Supplementary Information for:

The Growth, Geography, and Implications of Trade in Digital Products

Viktor Stojkoski[1], Philipp Koch[1], Eva Coll[1,2], César A. Hidalgo[1]

[1]Center for Collective Learning, ANITI, TSE-R, IAST, IRIT, Université de Toulouse, CIAS, Corvinus University

[2]LEREPS, Université de Toulouse, Sciences Po Toulouse

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1. Countries and digital sectors covered in the dataset

With our methodology we are able to provide estimates for bilateral trade in digital products between 189 countries and 29 digital sectors. Table S1 lists the countries that are included in the dataset. Table S2 gives the digital sectors included in the dataset and provides short definition for their coverage.

Table S1. List of digital product and service sectors included in the dataset.

Digital trade sector	Description
Cybersecurity	Cybersecurity services provide confidentiality, integrity, availability, and privacy of digital systems. These are measures for preventing and responding to cybercrimes, protecting computer systems, networks, programs, and data.
Mobile Application	A mobile application or app is a computer program or software application designed to run on a mobile device such as a phone, tablet, or watch.
Cloud Computing	Cloud computing is the on-demand availability of computer system resources, especially data storage (cloud storage) and computing power, without direct active management by the user
File Hosting Service	File-hosting services allow users to upload files that can be accessed over the internet after providing an authentication key.
Web Hosting	A web hosting service offers the facilities required for clients to create and maintain a site and makes it accessible on the World Wide Web.
Data Licensing	Data licensing is the service of providing organized collection of data that can be stored and accessed electronically.
Digital Advertising	Digital Advertising is the use of the internet to deliver marketing messages via various formats to internet users. This includes advertisements displayed on search engines and social media, as well as video and banner advertising on specific websites.
Digital Music Streaming & Downloads	Music Streaming & Download services offer unlimited access to content libraries for either monthly subscription fee or by purchasing them as per one-time transaction that afterwards allows permanent accessibility for the user.
Video on Demand	Video-on-Demand services can be 1) subscription-based – offering unlimited access to their content libraries for a monthly subscription fee; and 2) transaction based – offering time-limited access to video content that requires a usage-based one-time payment.
eBooks	An eBook is the digital or electronic version of a book and can be read on various devices such as specific e-Readers as well as on tablets, smartphones or computers.
Gaming Networks	Gaming Networks are paid subscription platforms for getting access to premium online video game content.
PC and Console Games	PC/console games are either video games that are sold online and which can be downloaded or played online.
Mobile Games	A mobile game is a video game designed to run on a mobile device such as a phone, tablet, or watch.
Online Dating	Online Dating are digital services that offer a platform on which its members can flirt, chat or fall in love.
Online Education	Online Education is the transfer of knowledge or skills through online platforms. This includes the areas of online university education, online learning platforms, and professional certificates.
Online Food Ordering	Online food ordering is the process of ordering food, for delivery or pickup, from a website or other application.
Online Gambling	Online gambling is any kind of gambling conducted on the internet. This includes virtual poker, casinos, and sports betting.
Online Marketplace	An online marketplace is a website acting as an intermediary for third-party vendors to offer their products and services to customers.
Operating System	An operating system is system software that manages computer hardware and software resources and provides common services for computer programs.
Payment Service	A payment service is a system that enables digital financial transactions between merchants and customers through various channels such as credit cards or bank accounts.
Business Intelligence Software	Business Intelligence Software is used for analyzing, visualizing, and presenting data and information in business context for rational business decisions. These tools help to access data, implement queries, create reports, and perform predictive analytics.
Customer Relationship Management Software	Customer Relationship Management Software is designed to help companies to manage the entire life cycle of a customer including sales, marketing, customer services and contact center.
Enterprise Resource Planning Software	Enterprise Resource Planning Software is software that helps companies to manage, integrate and optimize important business activities related to their resources. These are oriented towards the company itself and its internal business processes.
Other Enterprise Software	Other Enterprise Software aggregates revenues for enterprise software that is not specifically mentioned in the other software sectors. This includes, for example, content applications, management software, performance management software etc.
Supply Chain Management Software	Supply Chain Management Software is software that supports supply- and demand side-processes within a company to offer a product or service on the market.
Administrative Software	This is software used to perform administrative tasks within businesses or organizations. It comprises software for the administration of IT infrastructure as well as standalone human resources and payroll management software.
Collaboration Software	Collaboration Software contains software that is designed to support collaboration within an organization such as conferencing and email applications as well as file synchronization and sharing applications.
Creative Software	Creative Software includes single purpose visualization, sound- and video recording, and editing software.
Office Software	Office Software is a collection of productivity software including at least a word-processor, spreadsheet, and a presentation program.

Table S2. List of Countries Included in the Digital Trade Dataset.

Country			
Afghanistan	Dominican Republic*	Lebanon*	San Marino
Albania	Ecuador*	Lesotho	São Tomé and
Algeria	Egypt*	Liberia	Saudi Arabia*
Andorra	El Salvador	Libya	Senegal
Angola	Equatorial Guinea	Lithuania	Serbia
Antigua and Barbuda	Estonia	Luxembourg	Seychelles
Argentina*	Eswatini	Macau	Sierra Leone
Armenia	Ethiopia	Madagascar	Singapore*
Australia*	Faroe Islands	Malawi	Slovakia
Austria*	Federated States of Micronesia	Malaysia*	Slovenia
Azerbaijan*	Fiji	Maldives	Solomon Islands
Bahrain	Finland*	Mali	Somalia
Bangladesh	France*	Malta	South Africa*
Barbados	French Polynesia	Mauritania	South Korea*
Belarus*	Gabon	Mauritius	Spain*
Belgium*	Georgia	Mexico*	Sri Lanka
Belize	Germany	Moldova	Sudan
Benin	Ghana	Mongolia	Suriname
Bermuda	Greece*	Morocco	Sweden*
Bhutan	Greenland	Mozambique	Switzerland*
Bolivia	Grenada	Myanmar	Taiwan*
Bosnia and Herzegovina	Guatemala	Namibia	Tajikistan
Botswana	Guinea	Nepal	Tanzania
Brazil*	Guinea-Bissau	Netherlands*	Thailand
British Virgin Islands	Guyana	New Caledonia	The Bahamas
Brunei	Haiti	New Zealand*	The Gambia
Bulgaria	Honduras	Nicaragua	Togo
Burkina Faso	Hong Kong*	Niger	Tonga
Burundi	Hungary*	Nigeria*	Trinidad and Tobago
Cambodia	Iceland	North Macedonia	Tunisia
Cameroon	India*	Norway*	Turkey*
Canada*	Indonesia*	Oman	Turkmenistan
Cape Verde	Iran	Pakistan*	Tuvalu
Cayman Islands**	Iraq	Panama	Uganda
Central African Republic	Ireland*	Papua New Guinea	Ukraine*
Chad	Israel*	Paraguay	United Arab Emirates*
Chile*	Italy*	Peru*	United Kingdom*
China*	Ivory Coast	Philippines*	United States*
Colombia*	Jamaica	Poland*	Uruguay
Comoros	Japan*	Portugal*	Uzbekistan
Costa Rica*	Jordan	Republic of the Congo	Vanuatu
Croatia	Kazakhstan*	Romania*	Venezuela
Cuba	Kenya	Russia*	Vietnam*
Cyprus*	Kiribati	Rwanda	Yemen
Czechia*	Kuwait*	Saint Kitts and Nevis	Zimbabwe*
Denmark*	Kyrgyzstan	Saint Lucia	
Djibouti	Laos	Saint Vincent and the Grenadines	
Dominica	Latvia	Samoa	

Note: * Are countries with available consumption data in the AppMagic dataset. For the countries with ** we only have export data (estimated using data on subsidiaries via optimal transport).

2. Digital revenue and consumption summary statistics

In Figure S1, we present the summary statistics for the digital revenue and consumption data we have gathered.

Figure S1 A depicts the total revenue generated from the digital products in our dataset over time. It's evident that the revenue has experienced exponential growth—from approximately USD 1 trillion in 2016 to USD 2.3 trillion in 2021.

Figure S1 B demonstrates the evolution in the number of digital product brands and firms included in our dataset. Both metrics exhibit a growth trend: the count of products rose from just over 8,500 in 2016 to nearly 9,500 by 2021. Likewise, the number of firms increased from over 7,500 to surpass 8,500 in 2021. Notably, there was a slight dip in both brands and firms during 2018 and 2019.

Figure S1 C showcases the total consumption observed in AppMagic data spanning several years, specifically for mobile applications and games. The total consumption for these digital sectors escalated from USD 30 billion in 2016 to over USD 80 billion in 2021.

Figures S1 D-E illustrate the distribution of non-zero consumption proportions, both by country (percentage of products with non-zero consumption) and by product (percentage of countries with non-zero consumption). The data reveals that the median proportion of non-zero consumption remains around 0.5 for virtually every year—both for countries and products. However, there is a noticeable downward trend in the median proportion beginning in 2018.

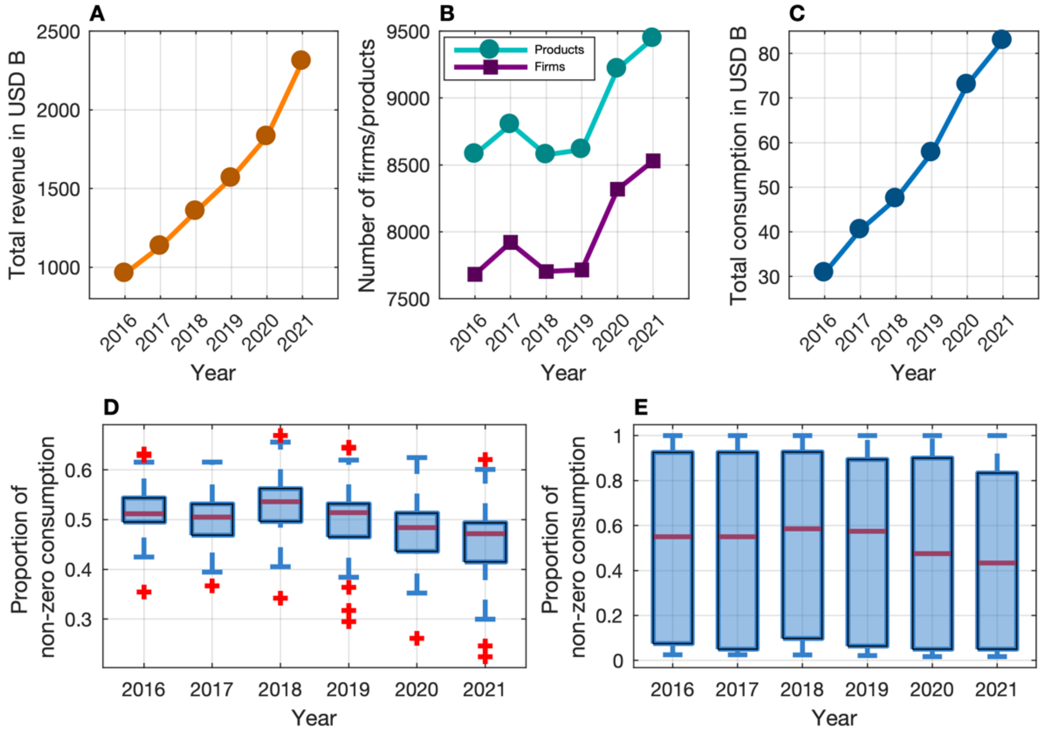

Figure S1. Digital revenue and consumption summary statistics . A Total revenues of all digital products over time observed in our dataset. **B** Total number of firms and digital product brands covered in our dataset over time. **C** Total consumption of mobile apps and games over time (from AppMagic) **D** Boxplots for the proportion of non-zero consumption across countries. **E** Same as **D**, just for products.

