material use (log)	Lifetime (log)
Minimum	1743	0.62	-12.13	0.00
First Quartile	1872	4.94	-6.17	1.87
Median	1910	7.12	-2.8	2.71
Mean	1902	9.53	-3.41	2.49
Third Quartile	1949	13.66	-1.59	3.31
Maximum	2011	25.79	6.52	4.28
NA Values	N = 303	N = 545	N = 467	N = 473

Table 1. Summary statistics for temporal context and technology characteristics.

Variable	Level	Count	Minimum	First Quartile	Median	Mean	Third Quartile	Maximum
Need for Customization	Standardized	880	0.03	0.12	0.20	0.28	0.38	0.98
	Mass-Customized	205	0.03	0.11	0.20	0.27	0.38	0.96
	Customized	468	0.02	0.07	0.11	0.16	0.20	1.00
	NA	2	--	--	--	--	--	--
Complexity	Simple	780	0.02	0.12	0.19	0.26	0.33	0.97
	Design-Intensive	332	0.03	0.11	0.19	0.30	0.44	0.98
	Complex	443	0.03	0.07	0.12	0.18	0.22	1.00
Type of Adopter	Firms	422	0.02	0.10	0.16	0.23	0.30	0.96
	Individuals	659	0.03	0.14	0.22	0.29	0.38	0.98
	Both	474	0.03	0.07	0.12	0.19	0.21	1.00
Replacement	Yes	749	0.02	0.09	0.13	0.20	0.21	1.00
	No	806	0.03	0.12	0.23	0.28	0.38	0.97
Feedstock	Yes	320	0.03	0.08	0.12	0.17	0.19	0.95
	No	954	0.03	0.10	0.17	0.27	0.37	1.00
	NA	281	--	--	--	--	--	--
Category	Appliances	435	0.03	0.09	0.13	0.22	0.22	0.98
	Chemicals and Industrial	19	0.06	0.11	0.16	0.23	0.28	0.94
	Digitalization	198	0.11	0.21	0.26	0.29	0.35	0.95
	Energy Supply	326	0.03	0.13	0.27	0.33	0.47	1.00
	Food and Health	203	0.05	0.13	0.22	0.31	0.42	0.97
	Infrastructure	213	0.02	0.05	0.08	0.09	0.11	0.41
	Materials	34	0.06	0.09	0.18	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	32	0.04	0.09	0.11	0.15	0.16	0.66

Table 2. Summary statistics for categorical technology variables.

	R&D spending	World Values Survey Response		State capacity	GDP per capita (log)
		Technology makes life better	*Technology makes life easier*		
Minimum	0.01	3.8	1.97	-1.40	6.34
First quartile	0.27	6.29	6.64	-0.16	7.95
Median	0.64	6.83	6.99	0.47	8.88
Mean	1.01	6.73	7.03	0.58	8.85
Third quartile	1.59	7.3	7.59	1.38	9.71
Maximum	4.31	8.84	8.91	2.89	11.21
Na values	N = 814	N = 1189	N = 1189	N = 268	N = 147

Table 3. Summary statistics for numerical country characteristics.

Variable	Level	Count	Minimum	First Quartile	Median	Mean	Third Quartile	Maximum
Economic Level	High	537	0.03	0.10	0.19	0.26	0.36	1.0
	Low	517	0.03	0.11	0.16	0.22	0.25	0.98
	NA	501	--	--	--	--	--	--
Government Type	Democracy	562	0.03	0.1	0.21	0.28	0.39	0.98
	Non-Democracy	796	0.03	0.10	0.15	0.21	0.26	1.0
	NA	197	--	--	--	--	--	--

Table 4. Summary statistics for categorical country characteristics.

2.10: GDP per capita is included as an explanatory variable in Table 1, but then it is not reported among results of bivariate regression in Table 2 and is not used in multivariate regressions reported in Figure 4. Income group is also mentioned among explanatory variables, but never shows up in the results.

Response: We add GDP per capita and income group to the bivariate regression results in table 4.

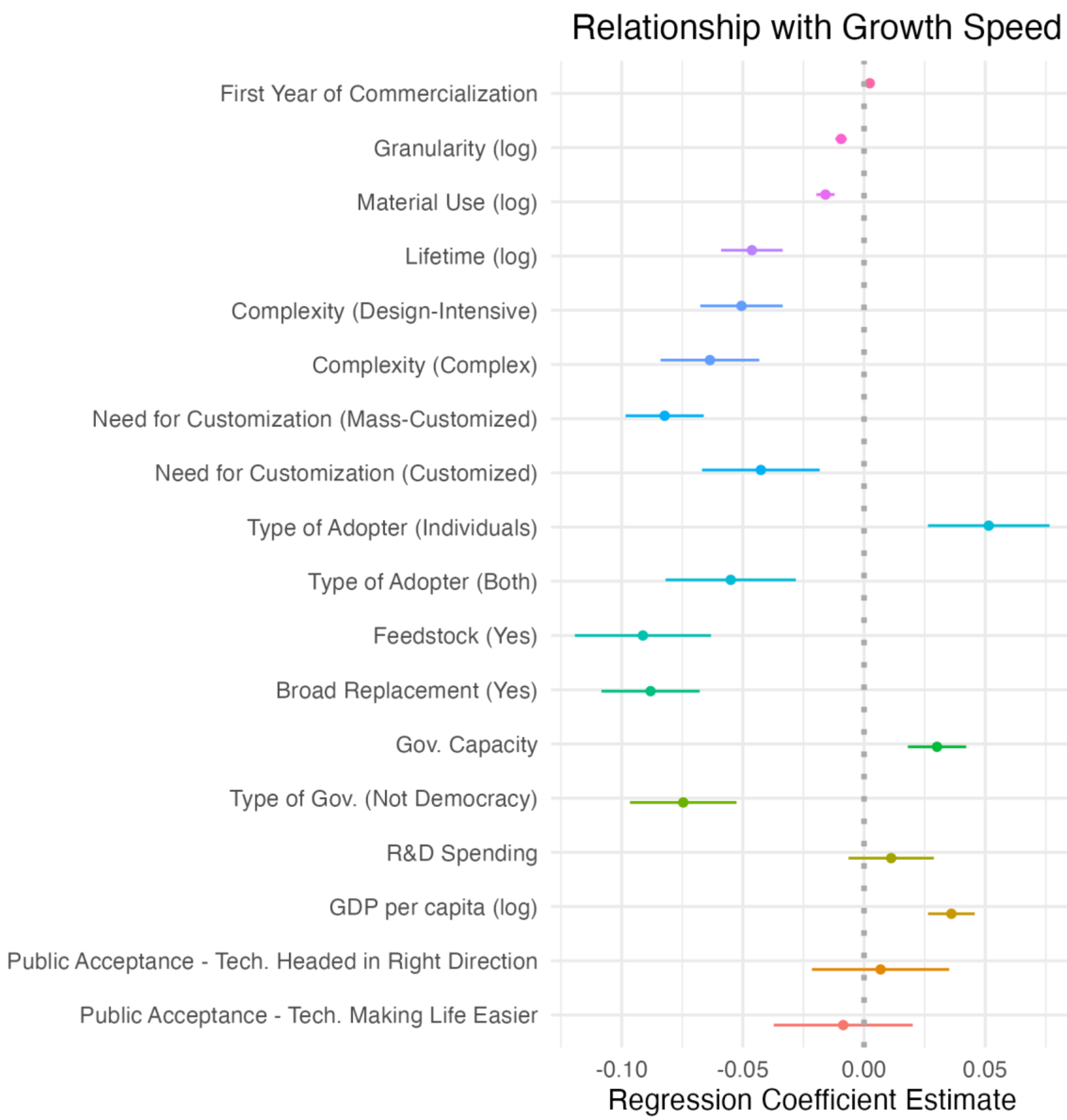
Economic development	Countries with higher income per capita are associated with faster technology adoption through more available resources.	Positive	Positive

GDP per capita is highly correlated with other country variables, which is why it is not included in multivariate regressions. We clarify that addition in text, lines 348 - 349.