In Figure S2, we illustrate the distribution of revenues across digital sectors over the years. Within our dataset, the bulk of the revenue each year is consistently dominated by three specific sectors: cloud computing, digital advertising, and online marketplaces.

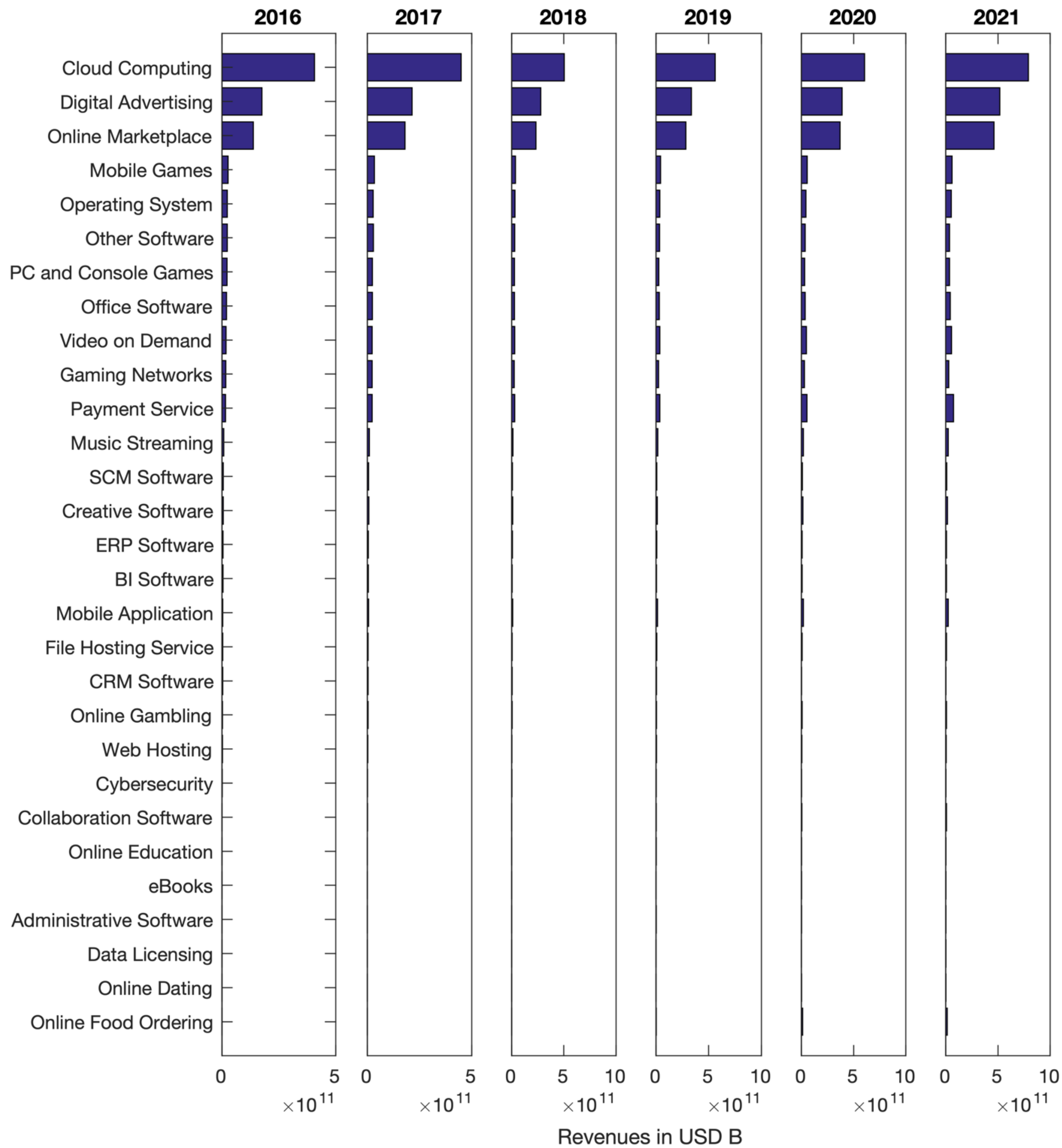

Figure S2. Sectoral distribution of digital revenues over the years.

3. Regression tree model features, data cleaning, and performance results

3.1. Model features

Table S3 lists the features used in our model and their data sources. We thereby emphasize that each feature is in its yearly value (e.g., to predict the Google Cloud consumption in 2016 we use GDP data for 2016). Only the Geography and Cultural & historical features, are fixed throughout the years. We also emphasize that in our regression tree model we always include logistic regression estimates for the probability of a non-zero consumption. The logistic regression uses the same features as the regression tree.

Table S3. Features used to predict product consumption across countries.

Feature	Data source (year)
Digital revenue features	
Total product revenues (in USD)	Own calculations using Orbis, Statista, and AppMagic data
Total country digital revenues (in USD)	Own calculations using Orbis, Statista, and AppMagic data
Total world revenues of the product's digital sector (in USD)	Own calculations using Orbis, Statista, and AppMagic data
Economic Size features	
GDP in constant 2017 USD PPP of the country of origin of the parent company of the product	World Bank World Development Indicators
GDP in constant 2017 USD PPP of the country where the product is consumed	World Bank World Development Indicators
Geography features	
Geographic distance (in km) between the most populated cities of the country of origin of the parent company of the product and the country where the product is consumed	CEPII Gravity database
World region of the country of origin of the parent company of the product	United Nations geoscheme
World region of the country where the product is consumed	United Nations geoscheme
Dummy variable for the contiguity between the country of origin of the parent company of the product and the country where the product is consumed	CEPII Gravity database
Cultural & historical features	
Dummy variable for common official language between the country of origin of the parent company of the product and the country where the product is consumed	CEPII Gravity database
Dummy variable for common unofficial language (spoken by at least 9% of the population) between the country of origin of the parent company of the product and the country where the product is consumed	CEPII Gravity database
Dummy variable describing whether the country of origin of the parent company of the product and the country where the product is consumed were ever in a colonial relationship	CEPII Gravity database
Dummy variable describing whether the country of origin of the parent company of the product and the country where the product is consumed shared a common colonizer post 1945.	CEPII Gravity database
Dummy variable describing whether the country of origin of the parent company of the product and the country where the product is consumed are currently in a colonial relationship	CEPII Gravity database
Dummy variable describing whether the country of origin of the parent company of the product and the country where the product is consumed were in colonial relationship post 1945	CEPII Gravity database
Dummy variable describing whether the country of origin of the parent company of the product and the country where the product is consumed were ever part of the same country	CEPII Gravity database
ICT Access Features	
Internet users as a share of population for the country of origin of the parent company of the product	The International Telecommunication Union
Internet users as a share of population for the country where the product is consumed	The International Telecommunication Union
Fixed broadband connections as a share of population for the country of origin of the parent company of the product	The International Telecommunication Union
Fixed broadband connections as a share of population for the country where the product is consumed	The International Telecommunication Union
Mobile broadband connections as a share of population for the country of origin of the parent company of the product	The International Telecommunication Union
Mobile broadband connections as a share of population for the country where the product is consumed	The International Telecommunication Union

3.2. Measuring feature importance

To measure the importance of each feature we use the permutation method. That is, we first train the regression tree on the training dataset. Once the model is trained, we record its performance on the validation set (the R-squared of the test set). This performance, using all features in their original order, serves as a baseline.

Then, for each feature we:

1. Make a copy of the validation set and shuffle (permute) the values of the feature in question. By doing this, we are essentially removing the relationship between the selected feature and the target variable.
2. Use the trained model to make predictions on this permuted validation set. Measure the performance of the model on the permuted data and calculate the percentage change in the R-squared.
3. For each feature, the importance is determined by the difference between the baseline performance (using all original features) and the performance using the permuted feature. A larger decrease in performance indicates that the feature is more important, as permuting it has a greater negative effect on the model's predictive capability.

3.3. Data cleaning

We investigate the model performance using only the latest, 2021 data. This reduces the potential non-stationarity issues that may arise in the data. Moreover, we clean the data from digital products whose consumption could be noisy. First, we remove each product with total revenues less than USD 10 million from the test and training datasets. Second, we remove each product with a significantly different consumption pattern compared to other products that have parent companies in same country. Formally, we define these products as having an average consumption patterns Pearson correlation of less than 0.3 with the other products that have a parent company located in the same country. In total, this leaves us with the consumption patterns of 424 digital products and services.

By applying these data cleaning steps, we aim to focus on the most relevant and consistent patterns in product consumption, minimizing the impact of noise and potential biases in the data. Removing products with total revenues less than USD 10 million helps us prioritize the information provided by the products that are more widely traded and have a stronger influence on the overall market dynamics. This prevents the model from being overly influenced by the consumption patterns of niche or less representative products.

Additionally, removing products with significantly different consumption patterns compared to other products with parent companies in the same country allows us to reduce the impact of outliers that may distort the overall consumption trends. By focusing on products with similar consumption patterns within their country of origin, we can better capture the general patterns and dynamics of digital products trade without being excessively influenced by unusual cases.

These data cleaning strategies help ensure that the model's performance evaluation and subsequent analyses are based on more reliable and consistent data, thus providing more accurate insights into the underlying digital products trade patterns, and improving the model's generalization capabilities.

3.4.Model performance

We investigate the model’s performance using 1) leave-one-country-out, and 2) leave-one-product-out cross-validation schemes.

In the leave-one-country-out cross validation scheme we train a model using data on all other countries except the one under evaluation, and then evaluate the model's performance on the held-out country. This approach helps assess the model's generalization capabilities by examining how well it can predict consumption patterns in a country that it has not been directly trained on. By systematically leaving out one country at a time and repeating the training and evaluation process, we can obtain a comprehensive understanding of the model's performance across different countries.

In the leave-one-product-out cross-validation scheme, we follow a similar logic but at the product level. For each iteration, we train the model using data on all products except one, and then evaluate its performance on the held-out product. This methodology allows us to assess the model's ability to predict consumption patterns for a specific product, even if it has not been directly trained on that product.

We tune the hyperparameters to minimize the cross-validated mean-squared error (MSE), using a grid search over several possible values for maximum number of splits (1, 3, 5, 10, 15, 20, 30, 50) and the minimum parents' size (3, 5, 7, 10), and fix the learn rate to 0.1 and the number of learning cycles to 150. But, because the different test sets (countries or products) may have varying levels of variance instead of the MSE, we report the coefficient of determination (R-squared) as the primary metric for evaluating the model's performance. The R-squared acts as a normalized MSE as it considers the proportion of variance in the target variable that can be explained by the model, making it a suitable metric to compare the model's performance across different test sets with potentially different levels of variability. The R-squared is valued between 0 and 1 with higher values implying better model performance.

An additional issue that could hamper the use of the MSE as a single metric for our model performance, is that the dataset is zero-inflated, meaning that a significant portion of the observations contain zero values (around 50% of our product-country consumption pairs have a value of 0). In this case, the MSE and the R-squared may not provide a complete understanding of the model's performance. Therefore, we also provide 3 additional metrics.

First, we calculate a restricted R-squared between the observed consumption patterns and the predicted consumption patterns only for the country-product pairs with non-zero consumption (we treat every country-product pair with less than USD 1,000 consumption as zero). By using this restricted R-squared, the evaluation focuses on the non-zero consumption patterns, considering the actual values and the relative scale of consumption. This approach provides a more specific and relevant assessment of the model's performance in predicting consumption for country-product pairs with non-zero values while considering the normalization factor to account for the overall consumption level in the test set.

Second, we calculate the accuracy of the model in classifying whether there is some consumption of a product in a country or not. The accuracy metric measures the proportion of correctly classified instances (i.e., correctly identifying the presence or absence of consumption) out of the total instances evaluated. It provides a straightforward assessment of the model's classification performance, indicating how well it can distinguish between countries where the product is consumed and countries where it is not.

Third, depending on the left out country, our test data could be imbalanced and in this case the accuracy values may be misleading. This limitation can be resolved by calculating the F1 score. When dealing with imbalanced data, where one class (e.g., no consumption) significantly outweighs the other class (e.g., consumption), accuracy alone may provide misleading results. This is because a model that predicts the majority class for all instances can achieve a high accuracy simply due to the class imbalance, without effectively capturing the minority class. To overcome this limitation, the F1 score is commonly used as a more appropriate metric for evaluating model performance in imbalanced datasets. The F1 score combines precision and recall, providing a balanced measure of the model's ability to correctly identify both the positive (consumption) and negative (no consumption) instances. The F1 score is bounded between 0 and 1, with higher values indicating better performance.

By calculating and reporting the accuracy and the F1 score of the model in this classification task, we gain insights into its ability to effectively identify the presence or absence of consumption for a specific product in different countries. This evaluation metric complements the assessment of the model's performance in predicting the actual consumption values, providing a comprehensive evaluation of its predictive capabilities in both regression and classification aspects.

Figure S3 gives the histograms for the distribution of the model performance metrics across 60 countries (estimated using the leave-one-country-out scheme), whereas Figure S4 gives the histograms for the distribution of the model performance metrics across 424 products (estimated using the leave-one-product-out scheme). To investigate the performance of our model, we pair the distribution histograms of the model performance metrics with results from a linear regression model that is estimated using the same features and training schemes.

Our initial findings indicate a promising performance of our model in both leave-one-country-out and leave-one-product-out schemes. The mean R-squared across all countries in the leave-one-country-out scheme was 0.74, demonstrating the model's substantial ability to explain variance in consumption data. Similarly, the mean R-squared in the leave-one-product-out scheme was 0.63, showcasing good predictive power at the product level.

The restricted R-squared, focusing only on non-zero consumption values, yields slightly lower but still respectable mean values of 0.50 for the leave-one-country-out scheme This discrepancy between the overall and restricted R-squared values is expected due to the model's difficulty in accurately predicting the actual consumption levels in countries with non-zero values. In contrast, the restricted R-squared was much higher for the leave-one-product-out scheme (restricted R-squared = 0.87). This is because the model was trained on a more diverse set of consumption patterns across multiple countries, and there were fewer non-zero values to predict. Consequently, it had a broader context to understand the distinct characteristics that influence the consumption of each product, enabling it to predict the non-zero consumption levels for the held-out product more accurately. Also, the relatively fewer non-zero values could have contributed to the higher restricted R-squared as it is easier for the model to make precise predictions when there are fewer targets. The model's ability to capture these varied consumption patterns underscores its strong predictive capabilities in differentiating product-specific factors that drive consumption.

In terms of classification performance, our model demonstrates a commendable ability to distinguish between countries where a product is consumed and those where it is not. The mean accuracy is 0.89 in the leave-one-country-out scheme and 0.85 in the leave-one-product-out scheme. Despite the imbalanced nature of our dataset, the model's F1 score is also relatively high with mean values of 0.91 and 0.74 for the leave-one-country-out and leave-one-product-out schemes respectively, signifying a balanced recognition of both consumption and non-consumption instances.

When compared to a simple linear regression model using the same features and training schemes, our model generally shows superior performance across all metrics. This suggests that the complexity of our model is beneficial for capturing the nuanced consumption patterns across countries and products.

However, it's important to note that the performance varied across different countries and products, as illustrated in Figures S1 and S2. Certain countries and products are harder to predict than others, potentially due to specific socio-economic factors or product characteristics that were not accounted for in the model.

In conclusion, our model's performance under both cross-validation schemes confirms its robustness and ability to generalize across different countries and products. Future research could focus on incorporating additional features to improve the model's predictive power for countries and products where the performance is currently sub-optimal. Additionally, given the significance of zero-inflation and imbalanced data, more sophisticated modeling strategies could be explored to better handle these challenges and further improve the model's predictive capabilities.

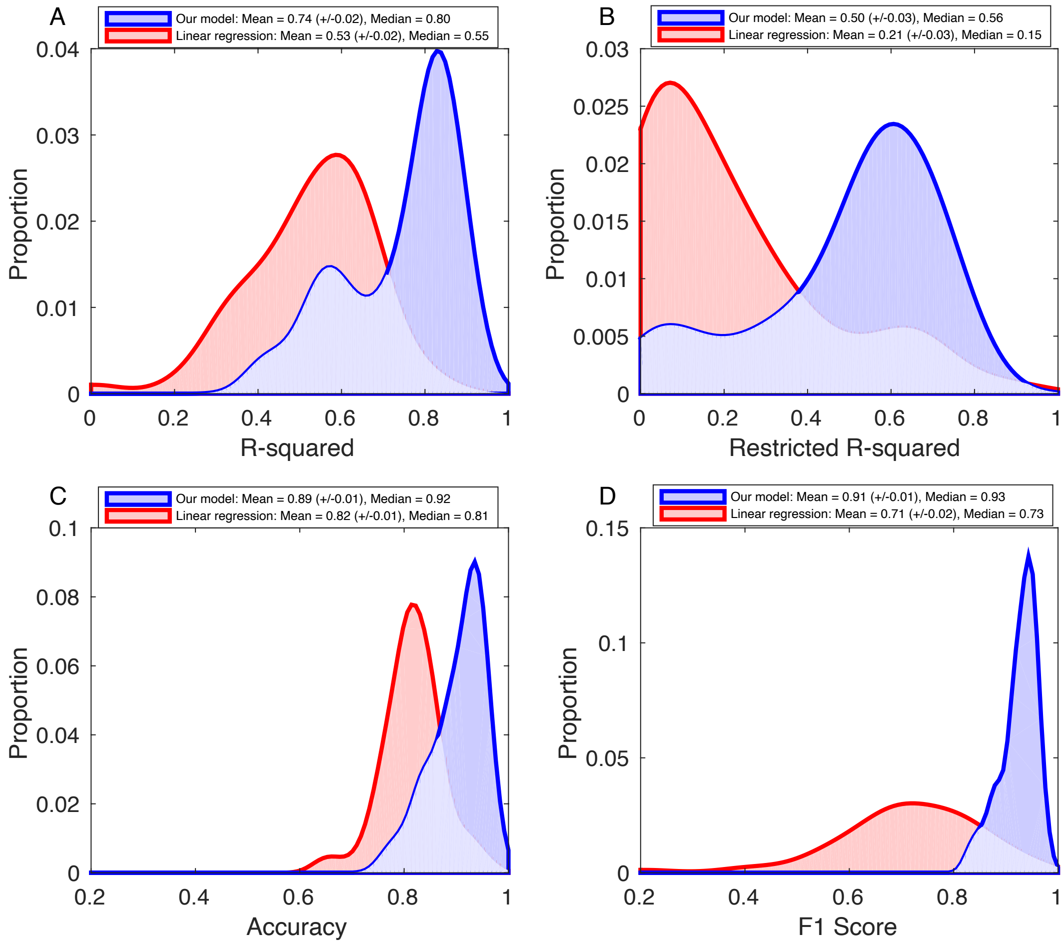

Figure S3. Histograms for the distribution of the model performance across 60 countries using 2021 data. A Histograms for the R-squared. **B** Histograms for the restricted R-squared. **C** Histograms for the accuracy. **D** Histograms for the F1 score.