> *"We do not include GDP per capita and state capacity in the same bivariate because of strong correlation, although both are significant."*

We also add a new section to Supplementary Information section B1 with a summary of the bivariate results. We reported the bivariates in Supplementary Information section B3, supplementary figure 14 previously, but the reviewer makes a helpful point to add these results in the main text, while clarifying that these variables are used as control variables. We added text to Section B1 of the Supplementary Information, lines 349 -360.

“A summary of the independent bivariate of each characteristic with technology growth speed is shown in Supplementary Figure 4. The dot represents the regression coefficient estimate for each variable with technology growth speed and the whiskers represent the confidence interval at the 95% confidence level. If the whiskers overlap with 0 (shown with a dotted gray line), the relationship is not significant. 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. Coefficient Plot for each variable. Plot shows the regression coefficient 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 and the whiskers represent the confidence interval at the 95% confidence level. If the whiskers overlap with 0 (shown with a dotted gray line), the relationship is not significant.*

2.11: In the last paragraph in page 10, the text mentions Figure 6, which is absent. Should it be Figure 4?

Response: Thank you for pointing out this error – this should be referring to figure 5 (because of an added figure from the Methods section to the Main text). We changed the reference to figure 5.

Text changed lines 364 and 369 of main text (changed text is underlined):

> *"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)."*

Reviewer 3

3.1: Thanks for having the opportunity to review your manuscript. I - as a specialist - gained interesting insights from reading your paper.

Response: Thank you for the thoughtful comments and thorough review. We are glad to hear that our paper yielded interesting insights!

3.2: However, I am not convinced it is worth a publication in Nature Communications. The paper provides a rich correlation analysis between different technologies, their characteristics & country environment and the speed of diffusion. This comprehensive detail may be very valuable when calibrating diffusion curves in a large scale IAM (as you mention) but to me this seems too technical to be relevant for a general interest readership like those of NComms.

Response: We understand the balance between two goals of the study – one goal is to enhance our understanding of technology diffusion processes, including validating previously hypothesized and studied diffusion dynamics using a large sample of heterogeneous technologies. The other is to inform empirical estimates of technology diffusion, including the example of large scale IAMs. But to be clear, the rate of adoption of technology is broadly accepted as crucial for addressing problems related to energy, the environment and climate change. To date the evidence has been mixed about how feasible it would be to scale up low-carbon technologies to meet net zero goals. One need not be an IA modeler to appreciate that better insight on technology adoption is needed and that they affect an array of systems of concern. We have rewritten the manuscript substantially to clarify the goals of the analysis and emphasize the findings, including how such finding can inform our understanding of climate change mitigation.

3.3: Also, many of the insights are not surprising or new, they have just never been documented at such a comprehensive scale which is a contribution.

Response: We agree that the comprehensive scale – of technologies, of characteristics of those technologies, and of country characteristics – is a contribution, in part synthesizing previous hypotheses and findings in previous work that has focused on a small number of technologies. We highlight the comprehensive scale of these contributions, both the HATCH dataset and the technology characteristics gathered for this analysis, and also highlight that these technology characteristics will be made publicly available for future studies as well.

We add text to lines 127-131 of the main text:

> *"The dataset is publicly available for future studies on technology diffusion speed and technology characteristics. 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 is one of the novel components of this study."*

3.4: However, to make the paper stronger, it would be necessary to develop a clearer story about what can be learned from your findings apart from technical insights for model calibration. Technologies are highly heterogeneous & it is also not always clear whether an s curve best captures their shape. What is with diffusion failures or technology replacement curves when the incumbent technological solution is simultaneously taken into account? For the energy transition, not only diffusion matters but especially the phase out of the carbon intensive incumbents while there are many different replacement candidates.

Response: We agree with the reviewer's note that technologies are highly heterogeneous. In terms of the functional form that best fits the shape of technology diffusion, we chose to fit a logistic function because it approximates an S-curve and is often used in technology diffusion literature. We further test an additional functional form (the Gompertz function, see below). We add description to the main text and the methods text to explain our use of the s curve and logistic function.

Main text page 3, lines 102-109 (added text is underlined):

> *"In this study, 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. <u>As technologies move through phases of development, the shape of the adoption over time follows an s-curve shape(Rogers 1962). The logistic function approximates this path and has been used extensively in empirical analyses of technology diffusion(Odenweller et al. 2022; Bento and Wilson 2016; Charlie Wilson 2012).</u> For each time series, we fit a logistic function to each time series and use the steepness parameter to represent technology diffusion speed, which is the dependent variable in our analysis. More details are described in the Methods section."*

In the methods section we add new text in two places:

Lines 36-40:

> *"The logistic function has been used to measure technology diffusion across sectors, such as in agricultural systems(Griliches 1957), energy technologies(C. Wilson et al. 2013; van Vuuren et al. 2018), and industrial systems(Van Ewijk and McDowall 2020). Many studies use other functional forms to measure diffusion(Zielonka, Wen, and Trutnevyte 2023; Nemet et al. 2023), 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(Cherp et al. 2021) in the Supplementary Information Section C1."*

Lines 78 – 83:

> *"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."*

The reviewer also points out the importance of the phase out of carbon-intensive technologies alongside the scale-up of climate technologies. We agree with the reviewer that this is an important consideration, although it is out of scope for this study.

We add a paragraph and citations to current research on this matter in the main text (lines 502-512):

> *"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(Xie et al. 2025). 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."*

To be clear though, our experience with working with a dataset of 100s of technologies shows that it is not always obvious how much an emerging technology substitutes for another, which ones and how much. For example, e-bikes are one of the fastest technologies we see growing in our data set. Whether those bikes substitute for analog bikes, cars, walking or other modes is not obvious even with a large literature directed toward that issue; that type of ambiguity is present for many technologies in our data.

3.5: I am also not too convinced of the type of empirical exercise: as mentioned it looks to me like a pure correlation study. A multivariate analysis that also considers policy related variables or time-specific external shocks would be appropriate, especially if your aim is to underline how the study helps in the context of fighting climate change. For example, technology costs change over time & can be changed by policy: just think of oil or emission prices.

Response: We are interested in the correlation between technology and country characteristics on technology diffusion, which has implications for the modelling of novel climate technologies but also builds on technology diffusion literature more broadly. One of the gaps we attempt to fill is providing an updated HATCH dataset which includes ten temporal and technology characteristics for each technology. We agree with the reviewer that policy variable and time-specific shocks are an important part of technology diffusion but extend beyond the scope of this analysis. There are two primary reasons that we do not include the role of specific policies on technology diffusion. First, as we discuss below, each technology-country growth rate is a single *value, so time variant events such as policies or shocks would not be consistent with our data structure. Second, the breadth of the technologies and countries we analyze does not allow for policy-specific analysis because policies vary both by the technology analyzed and the country analyzed, which would require collecting unique data for the 5,599 time series (assuming collecting data on only one policy per technology and country).*

We have added this to the discussion section of the main text to highlight the limitations of this approach and future work.