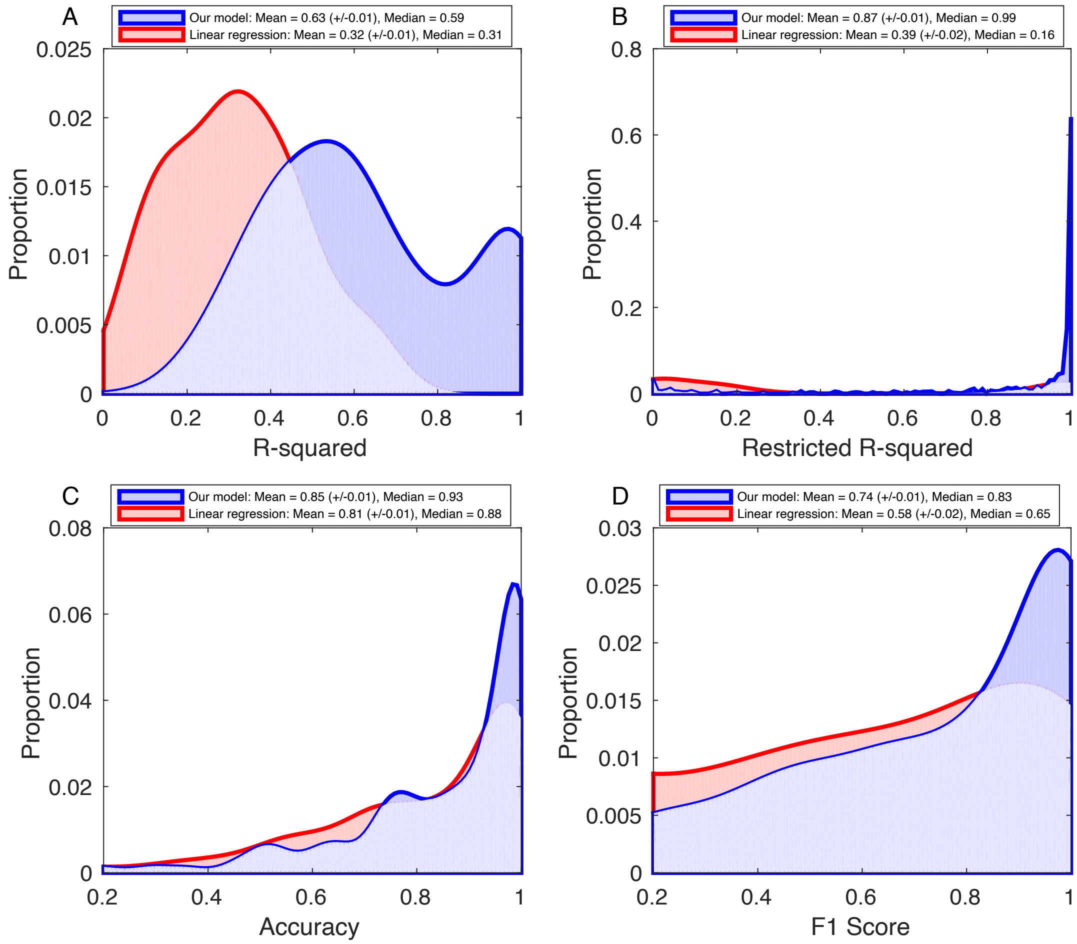

Figure S4. Histograms for the distribution of the model performance across 424 products using 2021 data. A Histograms for the R-squared. **B** Histograms for the restricted R-squared. **C** Histograms for the accuracy. **D** Histograms for the F1 score.

3.5.Final Model

To produce the final estimates, we pool the 2021 data from all 60 countries and products. We train a single model by using the leave-one-product technique to tune the model hyperparameters (since it has a more restrictive performance).

Figure S5 provides a heatmap for the average cross-validated mean-squared error across all hyperparameter choices. The minimum error occurs when the maximum number of splits is 5 and the minimum parents size is 10.

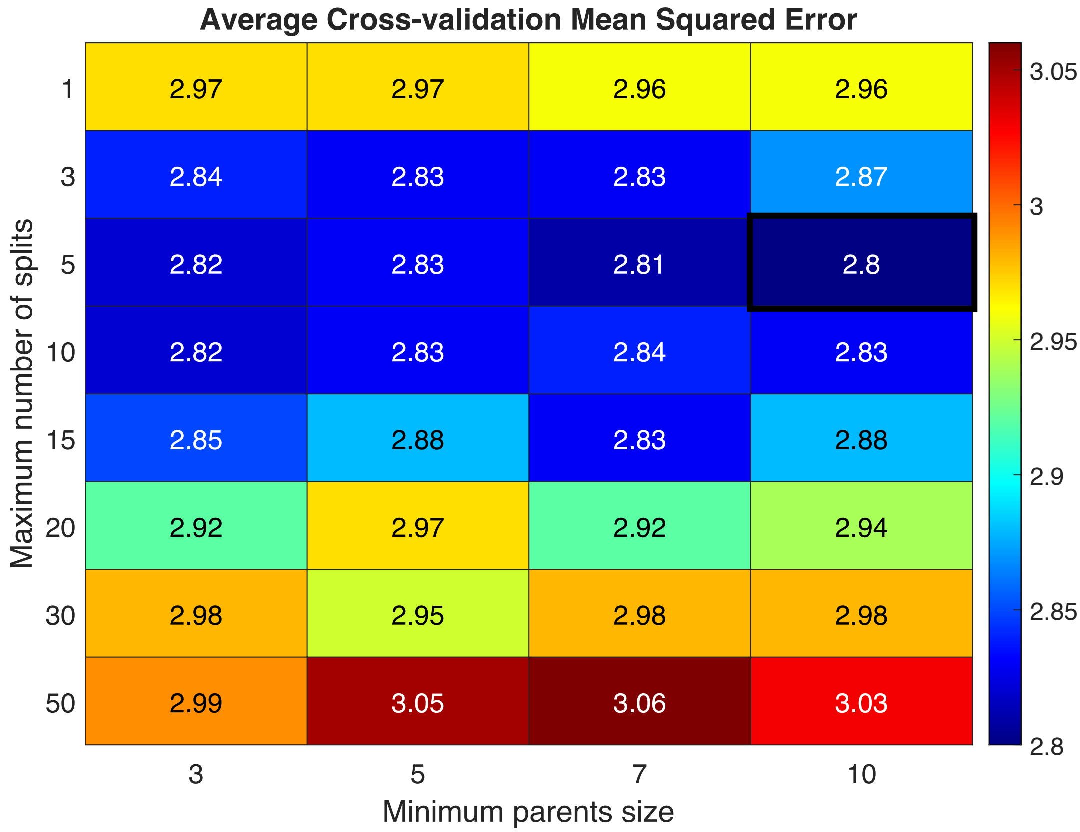

Figure S5. Final model average leave-one-product cross-validated mean squared error. The best model (with lowest mean-squared error) is highlighted with a black box.

Figure S6 shows the feature importance score (measured in percentage decrease of the coefficient of determination of the final model). We find that the bulk of the predictive power of the model goes to the Total revenues of the digital product (the R-squared decreases by almost 25%), followed by the Distance feature (R-squared decrease of 11.3%), and the GDP of the destination country (R-squared decrease of 6%). The other 8 features that constitute the final model are: the GDP of the origin country , the world region of the origin, the world region of the destination, the percentage of population using the internet in the destination country, the total revenues of the digital sector of the product, the total digital revenues of the origin country, the percentage of population with fixed broadband connections in the origin country, and the percentage of population with access to internet in the origin country. All these features have a decrease in R-squared of above 1%.

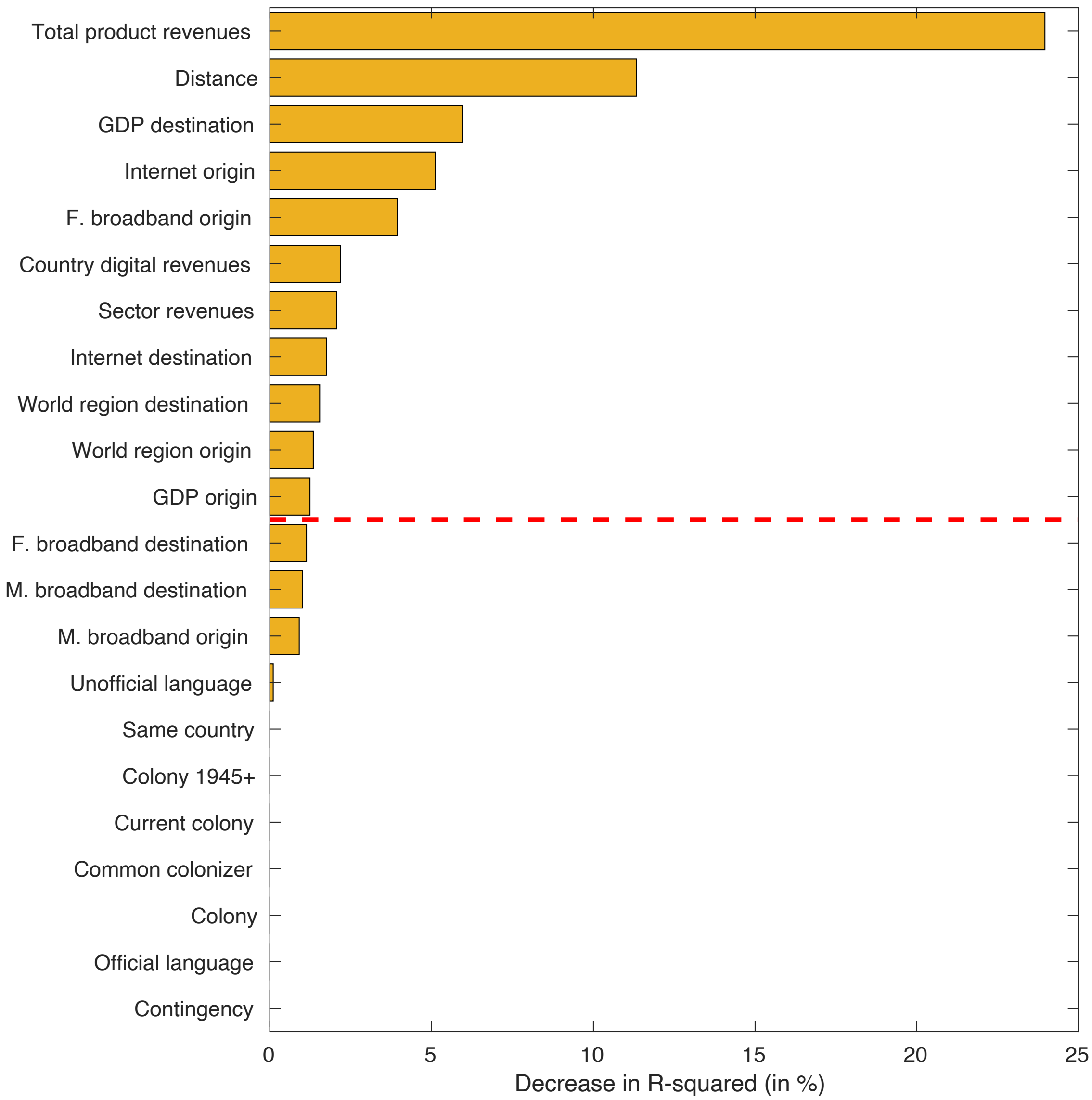

Figure S6 feature importance. The features above the red dashed line are the top 11 features included in the final model.

Finally, as we employ the final model to estimate digital consumption between 2016 and 2020, we also evaluate its predictive accuracy for consumption during these years. For this, we use all available AppMagic data on consumption per product between 2016 and 2020 and compare it with estimates given by the final model.

Figure S7 shows bar charts for the same the out of sample R-squared for each year (all products and countries are pooled). We also compare these results to the ones produced by the baseline linear regression model estimated on the full 2021 training dataset.