The following text is included on pp. 20-21 of the main text, lines 477-500:

> *"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 121 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 5,599 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."*

3.6: Generally, for telling a story about climate technology, I would have expected the empirical analyses to include elements that specifically analyze climate technologies (which are extremely heterogeneous covering probably all dimensions of technology characteristics that you list). Maybe your analysis can be helpful to inform technology selection (at the country level)? For example, choose those tech that diffuse fastest? This might be a direction to develop a paper that leverages the comprehensive descriptive knowledge that you collected.

Response: We agree with the reviewer that climate technologies are extremely heterogeneous. Some climate technologies are included in the HATCH dataset and this analysis, including solar and wind energy, air source heat pumps, and electric vehicles (for example). Because climate technologies are diverse in their characteristics, analyzing a wide range of technologies is a critical aspect of this analysis. This broadens the set of technologies that researchers can apply to climate technologies and provides more expansive lessons to drawn upon.

We add details to our explanation of the broad set of technologies in the introduction section to emphasize the broad nature of climate technologies.

Page 5 lines 164-172:

> *"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(Roberts and Nemet 2024) 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."*

We also add this consideration to the discussion section by emphasizing that growth speed is one, but not the only, consideration for selecting climate technologies.

Main text, page 20 lines 452-460:

> *"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."*

Finally, our motivation for making the effort to construct such a broad dataset is that there is as much to learn from the history of climate relevant technologies (such as EVs) as there is from non-climate related technologies (like mining or vaccines). The broader set give us a more representative set of dynamics.

3.7: I hope my comments - despite being harsh - help. Good luck with the article.

Response: Thank you for the thorough comments – we appreciate the time and attention that you gave to your review.

3.8: Also, the appendix was not self-contained for me. I was missing technical detail about the exact implementation of the curve fitting exercise & I could also not find it in the SM. Also code & data need to be provided. There was no code & data available to review this material. Also, some technical detail about the implementation of the curve fitting exercise was missing in the supplementary material/appendix.

Response: We include the code and data in this revision and thank the reviewer for pointing out this detail. The code is available at this GitHub repository: https://github.com/jennagreene22/National_Technology_Diffusion.

We also added further description about the curve fitting process beyond the description in the methods section and the Supplementary Information section A2 (page 22 of Supplementary Information).

In the methods section page 3 lines 48-59, we make the following changes (underlined text):

> *"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(Virtanen et al. 2020). 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. 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. 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."*

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

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).

In the Supplementary Information section A2, we make the following changes (underlined text):

> *"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(Virtanen et al. 2020). <u>The nonlinear least squares method implements the Levenberg-Marquardt algorithm to attempt a fit on the time series data.</u> We specify 5,000 function calls to attempt a fit. <u>The parameters are not bounded during the fitting process. The fitting results in an estimate of the three free parameters in the logistic function which is the result of the implemented Levenberg-Marquardt algorithm of least squares optimization.</u> The initial parameters used in function fitting are based on Cherp et al shown in table supplementary table 13 below, calculated for each time series(Cherp et al. 2021)."*

Responses to Reviewers NCOMMS-24-77209-T

Reviewer 1

1.1: The new version of the manuscript is significantly clearer and more transparent about its limitations. The authors now explain more clearly what they can and cannot do due to limited data availability. For instance, given the time and resource constraints, the decision not to include variables that vary at the country and technology level in the estimates for such a comprehensive analysis of technology diffusion seems reasonable. Additionally, the objective of the paper is now much clearer. In my view, the paper is not concerned with identifying causal patterns, but rather with patterns of relationships between country and technology characteristics, based on a uniquely comprehensive dataset. The results can therefore also be seen as a starting point for more in-depth investigations, such as the effectiveness of specific policy measures.

Response: Thank you for the detailed feedback in this review. We appreciate this comment! To ensure that the intent of the paper is clear, we add one sentence before the research questions are presented. We add one sentence to lines 84-85:

> *"This study analyzes patterns between technology diffusion speed and technology and country characteristics."*

1.2: The text now makes it clearer that broad technological coverage also serves the purpose of identifying characteristics that can help climate-friendly technologies spread more quickly. However, in your response, you refer to the "benefit to the public." But when I look at the list of technologies again, I find technologies such as beer production and oil refining capacities, and I think you should explain this better. It is unclear what public benefit they offer. I believe you are referring to Figure 2 in your response.

Response: We remove the reference to 'public benefits' in the abstract based on this feedback. The text on lines 20-21 now reads:

> *"These findings indicate that small technologies may be <u>adopted faster</u> than complex, large technologies, which may take longer to become adopted."*

1.3: The heterogeneity of technologies is very comprehensive, hence it would be good to show some heterogeneity analyses, for instance, if climate mitigation technologies, telecommunication technologies, or agriculture related technologies show a similar pattern. This might also further enrich the discussion. Given the emphasis on climate mitigation technologies in the abstract and introduction, heterogeneity tests for these technologies are in particular relevant. Your explanation for a broader technological focus (lines 178-184) is very useful, however, a test among climate mitigation technologies might still add to it in a significant way.

Response: We appreciate the reviewer's attention to climate mitigation technologies. Our paper is specifically interested in the lessons that we can learn from studying technology diffusion specifically for climate technologies. However, we include such a broad technological dataset because of the diversity of climate technologies themselves – the three technology categories that the reviewer mentions are all relevant, but so are the other categories covered. We avoid discussing climate technologies that are in the HATCH dataset directly, but instead add examples of how diverse climate technologies themselves are.

In the main text, we include the following addition in the Introduction section (lines 156 – 159):

"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. A more thorough discussion of the diversity of climate technologies is included in Supplementary Information Section A1."

We add the following table and discussion in Supplementary Information Section A1 (lines 100 – 110).

> *"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). Table XXX 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.

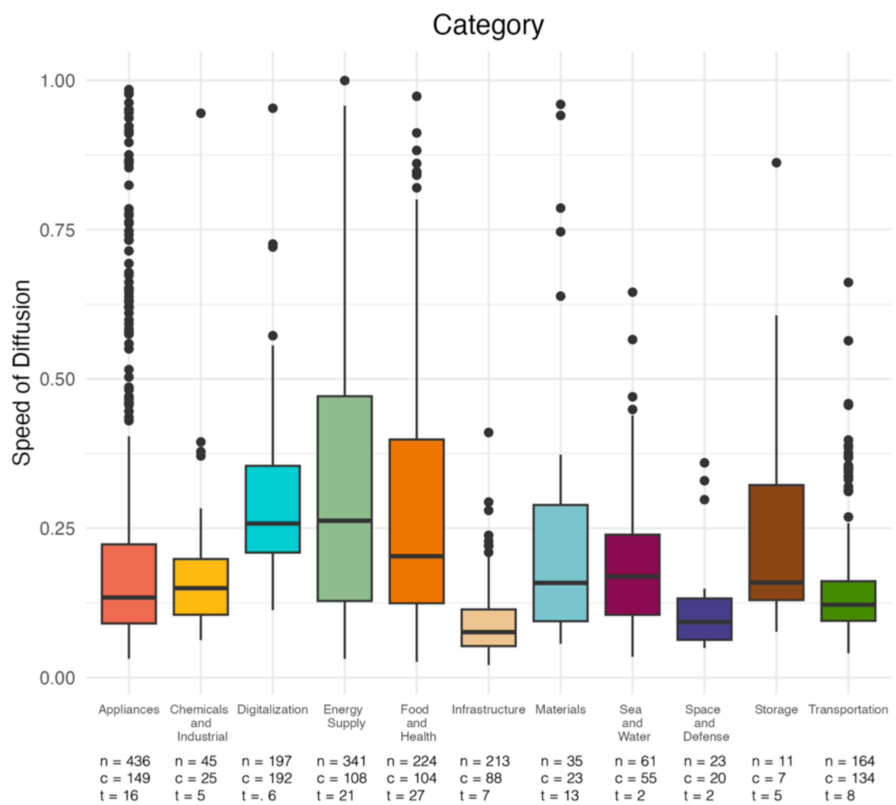
Energy Supply	Solar photovoltaic supplies renewable energy, reducing greenhouse gas emissions.
Food and Health	Cover crops can improve carbon storage in soils.
Infrastructure	CO_2 pipelines are infrastructural technologies used for the transport of carbon dioxide between carbon capture locations to storage 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 1. Technology Categories in HATCH and example climate technology for each category.