We find that the R-squared of our model is always above 0.7, whereas the linear regression has a restricted performance (R-squared is around 0.2 in each year). This further signifies the robustness of our model in predicting digital consumption patterns.

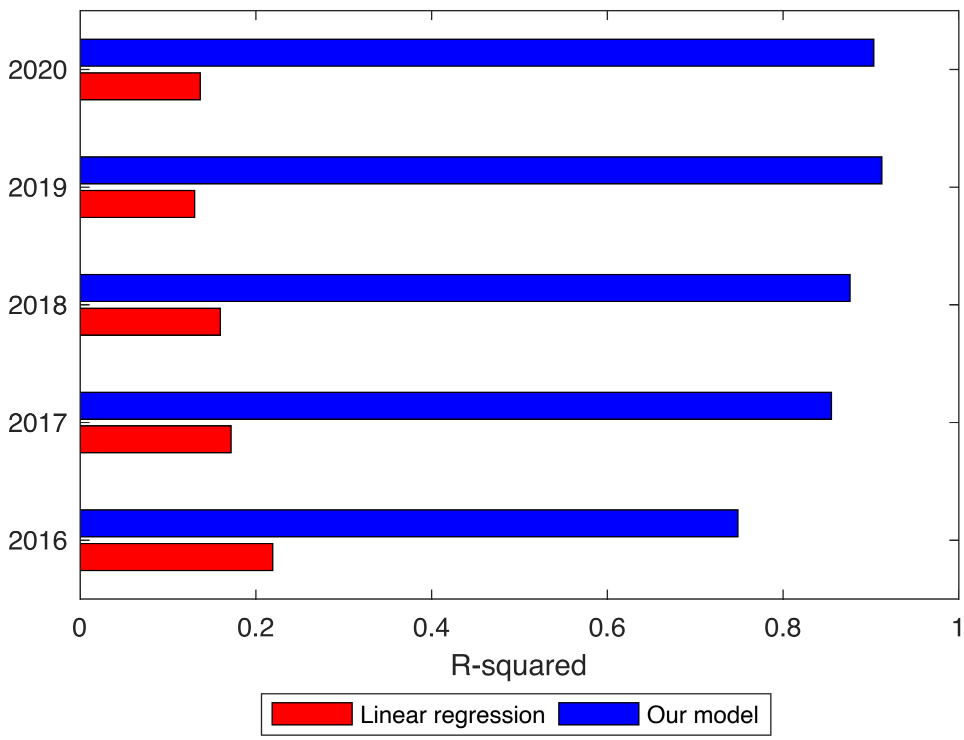

Figure S7. Model performance in predicting consumption patterns between 2016 and 2020.

4. Results with alternate allocation procedures for digital consumption

We also provide alternate results where we assign all product revenues to the parent firm of the product. This alternate procedure should increase the exports of the parent firms' origin countries towards the world. It could also decrease the imports of these countries coming from the subsidiaries' origin countries if the parent companies use these countries to outsource the production processes.

Figure S8 compares the volume of digital products trade over the years between our baseline estimates (with optimal transport) and the alternate estimates (without optimal transport). We find digital products trade to be slightly larger in volume when the optimal transport procedure is removed from the estimation, albeit this increase is only marginal (around 4% per year), and statistically insignificant. For instance, in 2021, digital products trade increases by 4% or USD 4B (from USD 1.02T to USD 1.06T). Hence, the global trends for digital products trade remain similar even when we allocate all the revenue to the parent firms.

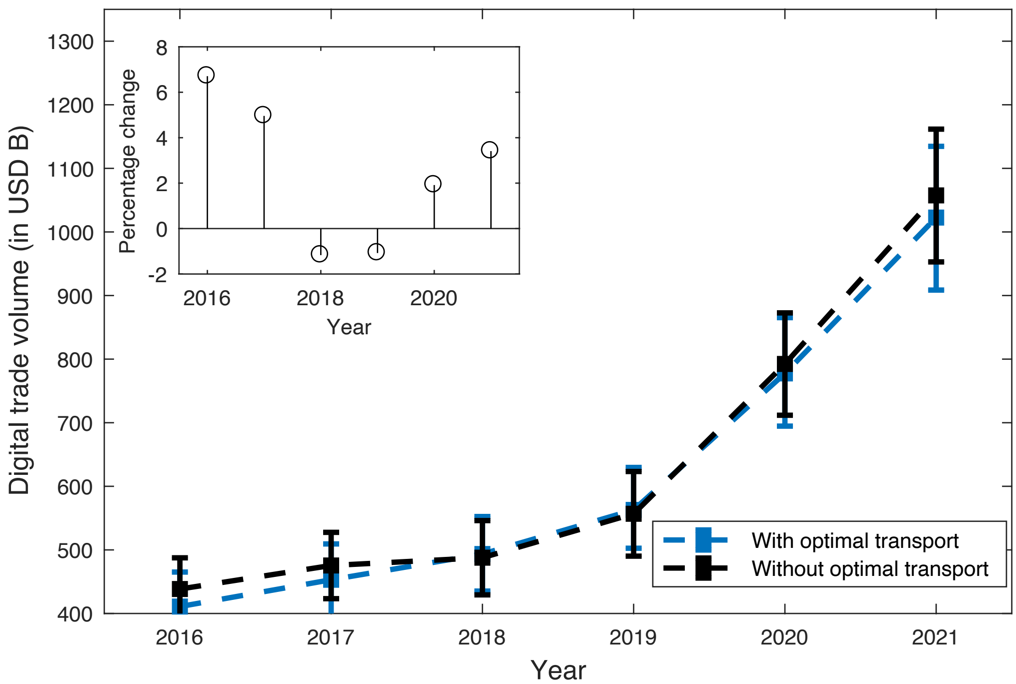

Figure S8. Digital products trade over the years for our baseline estimates (with optimal transport) and alternate estimates (without optimal transport). The inset plot shows the percentage change from our baseline to the alternate estimates.

Figure S9 reproduces Figure 2 from the main manuscript describing the geography of digital trade, but in this case, it presents the scenario under the alternate procedure where all product revenues are assigned to the parent firms. It reflects the geographic changes in digital trade volume when revenue attribution shifts to the countries where parent firms are based.

This visualization allows for a comparison of the relative changes in digital products trade volumes and highlights that the USA becomes even more central in the global digital products trade network under the alternate procedure. We also find that, in this case, digital products trade is even more concentrated, with 2% of countries accounting for 80% of total exports (3 countries). Digital imports, in contrast, even less concentrated as when we include subsidiaries (45% of countries account for 80% of imports). Finally, in the digital products trade network tax havens have a much lower centrality (for example, we lose Luxembourg because it hosts only subsidiaries).

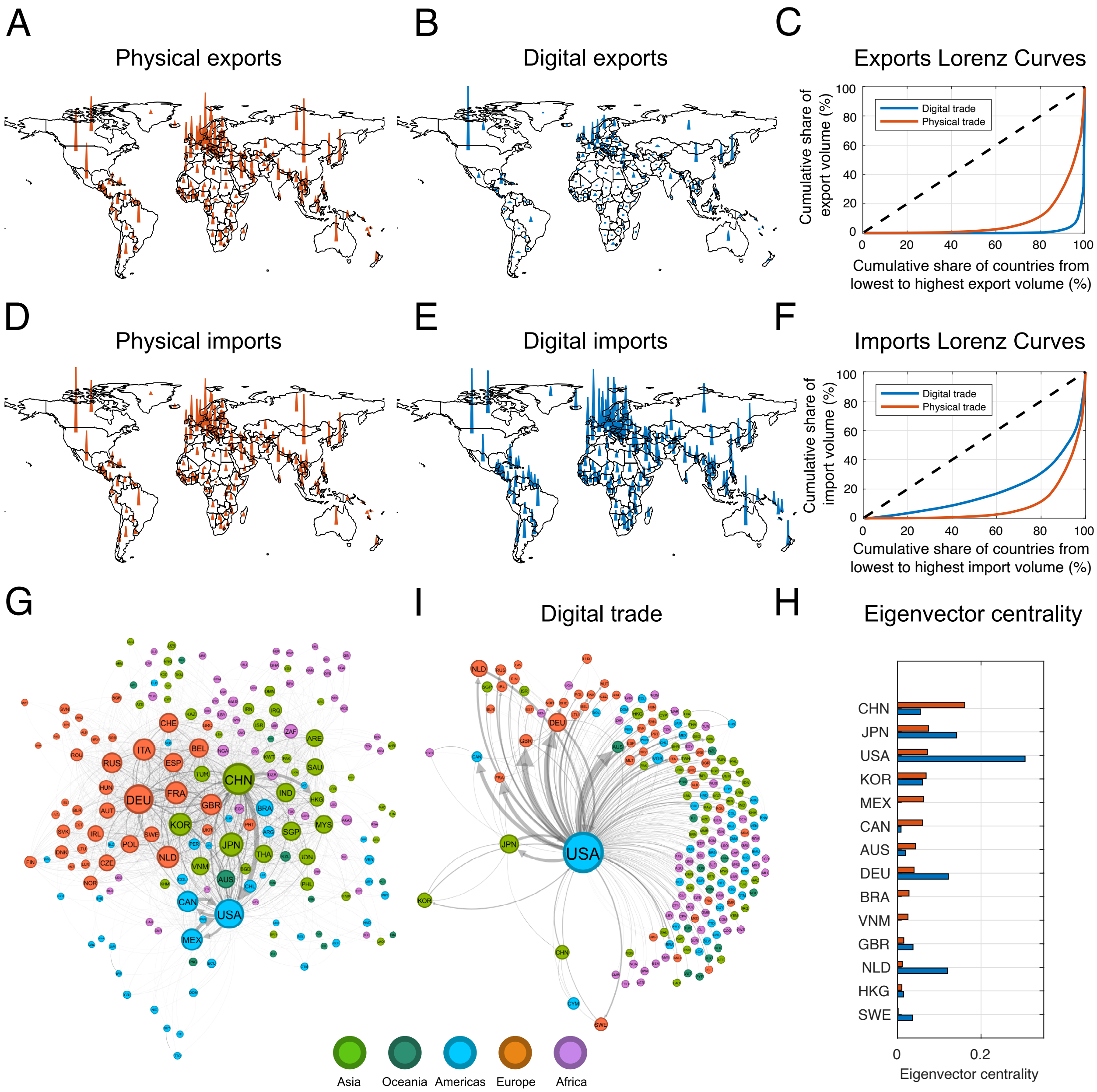

Figure S9. The geography of digital products trade without optimal transport. **A-B** Spike maps showing the spatial concentration of physical (**A**) and digital (**B**) exports. **C** Lorenz curves for the distributions shown in **A** and **B**. **D-F** Same as **A-C** but for imports. **G-I** Physical and digital products trade networks with revenues assigned to parent companies. For each country we show the top import and export destination. We also highlight all bilateral trade flows with a volume above USD 1B. **H** Eigenvector centralities for the top 10 countries in terms of eigenvector centralities in both networks. Figures **A-H** use average bilateral trade flow data between 2016 and 2021.

5. Comparison with digitally deliverable services datasets

We compare the size and distribution of our estimates to UNCTAD's digitally deliverable services dataset (available at: https://unctadstat.unctad.org/EN/Index.html). This dataset represents baseline digitally deliverable services trade data constructed using data from the Extended Balance of Payments Statistics (EBOPS). Hence, the comparison can be used as another test for the predictive performance of our model, and as an additional argument that our estimates are only a lower bound for the total digital products trade in the world.

However, there are important differences between our estimates and the data provided by UNCTAD that limit the comparison to only simple relative statistics.

Namely, digitally deliverable services are the combination of EBOPS items SF (Insurance and pension services), SG (Financial services), SH (Charges for the use of intellectual property not included elsewhere), SI (Telecommunications, computer, and information services), and the sub-item SK1 (Audiovisual and related services). These are very coarse sectors and there is not always a one-to-one aggregation of our sectors that could lead to compatible comparison. Moreover, digitally deliverable services are services which have potential to be delivered digitally but this is not necessarily the case. As a result, the sectors usually include other services that might not always be digitally delivered. For instance, computer services also include maintenance and repairs of computers which are often physically delivered. Also, while nowadays Insurance and pension services and many of the Financial services are usually digitally delivered, we do not include most of them in our dataset as they do not represent pure digital products. We include only online payment services that earn revenues by facilitating digital transactions, managing payment data, and providing developer-friendly tools and APIs. This suggests that we should expect a much lower trade volume in our estimates compared to the two datasets.

Bearing in mind these differences and limitations, in Figure S10, we compare the distributions of total country exports and imports between our estimates and UNCTAD's data in 2021.

We find a high correlation of 0.83 between our estimated export volumes and UNCTAD's volumes, indicating that these datasets provide similar information about the relative distribution of digital export volumes. The correlation between imports is also strong (0.76), but slightly smaller.

Moreover, the UNCTAD's trade data suggests much larger digital products trade volume, as expected (USD 3.26T trade in 2021 compared to our estimates of average trade of USD 1.02T). Another difference between UNCTAD's data and our estimates stems from the data collection process. Specifically, many countries have zero exports in our data because they do not have any companies present in our collected dataset for firm revenues (in these countries there are no companies with revenues above USD 1B, subsidiaries of these companies and significant app/mobile game developers). This results in an underrepresentation of these countries in our model's exports output. This caveat should be considered when interpreting our results, as the geographic distribution of digital exports might be more evenly spread if data from these countries were available. Our model's estimates therefore provide a lower bound for the digital products trade volumes in these countries and globally.

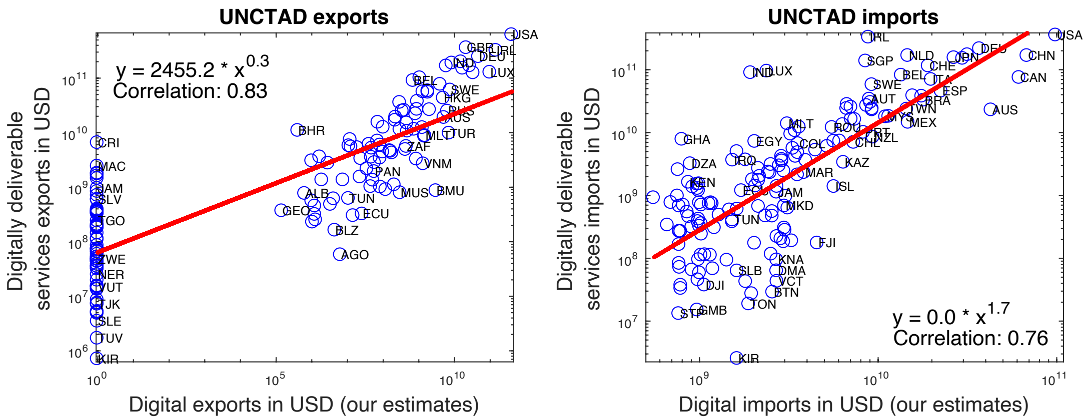

Figure S10. Scatterplots comparing the geographic distribution of our digital products trade estimates with UNCTAD's digitally deliverable services dataset in 2021.

We utilize the high correlation between our data and the UNCTAD's dataset to provide an approximate estimation of the missing digital products trade. To achieve this, we initially select data with non-zero exports from our dataset. Then, we construct a linear regression model where the dependent variable is the logarithm of our total digital exports estimate, and the independent variable is the corresponding UNCTAD digital deliverable services exports. Using the estimated coefficients from this model, we predict the digital products trade for each country. Subsequently, we calculate the maximum between these regression predictions and our original estimates, creating an upper-bound estimate for digital products trade. The discrepancy between these enhanced estimates and our original ones represents our rough estimate of the missing digital products trade. Our calculations indicate that in 2021, this difference is around USD 420 million, which is negligible compared to our total digital products trade estimates. This suggests that our model, while not perfect, is fairly robust, capturing a significant portion of global digital products trade activity. Despite certain limitations and potential underrepresentation of some countries, our model provides a largely accurate depiction of global digital products trade volumes.

Altogether, these results indicate that the relative geographic distribution of our digital products trade estimates is comparable to the standard datasets used for evaluating digital products trade.

6. Structure of digital products trade over the years

In Figure S11 we visualize the sectoral distribution of digital products trade between 2016 and 2021. We find that more than 70% of digital products trade between 2016 and 2021 is explained by three sectors. Cloud computing was the most traded digital product in 2016, accounting for 39% of world digital products trade, followed by digital advertising (16% of world trade) and online marketplaces (15% of world trade). While the ranking of sectors did not change much between 2016 and 2021, the composition of sectors became less concentrated on cloud computing (32%), with digital advertising and online marketplaces growing to around, respectively, 20% and 21% of global digital products trade.

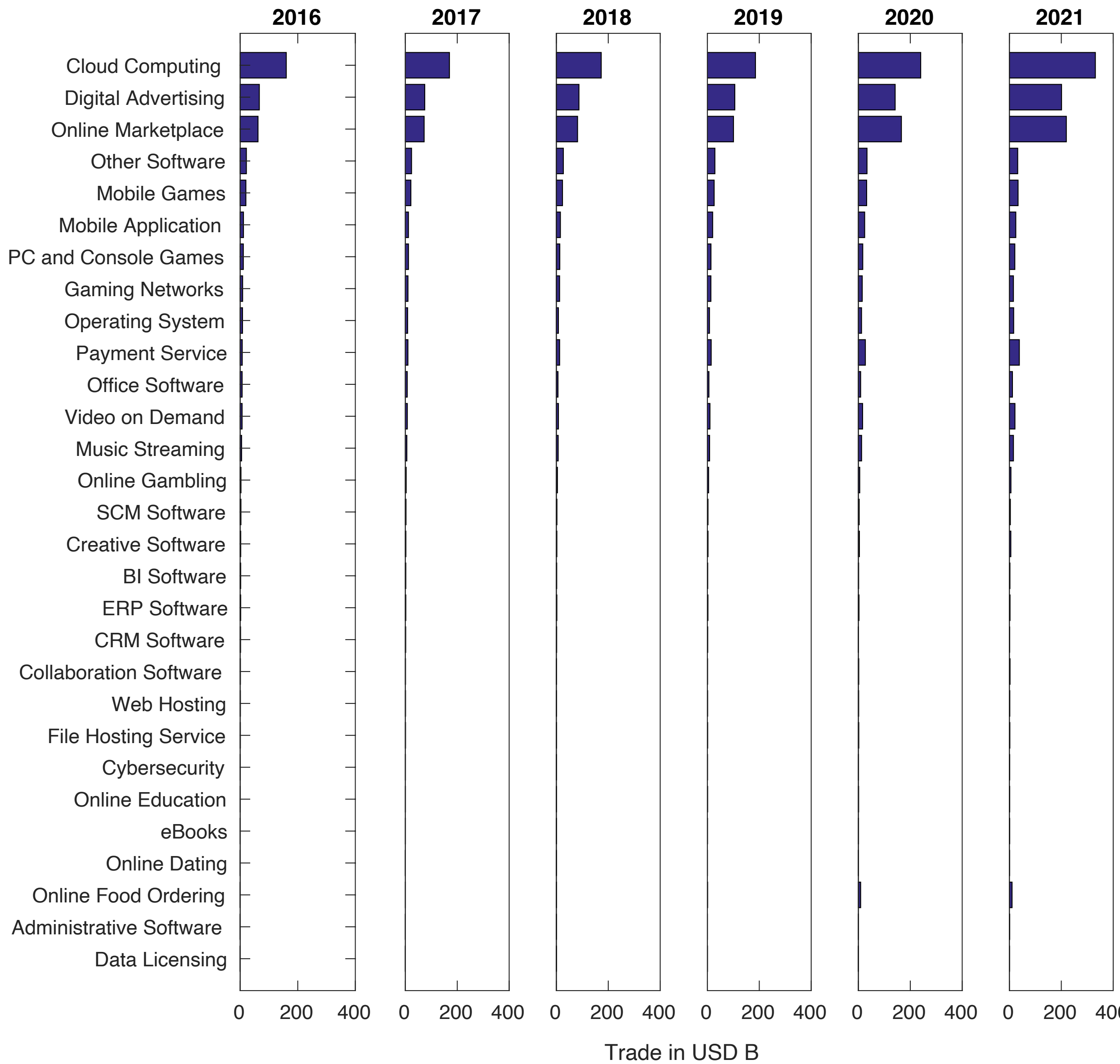

Figure S11. Sectoral distribution of digital products trade over the years.

7. Concentration of digital products trade

Here we compare in more detail the concentration of digital products trade and physical trade using the Shannon Entropy measure of concentration. The Shannon Entropy of a product category is defined as:

$$E_p = -\sum_c y_{cp} \log (y_{cp}),$$

where $y_c = \frac{X_{cp}}{\sum_c X_{cp}}$, with X_{cp} being the exports of country c in p, is the market share of the country in that product. Higher entropy values imply lower concentration.

We compare the Shannon Entropy of digital products trade to the Shannon Entropy of each of the 21 sections of the HS physical goods classification (the section definitions can be seen here: https://oec.world/en/product-landing/hs). Also, we undertake a simulation where we randomly select HS4 products such that their total trade matches that of digital products trade. We estimate the Entropy of this random sample of products and use it as a benchmark to understand the unique concentration patterns of digital products trade (we repeat this process 1000 times and report the average Entropy).