Beyond a discussion of the diversity of climate technologies, we also include a description of the differences in growth speed of technology categories within HATCH by adding Supplementary Figure 15 and new text in lines 533 - 537:

> *"Each technology in the HATCH dataset is categorized as one of eleven categories (n = 1,750). 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 1. 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).

1.4: The findings of the polynomial approximation should also be (briefly) mentioned in the manuscript. It nuances for instance the previous finding that the technology lifetime is negatively related with speed of diffusion. I could only see the reference to the supplementary material in the main text.

Response: We have added the polynomial approximation summary to the main text, along with references to the Supplementary Information analysis.

New text in Results, lines 263-267:

> *"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."*

New text in Results, lines 279-286:

> *"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."*

1.5: The country characteristic is calculated from the first year of adoption for a country-technology pair until the inflection point … Then the values between these two points are averaged. Please describe the rational for this way of calculating the country characteristics and explain why the value at the inflection point is used for „income"?

Response: We thank the reviewer for pointing this out. For the income group variable, we use the most common value in the period of interest for each country-technology pair. The previous description described an older method.

We corrected this in the Supplementary Information text, lines 260 – 261.

> *"This is measured as the most common income level between the first year of data and the inflection year."*

Regarding the other variables, we describe the reasoning for the 'period of interest' between the first year of data and the inflection year in lines 235 – 236 to capture the average adoption context between the formative and accelerating phase of technology diffusion, before diffusion slows.

We add text to the Introduction section of the main text (lines 237-238):

> *"<u>Using either the average or mode of a country characteristic</u> gives an indication of that adoption context between the formative and accelerating phase of technology diffusion."*

1.6: As explained in the manuscript, the omission of variables can significantly distort the results. Given how comprehensive the study is, I don't think there is much else the authors can do except describe this as a limitation in more detail in the supplementary part to the manuscript.

Response: We thank the reviewer for this comment. We have added a supplementary note in Supplementary Information Section D, a new supplementary section on limitations (lines 1020-1041).

"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 17. 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."

1.7: This sentence does not make much sense: The Gompertz function is similar to the logistic function, except it is asymmetrical, with slowing growth after the inflection point until reaching the inflection point (Section C Sensitivity Analyses: lines 1039-1041)

Response: Thank you for pointing out this mistake. Lines 777-778 of the Supplementary Information Section C1 now reads:

"The Gompertz function is similar to the logistic function, except ***it <u>is an asymmetrical model</u>.*** *It estimates slower growth after the inflection point approaching the asymptote."*

1.8: „Former Czechoslovakia has a unique ISO-3 code of CSR, used in this analysis (p. 22, line 328)." Since Slovakia and the Czech Republic separated in 1993, I do not think it makes sense to combine them in the analyses after 1993. Their economic and technological development has been very different since the separation. I wonder whether it makes sense to remove the country from the analyses. A similar problem could arise in connection with the former Yugoslavia.

Response: We have clarified the treatment of countries without an ISO-3 country code as well as the Slovakia/Czechia overlap that the reviewer has pointed out. We have changed the description in the Supplementary Information Section A2 (lines 314 - 323):

> *"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."*

We have changed the caption of Supplementary Table 3 to describe this (lines 90-98):

> *"Supplementary Table 2. Number of technologies for each country included in the HATCH dataset used in this analysis. Filtered through process depicted by supplementary figure 1 and filtered based on logistic fit R2 > 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."*

1.9: B5 Country-specific characteristics: A polynomial approximation could also improve the fit here, at least for some variables. I think it's worth a try.

Response: We thank the reviewer for this suggestion. We have added a polynomial approximation for each of the numerical country characteristics. This does not impact the main results of the R&D spending, sociocultural acceptance, or state capacity results, although the squared term is significant for the GDP per capita variable. The changes to Supplementary Information Section B5 are detailed below.

Lines 651 – 653 (on GDP per capita):

> *"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."*

Lines 656 – 659 (on R&D spending):

"We do not find a significant relationship between R&D spending and speed of diffusion with a linear relationship ($p = 0.42$), nor when we add a squared term to the estimate ($p = 0.13$ for linear term, $p = 0.69$ for quadratic term)."

Lines 669 – 671 (on socio-cultural variables from World Value Survey):

"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)."

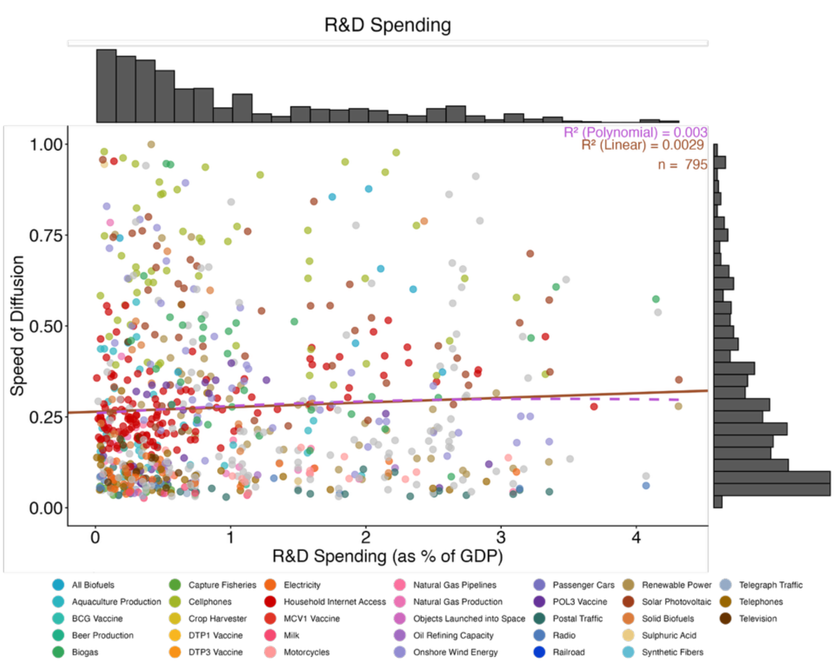
Lines 690 – 693 (on State Capacity):

"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 ($p = 0.99$)"

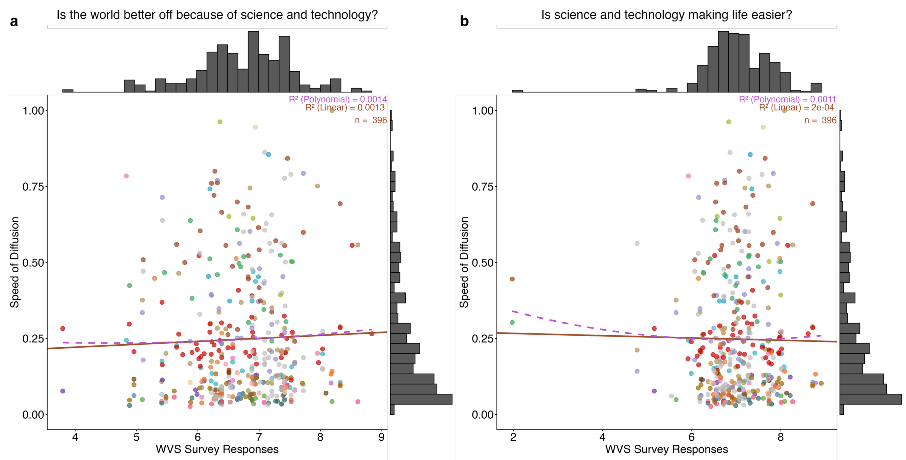
1.10: Supplementary Figure 17 and 18 the R2 values are not visible in the figures.

Response: Thank you for pointing out the cutoff. We adjusted these two figures in the Supplementary Information.

Supplementary Figure 18 (line 660):



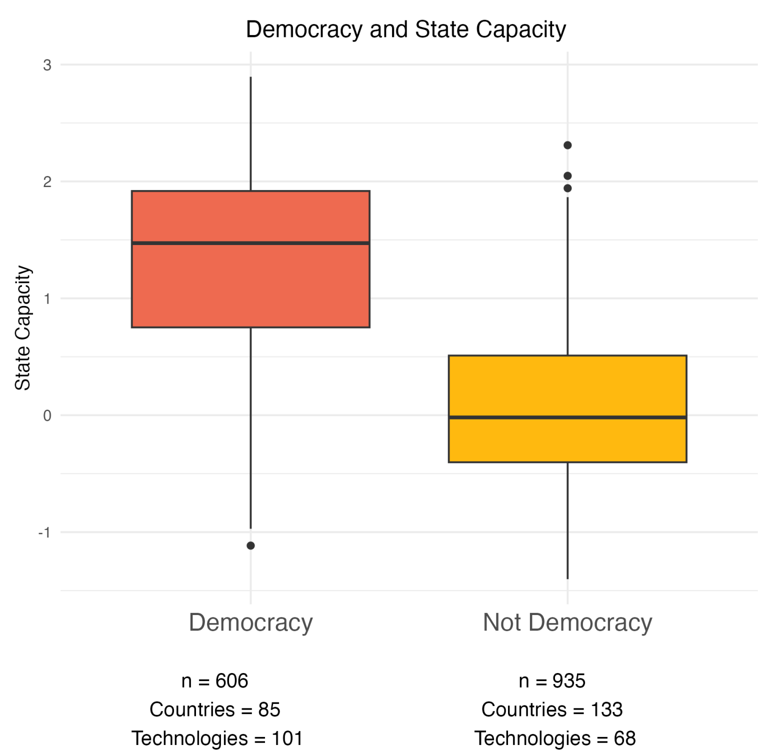
Supplementary Figure 19 (line 676):



1.11: Supplementary Figure 22: According to the text it should show the relationship between democracy and state capacity, however I see „democracy“ and „not democracy“ on the x-axis and „speed of diffusion“ on the y-axis. Please explain/correct this.

Response:

Thank you for pointing out this error. The axis was labelled incorrectly, although the data was accurate. We have made the label change to Supplementary Figure 23 (line 748):



1.12: „For each time series, we fit a logistic function to each time series…“. No repetition of „each time series“ is necessary. (line 113)

Response: Thank you for pointing this out. In response to another comment, we have changed this line. The text on lines 108-110 of the main text now reads:

> *"For each time series, we fit a logistic function with three free parameters using nonlinear least squares optimization."*

1.13: Similar issue: „…having the fastest growth ($p < 0.05$) and technologies that are adopted by firms adopted more quickly than technologies adopted …“ (lines 306 and 307)

Response: The text on lines 300-303 now reads:

> *"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 ($p < 0.05$) (**Error! Reference source not found.**, panel c)."*

1.14: Typo in text below Figure 3: „… withinin box indicates median, …“

Response: Thank you for pointing out the typo. The text on lines 311-312 now reads:

> *"Box edges show the inter-quartile range, line within box indicates median [...]"*

Reviewer 2

2.1: I appreciate the changes made to the manuscript, particularly the explicit mentioning of the temporal context, detailed description of independent variables, and more articulated discussion. However, there are few points that I would recommend to address before publishing. I consider one of them (numbered 1 below) critical.

Response: We thank the reviewer for their detailed review. We have made changes to the manuscript based on these recommendations.

2.2: 1. The key point from my initial review concerning the growth metric (steepness of the logistic curve, k in the logistic equation) remains essentially unaddressed in the revised version. The entire discussion of the dependent variable in the main text boils down to a single sentence – "For each time series, we fit a logistic function to each time series and use the steepness parameter to represent technology diffusion speed, which is the dependent variable in our analysis" (lines 112-114 in the version with revisions) – which is in a striking contrast with the detailed treatment of independent variables in the revised manuscript.

Response: We agree with the reviewer that the calculation of the technology diffusion speed metric is crucial to this study. Although much of the details remain in the Methods section because of the journal conventions, we add more description into the main text.

In lines 108 – 111 in the introduction section, we add more description about the k parameter:

> *"For each time series, we fit a logistic function <u>with three free parameters using nonlinear least squares optimization. We use the steepness parameter to represent technology diffusion speed, which is the dependent variable in our analysis (further described in the Methods section)."</u>*

2.3: As explained in detail in my original review, the steepness of the fitted logistic curve (k) reflects only one aspect of growth (speed "relative to the ceiling of the respective S-curve"), and a curve with a greater k may represent slower growth in terms of absolute or normalised units (absolute: e.g. mobile phones or GWh from the electricity source in question; normalised: e.g. mobile phones per person or generation from a source as a proportion of total power generation).

Response: We thank the reviewer for this comment. Because of the scale of the HATCH dataset and the diversity of the technologies included, most operate in different markets and across many different unit types. The choice to include technologies with many metrics without standardizing or normalizing is a tradeoff of this analysis. On one hand, the unitless nature of 'k' allows us to explore the dynamics of many different types of technologies across different markets. On the other hand, comparing different types of markets and metrics may obscure the results, as faster growth may be associated with a certain metric rather than a characteristic of that technology. We include an analysis of the association between the technology adoption metric (share, annual production, capacity/power, and total number of units) in the Supplementary Information Section C5.

To address this point in more detail, we have added a paragraph on the k parameter to the limitations section of the discussion, including a reference to these robustness and sensitivity analyses.

New text in Discussion section, lines 580 – 594:

> *"Finally, the diffusion speed metric k 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 will require certain assumptions to be made by the modeler based on the metric used in this dataset, depending on the context represented by the given modelling framework. We include*

robustness tests and sensitivity analyses of the results based on the measures technology adoption (Supplementary Information section C5), 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). 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."

2.4: This limits the relevance of the results to "integrated assessment models, across different scenarios, and for technology forecasts" (lines 457-458), because (a) k alone may not adequately represent the growth speed in which modellers and policy-makers are interested; (b) strictly speaking, the steepness parameter is meaningful only in the context of the logistic curve, so it is not directly applicable when a scenario or a forecast does not imply logistic growth (which is often the case).

This concern is not about growth ceiling as such (so it is not addressed by the text added to Discussion, lines 535-536: "while our study focuses on the speed rather than the final extent of technology diffusion"). It is about the limitations of the specific growth metric, which may not capture relevant aspects of technology growth. As the authors correctly note in their response, the advantage of k is its applicability across different technologies due to its dimensionless nature. This comparability, being essential for this particular study, comes at a price of a limited informativeness and policy relevance.