Figure S12 gives the results. We observe that digital products exports are more concentrated than all HS Section exports. Also, digital exports are much more concentrated than our random baseline. Digital imports, in contrast, are much less concentrated than all HS sections, and they are much less concentrated than our random baseline. These results strengthen the findings presented in the main manuscript about the underscoring the distinct dynamics that govern digital products trade.

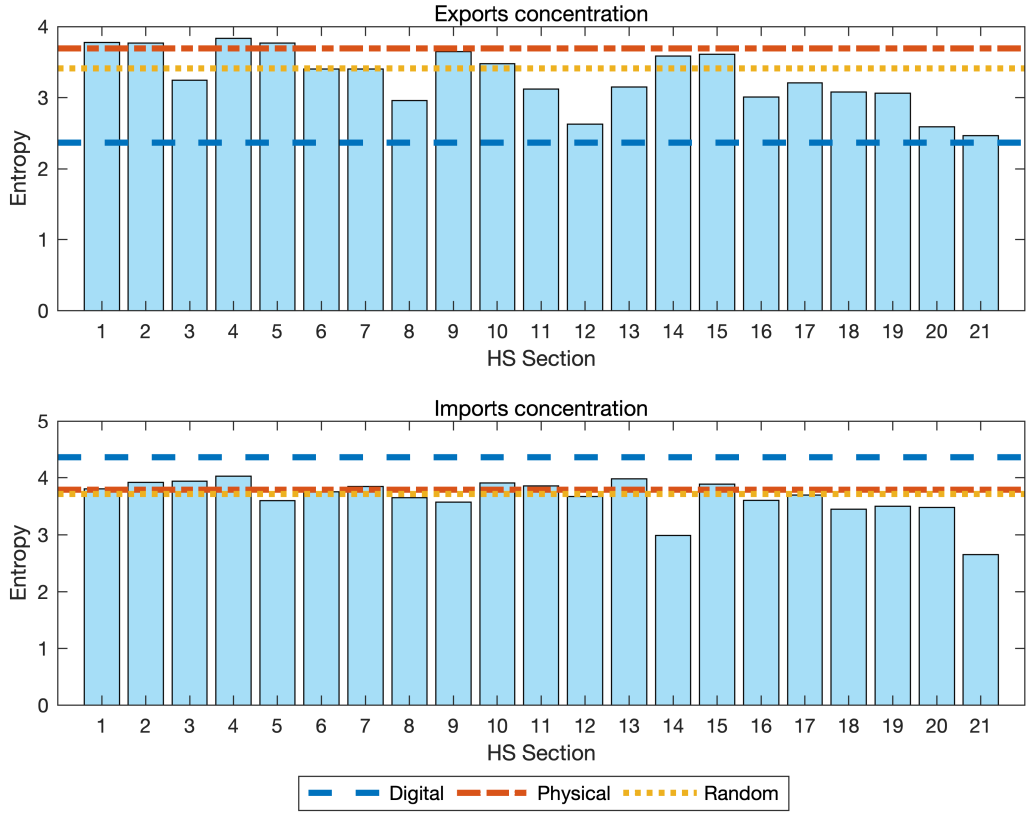

Figure S12. Bar charts for the estimated Entropy (concentration) of physical trade compared to digital trade. See: for HS Section definitions.

8. Decoupling definitions and robustness checks

8.1. Decoupling definition

We formally define decoupling using the *Decoupling Index* (DI)[1–5]. For each country, this index can be calculated using the following equation

$$DI = \frac{\Delta\text{GDP\%} - \Delta\text{Em\%}}{\Delta\text{GDP\%}},$$

where,

$$\Delta\text{GDP\%} = \frac{GDP_1 - GDP_0}{GDP_0},$$

is the relative change in GDP per capita between 2016 and 2019, (GDP_1 is the GDP per capita in 2019 and GDP_o is the GDP per capita in 2016), and

$$\Delta\text{Em\%} = \frac{Em_1 - Em_0}{Em_0},$$

is the relative change in greenhouse gas emissions in kilotons CO2 per capita between 2016 and 2019 (Em_1 is the greenhouse gas emissions in kilotons CO2 per capita in 2019 and Em_o is the greenhouse gas emissions in kilotons CO2 in 2016).

A country that has decoupled economic growth from emissions has a DI of above 1. This is also known as "absolute decoupling" and refers to a decline of emissions in absolute terms while GDP per capita grows.

For this analysis, we collect the data for GDP per capita (in PPP 2017 USD) and population from the World Bank development indicators. Production and consumption emissions are from the Global Carbon Budget (https://meta.icos-cp.eu/objects/lApekzcmd4DRC34oGXQqOxbJ).

8.2. Decoupling between emissions and growth for all countries

We investigate the robustness of our results given in Figure 3 c from the main, by re-estimating the trade patterns using data on all countries.

Figure S13 gives the results. We again observe that countries who achieved decoupling (both in terms of production and consumption emissions) have much larger digital exports, compared to non-decoupling economies. In this case, though, there are significant differences in the volume of physical exports in terms of production emissions. That is, countries that have achieved decoupling in terms of production emissions, also have much larger physical exports.

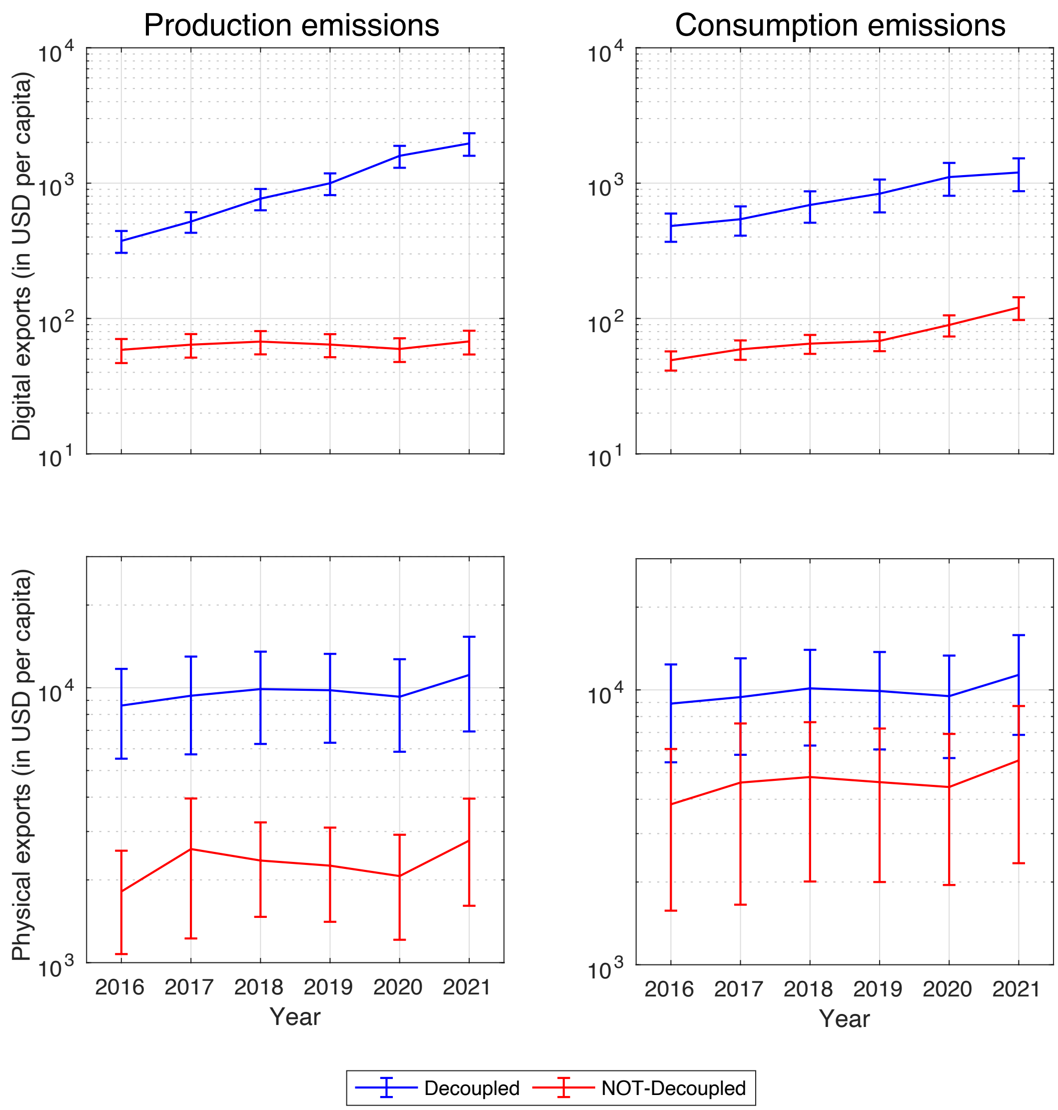

Figure S13. Digital products trade and twin transition using data on all economies. Average digital and physical exports per capita between 2016 and 2021 for all economies depending on whether they decoupled growth from emissions or not.

9. Economic complexity definitions, rankings, and regression analyses

9.1. Economic Complexity Index definition

Economic complexity metrics are derived from specialization matrices, summarizing the geography of multiple economic activities (using dimensionality reduction techniques akin to Singular Value Decomposition or Principal Component Analysis) [6,7]. In particular, given an output matrix X_{cp}, summarizing the exports, patents, or publications of an economy *c* in an activity *p*, we can estimate the economic complexity index ECI_c of an economy and the product complexity index PCI_p of an activity, by first normalizing and binarizing this matrix:

$$R_{cp} = {}^{X_{cp}X}\!\Big/_{X_pX_c},$$
$$M_{cp} = \begin{cases} 1 & if\ R_{cp} \geq 1 \\ 0 & otherwise \end{cases}, \tag{1}$$

where muted indexes have been added over (e.g., $X_p = \sum_c X_{cp}$) and R_{cp} stands for the revealed comparative advantage of economy *c* in activity *p*. Then, we define the iterative mapping:

$$ECI_c = \frac{1}{M_c}\sum_p M_{cp}PCI_p,$$
$$PCI_p = \frac{1}{M_p}\sum_c M_{cp}ECI_c\ . \tag{2}$$

That is, according to (2), the complexity of an economy *c* is defined as the average complexity of the activities *p* present in it (and vice-versa). The normalization steps in (1) and (2) are required to make the units of observation comparable (e.g. China and Uruguay are very different in terms of size). The solution of (2) can be obtained by calculating the eigenvector corresponding to the second largest eigenvalue of the matrix:

$$M_{cc'} = \sum_{pc'} \frac{M_{cp}M_{c'p}}{M_cM_p} \tag{3}$$

Which is a matrix of similarity between economies c and c' normalized by the sum of the rows and columns of the binary specialization matrix M_{cp} (it considers similarity among economies counting more strongly rare coincidences).