Response: We thank the reviewer for this point. We agree with the reviewer that the 'k' metric itself cannot be used by modellers and is not used by policy-makers, per se. We use the approach of fitting a logistic function and extracting the 'k' parameter because it is rooted in the theory of technological change and has been used for decades in technology diffusion research. We have clarified the usefulness of the 'k' metric directly in text, as well as adding more details about alternative approaches for measuring growth, including a compound annual growth rate which is used more commonly in models and by policymakers.

We agree that there is a tradeoff in using the k metric: the applicability due to its dimensionless nature is well fit to the broad nature of the HATCH data, but the metric itself is not as directly applicable for policy or modelers than other metrics. To address this tradeoff, we add text to the Introduction section:

New text in introduction section lines 116 – 124:

"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 for insights to be generated that are relevant, especially about relative growth across different technologies."

We have also adjusted the framing of the results in the discussion section by clarifying that although the results of this study may inform assumptions of technology diffusion, the k metric itself may not be used directly.

New text in discussion section lines 429 – 432:

> *"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."*

2.5: As a minimum, the introduction of the growth metric as the dependent variable in the main text should be accompanied by a discussion of other growth metrics used in the literature, their advantages, disadvantages, and reasons for choosing the metric used in the article. The results should be properly qualified, given the limitations inherent in the selected growth metric.

Response: We thank the reviewer for this suggestion. We have added more description about other functional forms, potential limitations of the k metric, and a description of other studies that have looked more extensively into differences in growth metrics and functional forms.

New text in Main text (lines 111 – 114):

> *"Other functional forms and growth metrics have been studied, including exponential[15], Gompertz[23], and Bass[34] functions, although none are as extensively studied as the logistic function (further discussed in Supplementary Information Section D2)."*

Beyond these points, we agree with the reviewer that there are many functional forms and growth metrics from which to choose. Indeed, several studies have explicitly studied the differences in growth metrics and functional forms, including in recent years, which demonstrates that this is an important topic. However, it is outside the scope of this analysis to analyze the many functional forms and growth metrics that can describe technology diffusion. We appreciate the suggestion to make this limitation more clear and explicit. We have added several references to the reasons that we have chosen the "k" metric from the logistic function, limitations of this choice, and references to other studies that have analyzed other ways to measure technology diffusion.

We have added a section to the Supplementary Information section that describes these limitations and summarizes some other approaches.

New text in Supplementary Information Section D2 (lines 1043 – 1077):

"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[18], although other metrics and techniques are sometimes used. In Supplementary Table 3, we summarize advantages and disadvantages of a few ways to measure technology diffusion. Many other studies have more deeply discussed different s-curve models[18–21]. 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[20]*	*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[20].*
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*	*The k metric measures the speed of diffusion relative to the asymptote, or ceiling, which varies by technology.*

	adopting users (firms or individuals).	
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 3. 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[18,21,22]. 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."

2.6: 2. It would be good to give the reader a more intuitive understanding of what the particular values of the growth metric mean. For example, the article could state that k = 0.25 corresponds to the growth duration (time from 10% to 90% of the ceiling) of 17.6 years*, and the increase of this particular k of by 0.02 would reduce the growth duration by 1.3 years. 0.25 here is just an example, it would make more sense to use a median k across the technology or country-technology sample used in the article. Along the same lines, the phrase "the median diffusion speed has increased from 0.10 to 0.61" (lines 255-256) could be complemented with something like "i.e., growth duration reduced from 44 to 7.2 years", provided the growth duration is defined prior to that.

* Growth duration dT for the logistic curve is calculated as ln(81)/k, according to Wilson (2012).

Response: We thank the reviewer for this suggestion. We add this analysis in two places.

First, we add the description to the Introduction section lines 120 – 128:

> *"The downside of using a unitless steepness parameter is that the numbers can be difficult to contextualize. The metric can be transformed into the number of years that it takes to move from the early to later stages of adoption (further described in Methods section). 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. This transformation process is further described in the Methods section."*

Second, we add the growth duration to the results section (lines 259 – 262, new text is underlined):

> *"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). <u>This translates to a difference in median growth duration of 44 years in 1743 to 7.2 years in 2011."</u>*

2.7: Iyer et al. (2015), using a closely similar metric for global technology growth based on logistic fit, rank ca. 40 technologies from "slow" to "fast" (Table 1 in their paper). It would be important to see if their findings are in line with the profile of fast and slow technologies according to the manuscript.

Response: We thank the reviewer for this idea of looking at Table 1 of Iyer et al's analysis. We conducted a supplementary analysis that is included in full in the Supplementary Information Section C7 as well as references in the discussion section and methods section.

New section (lines 987 – 1019): Supplementary Section C7:

"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)[17].

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 the Iyer et al. data set 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 the Iyer et al. paper: growth_rate = 219.7 / ΔT with $\Delta T = \ln(81) / logistic\_growth\_rate$. After filtering out the technologies in *the Iyer et al. dataset for which there is not an associated technology in HATCH, we rank the growth rates by speed of each dataset (shown in the table below).*

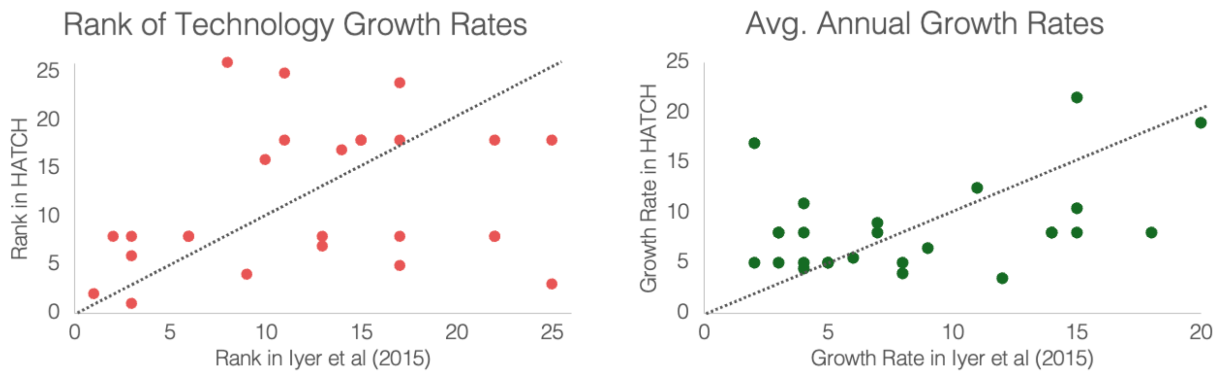
Technology in Iyer et al	**Region in Iyer et al**	**Avg annual growth rate**	**Rank in Iyer et al**	**Associated Technology in HATCH**	**Logistic Growth Rate in HATCH**	**Calculated avg. annual growth rate**	**Rank in HATCH**
Washing detergent (as a substitute for soap)	USA	24	--	No direct match	--	--	--
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 4. Comparison of Growth Rates in [17]

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 figure xxx), there is no clear bias.

The comparison of these ranks and the annual growth rates is shown in the figure xxx, 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 (Grübler et al., 2016) *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 2. Comparison of ranking of technology growth speed and average annual growth rates in HATCH dataset and Iyer et al (2015) dataset.

New text in Discussion lines 432 – 440:

> *"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)."*

New text in Methods section lines 84 - 101:

> *"We benchmark our extracted k growth parameter with another study that combines 38 technology growth rates[15]. 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[15], 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 for full analysis).*

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

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

$$average\ annual\ growth\ rate\ = 219.7/\Delta T$$

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."

2.8: The discussion could benefit from further streamlining.

- In particular, it looks like there is a certain overlap between the messages of the second paragraph (466-476, "lessons for future technology diffusion") and the sixth (503 etc., "implications for climate technologies").

Response: Thank you for this suggestion. We have reorganized the discussion section to address this point.

In the initial discussion, we shorten the implications of the findings for technology diffusion generally (new text on lines 446-448, bolded and underlined):

> *"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**."*

We updated the text in the implications for climate technologies specifically (lines 488 – 491), new text bolded and underlined:

> *"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**."*

2.9: The point that technologies with "fasted growth profile" may still need policy support can be connected to the point that the factors tested in the article explain only a fraction of the variance in growth speed.

Response: This is a helpful connection, we thank the reviewer for this comment. We have added a sentence to the discussion that highlights this point

New text, lines 498 – 500:

> *"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."*

2.10: The sentence "Third, we find a wide range of technology diffusion speeds across countries that are not accounted for by country characteristics broadly" (523-524) seems to merge two different findings of the article – (a) that only a fraction of the variance in growth speed is explained by any variables in the study and (b) that the effect of country characteristics is less pronounced than that of technology characteristics. Perhaps they need to be addressed separately.

Response: We thank the reviewer for this suggestion. We have separated these two points in the discussion

New text in the discussion section is bolded and underlined below (lines 494-500).

> *"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.****"*

2.11: Finally, it would be good to signal explicitly when the Discussion switches to the limitations of the current study.

Response:

Thank you for this suggestion. We have reorganized the discussion section to make this more clear and add a paragraph to introduce the limitations portion of the discussion section.

New text added in lines 502 – 505:

> *"It is important to acknowledge the limitations of this study. There are three main limitations, 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."

New text added to introduce each limitation section:

Lines 507 – 508: "First, the growth speed of climate technologies is one factor that impacts mitigation potential, but not the only factor.

Lines 534 – 535: "Although the HATCH dataset is extensive, there are also limitations associated with the technologies included in the dataset."

Lines 553 – 554: "The third set of limitations are related to the metrics used to measure both technology diffusion and the characteristics."

2.12: There's no README file with instruction for running the code, which would be particularly important given that the released code is in two different languages. It should also contain the description of expected results, e.g. names and format of output files. There's no data file in the repository; if the file is released elsewhere, README should contain instruction for obtaining the file and making the code compatible with the file (e.g. in which folder to place the file; where to modify the filename in the code if necessary etc.)

Given the absence of instructions and the data file in the repository, I didn't try to run the code.

Response: Thank you for this suggestion. We have added a ReadMe file to the repository, which also now includes the data files necessary to replicate the analysis. The repository can be found at this link: https://github.com/jennagreene22/National_Technology_Diffusion

Reviewer 4

4.1: This paper investigates the effects of technology- and country-specific characteristics on the speed of diffusion for 121 technologies across 229 countries. I congratulate the authors for bringing new empirical evidence to an important question—understanding the determinants of technology diffusion—which is also relevant for assessing the feasible dynamics of climate mitigation. The extended dataset, clear documentation, and consistent methodology provide confidence in the results presented.

The paper advances our understanding of innovation diffusion, for example by highlighting how certain characteristics—such as smaller, more granular technologies—are associated with faster diffusion. However, some claims are arguably based on weak evidence, particularly the assertion that the diffusion of technologies has accelerated over time. My recommendation is to accept the article with minor revisions.

Response:

Thank you for the detailed review. We have made changes to the manuscript based on the reviewer's feedback, detailed below.

4.2: My main concern relates to the claim of diffusion acceleration over time. Older technologies might have been more fundamental, complex, and radical (e.g., steam engines), which may explain the greater availability of historical data for such innovations compared to simpler, more recent substitution technologies (e.g., ebook reader). This potential selection bias could produce an artificial appearance of acceleration. At the very least, this issue should be discussed or acknowledged in the paper. For instance, the observed acceleration could be presented as a pattern specific to this sample (albeit a large one), warranting further research to ensure comparisons are made between comparable technologies ("comparing apples with apples").

Response:

We thank the reviewer for this important comment. We agree that the observed acceleration in diffusion could be influenced by selection bias if earlier technologies are systematically more fundamental, complex, or radical, and therefore more likely to be observed over long historical periods than more recent, potentially simpler substitution technologies. Such a bias could contribute to an apparent acceleration even in the absence of a true temporal change in diffusion dynamics. We now address and acknowledge this concern explicitly.

First, we add a sentence to the abstract to clarify the purpose of this paper, which is to investigate trends and provide data for future analysis (lines 22 – 23):

> *"Future work can build upon this expanded HATCH dataset to investigate these trends and the robustness of initial insights in more detail."*

Second, we add this multivariate regression to table 30 in Supplementary Information with only the first year of commercialization and complexity included, as well as a discussion of the results.

New text in Supplementary Information Section B3 (lines 582 – 588):

> *"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."*

Third, we add text to the limitation section about potential bias in this dataset. While not all technologies can be directly compared to one another, we focus on acknowledging the vast lessons that can be learned from a wide range of technologies, including recent technologies that may be less fundamental than older technologies.

New text lines 545 – 552 in Discussion section of main text:

> *"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 bia, and further test the robustness of our initial insights."*

4.3: Furthermore, the empirical evidence supporting the acceleration claim appears weak. Figures 2a and 2b suggest possible heteroscedasticity—i.e., differing error variances over time—and Figure 26 in the Supplementary Information consistently shows zero values for the year of first commercialization.

Response: We thank the reviewer for this careful assessment. We agree that heteroskedasticity is present in the relationship between diffusion speed and year of first commercialization and that this issue must be explicitly addressed when evaluating the strength of the empirical evidence. We address this point now in the main and supplementary text as presented below.

In the main text:

> ***Lines 254 – 256:***
>
> *"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)."*
>
> ***Lines 267 – 269:***
>
> *"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."*

Added analysis in Supplementary Information section C6, lines 977-985:

"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."

With regards to Supplementary Figure 26 (now 27), we have updated the aesthetics of the figure to make it more readable, we thank the reviewer for pointing this out. We add a sentence specifically analyzing the first year of commercialization results, since the coefficients are close to zero, although for three of the four metrics, the results are significant.

New text added to Supplementary Information Section C5 (lines 921-926):

"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)."

Updated figure with circles on the dot and whisker plot indicating the significance of each regression estimate:

Supplementary Figure 3. Bivariate of each metric and each variable in the analysis. Plots show the coefficient for each individual bivariate regression. Dots show the coefficient estimate, with whiskers on either end showing the 95% confidence interval. If whiskers extend past the dotted line (shown at 0) then the estimate is not significant at the 95% confidence level. If dots are closed circles, the results are significant at a 95% confidence level. If dots are open circle, the estimate is not significant at a 95% confidence level.

4.4: The title "…Diffusion Speed Across Countries" is somewhat misleading. It suggests a focus on spatial diffusion across countries, whereas in reality, countries are treated as contextual factors influencing diffusion speed. The analysis does not explicitly address whether diffusion increases, decreases, or varies in scope across countries or among latecomers. A minor adjustment could improve accuracy and reader expectations. For instance: "Drivers of Diffusion Speed: Technology and Country Characteristics."

Response:

We thank the reviewer for this suggestion. It is true that we do not include a spatial component in this analysis, which is implied in the word "across" in the title. We therefore change the title to "Drivers of Technology Diffusion Speed in Countries" to better indicate that this analysis investigates different drivers of technology diffusion and the data is at the country level.

4.5: Please clarify the metrics used to measure diffusion and extract the parameters, in the main text. It is unclear from the main text whether market share is used alone or in combination with other indicators, and how the relevant market boundaries are defined. A more explicit explanation would improve transparency and replicability.

Response: Thank you for this comment. We include details of the fitting and metrics used in the Methods section, but we add more to the main text as suggested by the reviewer.