To obtain ECI_c, the values of the eigenvector are normalized using a z-score transformation (meaning that the average complexity is 0). In regression analyzes we further normalize the values of ECI_c to be non-negative using a max-min technique (i.e., they are between 0 and 1).

We build our results using the standard definition of ECI[6,8] because this is a widely used definition, making our results more readily comparable with previous research.

9.2. Digital product complexity rankings

Figure S14 gives the PCIs of all digital products in 2021. The most complex digital products were Digital Advertising, Operating System, and Office Software, whereas the least complex was Mobile Applications.

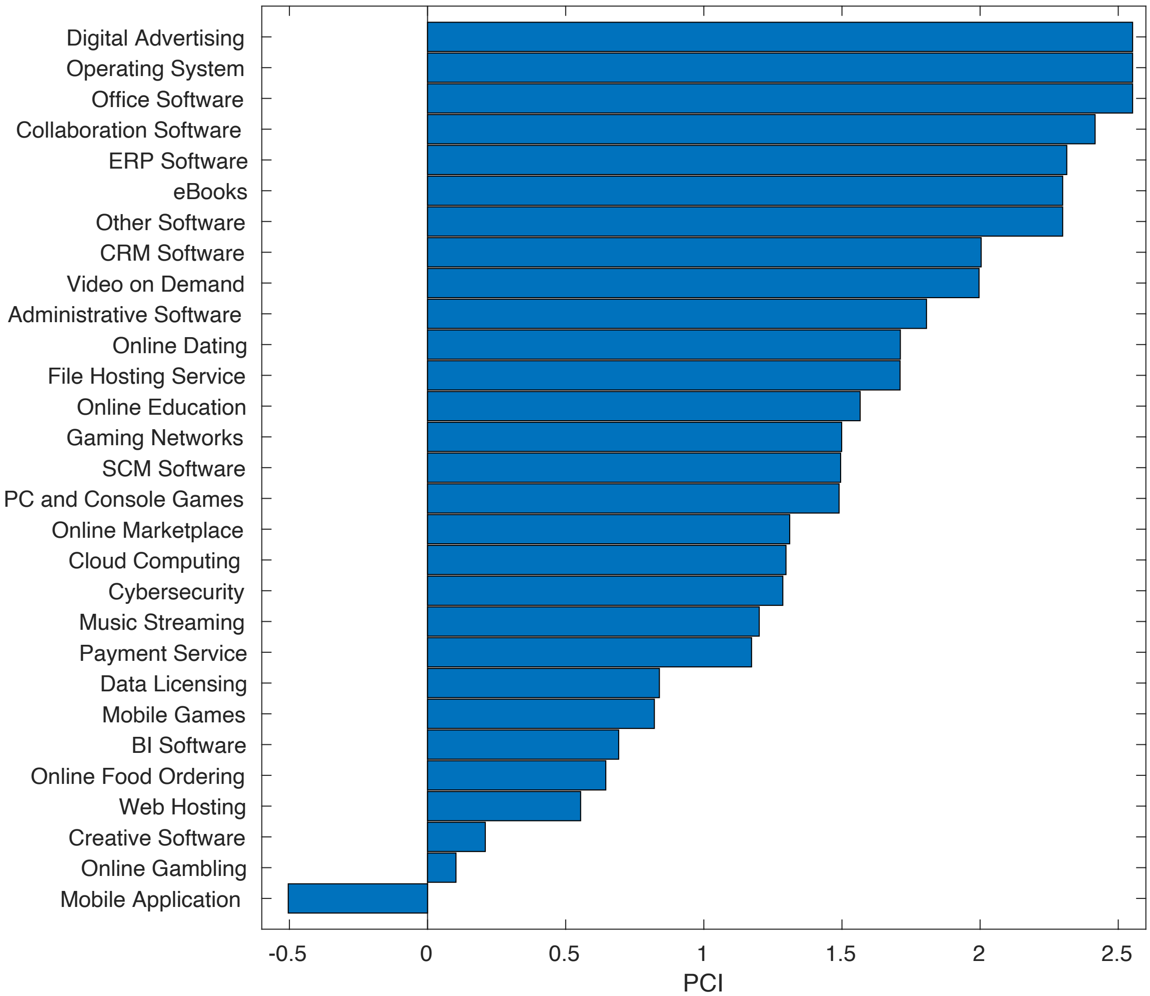

Figure S14. Digital products complexity rankings in 2021.

9.3. Complexity in digital products and services and inclusive green growth

We also explore how complexity in digital product and services could contribute to explaining inclusive green growth by following the economic complexity literature[8–10]. Specifically, for this analysis we follow the setup of Stojkoski et al.[11] and explore whether the combined ECI including physical and digital products trade could improve the explanatory power of the model using just physical trade in explaining international variations in economic growth. That is, we set up regressions of the form

$$y_c = b\, ECI_c + a^T X_c + b_0 + e_c,$$

where y_c is the dependent variable for country c (economic growth, emission intensity), ECI_c is the economic complexity index of the country (estimated with just physical trade, or by combining physical and digital products trade), X_c is a vector of control variables that account for other key factors (e.g. population, GDP per capita, etc.), b_0 is the intercept, and e_c is the error term. We refer to Stojkoski et al.[11] for formal definitions and data sources of the variables used our regression models.

Note that, the ECI has also often been related with income inequality (Gini index). However, due to limited time-series (the data used in Stojkoski et al.[11] for exploring the income inequality relationship is limited to 2015), we are unable to explore this relationship. Also, the regression analyses in Stojkoski et al.[11] are using panel data. Again, due to limited time-series here we restrict ourselves to the latest period.

Economic growth: We test the effect of digital products trade on economic growth by looking at the annualized GDP per capita growth (in constant 2017 PPP dollars) between 2016 and 2021 (the longest period with available data). The baseline model includes the log of the initial GDP per capita (in constant 2017 PPP dollars). This captures Solow's idea of economic convergence[12] (baseline model is presented in column 1 of table S4).

Table S4 shows the effect of digital products trade on the ability of economic complexity metrics to explain economic growth. We find that physical trade complexity (ECI (physical)) is a significant and positive predictor of economic growth (column 2). Moreover, ECI (physical) is robust when adding other potential covariates: human capital, natural resources, and population (column 3, see Stojkoski et al. for formal definitions and data sources).

Combining physical trade and digital products trade (ECI (physical and digital)) yields similar results (columns 4 and 5 of table S4). When we include ECI (physical and digital) and ECI (physical) in one regression model together, we find that both ECI (physical and digital) and ECI (physical) lose significance (column 6 of table S4). Hence, both complexity indexes have similar power in explaining economic growth. Nevertheless, we emphasize that our models are restricted to the latest 6 years, and as such, have limited explanatory power. We believe that with further advancements in data availability and the inclusion of longer time-series, we can build upon this preliminary analysis to construct even more nuanced models.

Table S4. Economic Growth Regressions.

	Dependent variable:					
	GDP per capita growth (2016-2021)					
	(1)	(2)	(3)	(4)	(5)	(6)
ECI (digital and physical)				4.692***	4.191***	-7.718
				(1.230)	(1.204)	(26.498)
ECI (physical)		4.772***	4.242***			11.892
		(1.234)	(1.189)			(26.315)
Log of human capital			-0.149		-0.111	-0.198
			(0.914)		(0.929)	(0.891)
Log of natural resource exports per capita			-0.628		-0.646*	-0.601
			(0.384)		(0.384)	(0.381)
Log of population			-0.148		-0.156	-0.131
			(0.156)		(0.156)	(0.172)
Log of GDP per capita	0.157	-0.626***	0.232	-0.619***	0.243	0.239
	(0.165)	(0.237)	(0.685)	(0.236)	(0.689)	(0.686)
Constant	-0.407	4.748**	3.840	4.804**	3.996	3.318
	(1.610)	(1.908)	(3.386)	(1.916)	(3.480)	(3.981)
Observations	127	127	127	127	127	127
R^2	0.006	0.095	0.126	0.090	0.124	0.128
Adjusted R^2	-0.002	0.080	0.090	0.076	0.088	0.084

Note: Robust standard errors in brackets. *p< 0.1 **p < 0.05 ***p<0.01.

Emission intensity: We explore whether digital products trade adds to the ability of economic complexity to explain emission intensity by modelling the logarithm of a country's yearly greenhouse gas emissions per unit of GDP (in kilotons of CO2 equivalent per dollar of GDP). Larger values represent larger emission intensity. For this analysis we use averaged data between 2016 and 2019. The baseline model includes the log of the GDP per capita (column 1 of table 25).

We find that physical trade complexity (ECI (physical)) is a significant and robust negative predictor of emission intensity (columns 2 and 3 of table S5). ECI (physical and digital) is also significantly and robustly related to emission intensity (columns 4 and 5 of table S5). However, when we combine the two ECI in one regression model, both lose significance. This suggests that digital products trade complexity, for now, does not add significant new information about emission intensity.

Table S5. Emissions Intensity Regressions.

	Dependent variable:					
	Log of GHG emissions per GDP (2016-19)					
	(1)	(2)	(3)	(4)	(5)	(6)
ECI (digital and physical)				-0.277^{***}	-0.270^{***}	0.384
				(0.081)	(0.085)	(0.583)
ECI (physical)		-0.279^{***}	-0.271^{***}			-0.649
		(0.081)	(0.084)			(0.578)
Log of human capital			0.501^{**}		0.496^{**}	0.504^{**}
			(0.252)		(0.250)	(0.254)
Log of natural resource exports per capita			0.204^{***}		0.204^{***}	0.207^{***}
			(0.066)		(0.066)	(0.066)
Log of population			0.070^{**}		0.072^{**}	0.067^{**}
			(0.033)		(0.033)	(0.033)
Log of GDP per capita	-0.287^{***}	-0.074	-0.451^{***}	-0.073	-0.447^{***}	-0.463^{***}
	(0.050)	(0.074)	(0.133)	(0.075)	(0.136)	(0.138)
Constant	-12.147^{***}	-14.165^{***}	-14.215^{***}	-14.172^{***}	-14.264^{***}	-14.068^{***}
	(0.487)	(0.702)	(1.053)	(0.712)	(1.085)	(1.094)
Observations	105	105	105	105	105	105
R^2	0.223	0.312	0.388	0.310	0.386	0.389
Adjusted R^2	0.216	0.298	0.357	0.296	0.355	0.351

Note: Robust standard errors in brackets. $^{*}p< 0.1$ $^{**}p < 0.05$ $^{***}p<0.01$.

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