In the main text, lines 159-163, we clarify in the text what the data in HATCH includes (new text is bolded and underlined):

> *"The data in the HATCH dataset differs from other datasets on technology diffusion in the number of technology and country combinations included as well as the unit of measurement of technology adoption (**<u>the HATCH dataset uses market share, production, or capacity data, whereas the CHAT dataset uses intensity of use measures</u>**)"*

In the Methods section, we add a description of the type of data included in lines 42-44:

> *"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."*

In the Main text, we add more description to the fitting process and references to the methods section, lines 107 – 114 (new text is bolded and underlined):

> *"The logistic function approximates this path and has been used extensively in empirical analyses of technology diffusion[15,19,20].* ***<u>For each time series, we fit a logistic function with three free parameters using nonlinear least squares optimization.</u>*** *We use the steepness parameter to represent technology diffusion speed, which is the dependent variable in our analysis* ***(<u>further described in the Methods section</u>).*** *Other functional forms and growth metrics have been studied, including exponential[15], Gompertz[23], and Bass[34] functions, although none are as extensively studied as the logistic function (further discussed in Supplementary Information Section D2)."*

4.6: Check the journal's formatting and style guide to avoid having multiple tables with the same numbering (e.g., two Table 1s, 2s, or 3s in the main text).

Response:

We thank the reviewer for pointing out this error! We have fixed the numbering of the tables in the main text.

Responses to Reviewers NCOMMS-24-77209-T

Reviewer 2

2.1: The authors have done a good job revising the paper, having addressed my comments and added proper qualifications. I believe that the article in its current form is worth publishing in Nature Communications. I have a handful of small suggestions regarding the language, but I think that they do not warrant another round of revisions and can be handled during the copyediting process. In any way, my recommendation to publish is not conditional on the authors accepting these suggestions.

Response: Thank you for the comment. We have addressed all language suggestions and code updates in the text.

2.2: p.2 67-68. "technology moves sequentially through distinct phases with feedbacks of knowledge flows to earlier stages" – this reads like technology flows back in time, please clarify (e.g. knowledge spillover from later phases in early adopter countries to earlier phases in other countries).

Response: Thank you for this suggestion. We have updated the text to clarify this point, lines 50-52:

> *"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"*

2.3: p. 3, 99. "patterns between technology diffusion speed and technology" – "patterns in the relationship between technology diffusion speed and technology" may be clearer

Response: Thank you for this suggestion. We have updated the text as the reviewer suggested, lines 83-84:

> *"This study analyzes patterns in the relationship between technology diffusion speed and technology and country characteristics."*

2.4: p. 3, 113-115. "to understand the direction and strength of relationships between technology characteristics, country characteristics, and the combination of the two on technology diffusion speed." – "to understand the direction and strength of EFFECT OF technology characteristics, country characteristics, and the combination of the two on technology diffusion speed."

Response: Thank you for this suggestion. We have updated the text as the reviewer suggested, lines 96-99:

> *"To do this, 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."*

2.5: p. 3, 138. "It in any case allows for insights to be generated that are relevant, especially about" – "It in any case allows to generate relevant insight, especially about" (streamline).

Response: Thank you for this suggestion. We have updated the text as the reviewer suggested, lines 122-123.

> *"It in any case allows researchers to generate relevant insight, especially about relative growth across different technologies."*

2.6: p. 4, 146. "a growth duration of 27.5 years." – when growth duration is first mentioned, it makes sense to define it and give a reference (Wilson et al. 2013).

Response: Thank you for this suggestion. We have added a reference to the first reference to growth duration, in line 126 of the main text.

2.7: p. 15, 435-436. "State capacity and the type of government (democracy or non-democracy) are both associated with higher diffusion speeds." It's either type of government (as a variable) _affects_ diffusion speed, or specific values of that variable (e.g. high level of democracy, democratic type of government) is associated with high diffusion speed.

Response: Thank you for this suggestion. We have changed the wording as the reviewer suggested, lines 317-319.

> *"State capacity and democratic governments are both associated with higher diffusion speeds (Supplementary Figures 20 and 21)."*

2.8: Reviewer #2 (Remarks on code availability):

I tested the code available at the Github repo cited in the text.
I got the code running (following the instructions in README) with minor manual modifications, and it produced what looks like the actual results reported in the paper. My recommendations would be:

2.9: 1. The relationship between the Python and the R parts of the code should be described at the very beginning of README, in Overview (like Python code produces growth speeds based on HATCH dataset, and subsequent analysis of these speeds is done in R. In this repo, the results of running the Python code are available in... so you can copy them to... and run only the R part).

Response: Thank you for this recommendation. We have updated the ReadMe, including the very beginning in the Overview section, to detail the relationship between the Python and R code.

"This code is used to analyze temporal, technology, and country characteristics that impact the speed of technology diffusion using a dataset of historical technology adoption.
Python code produces growth speeds based on time series in the HATCH dataset using curve fitting. Further analyses of growth speeds generated in the Python file is done in R. In this repository, the results of the python growth speed analysis are available in `Analysis-Code/00_data` if the user is only running the R portion of the analysis."

2.10: 2. Different R files have different expectations regarding working directory (sometimes provided in the form of commented out setwd statements). While it is possible to make it work, this is not a good practice. A better approach would be so set a single working directory once, in the first file to run, or initialization/pipeline script (see below), and make all R scripts use paths relative to that directory.

Response: Thank you for this comment. We have updated the structure of the code to now include an initialization script that loads packages, sets working directories, and then runs each function necessary for the analysis. The file is included in the code link, called "00_national_tech_diffusion_initialization."

2.11: 3. It would be good to create a single workflow/pipeline script for R – a thin wrapper smoothly running all R scripts in the proper order without requiring additional user intervention (optional scripts can be commented out, but when uncommented they should also run smoothly as part of the pipeline). Common initialization – working directory, package loading (it's good to have all necessary packages listed in a single place) – can be handled either at the beginning of the pipeline file or in a separate initialization file to be run first.

Response: Thank you for this suggestion. We have created an initialization file that loads packages, sets working directories, and runs each function necessary for the analysis. The file is included in the GitHub Repository included in the code availability link, called "00_national_tech_diffusion_initialization."

2.12: 4. clean_hatch_data.R is missing a datafile loading statement – I had to add it manually.

Response: Thank you for pointing out this error. We now include a data file loading statement.

2.13: 5. README contains what seems to be instructions for running R files:
R
- Create R environment
- Run scripts:)
- (list of scripts)

... but then there's a section ## Usage / Workflow, which also lists files to be run (with additional comments/explanations). Consider whether it makes sense to integrate the two sections into one.

Response: Thank you for this suggestion. We have combined the sections into one in the ReadMe, titled "Workflow."

2.14: 6. Instructions for Python code:

Python
- Create environment and install:
- python3

...here list necessary modules (or include requirements.txt in the repo and refer to it).

Response : Thank you for this suggestions. We now include a section in the ReadMe that details *this:*

> *"Load the following modules:*
> *- pandas, numpy, math, matplotlib.pyplot, warnings, os.path, sklearn.metrics, scripy.optimize"*

Reviewer 4

4.1: I would like to thank the authors for their detailed revisions and am satisfied with the responses provided.

As a suggestion, Supplementary Figure 1 could benefit from the inclusion of a third axis showing the years, which would enhance clarity for readers—this was also noted by the other reviewer.

I therefore strongly recommend the paper for publication.

Response: Thank you for the comment. Supplementary Figure 1 describes the data cleaning process, rather than two axes on which to add a third. Therefore we did not update the figure because we are not sure to which figure the reviewer is referring.