ECONSTOR
Make Your Publications Visible.

A Service of

ZBW Leibniz-Informationszentrum Wirtschaft
Leibniz Information Centre for Economics

Bekkers, Eddy; Kalachyhin, Hryhorii; Teh, Robert

Working Paper

The long-run impact of digitalization on trade patterns

WTO Staff Working Paper, No. ERSD-2025-01

Provided in Cooperation with:
World Trade Organization (WTO), Economic Research and Statistics Division, Geneva

Suggested Citation: Bekkers, Eddy; Kalachyhin, Hryhorii; Teh, Robert (2025) : The long-run impact of digitalization on trade patterns, WTO Staff Working Paper, No. ERSD-2025-01, World Trade Organization (WTO), Geneva

This Version is available at:
https://hdl.handle.net/10419/309423

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.

WWW.ECONSTOR.EU

Mitglied der Leibniz-Gemeinschaft

Staff Working Paper: Research ERSD-2025-01 **4 December 2024**

World Trade Organization

Economic Research and Statistics Division

THE LONG-RUN IMPACT OF DIGITALIZATION ON TRADE PATTERNS

Eddy Bekkers*, Hryhorii Kalachyhin*, Robert Teh*

**World Trade Organization*

Manuscript date: 4 December 2024

Disclaimer: "The opinions expressed in these papers are those of the authors. They do not represent the positions or opinions of the WTO or its Members and are without prejudice to Members' rights and obligations under the WTO. Any errors are attributable to the authors."

The long-run impact of digitalization on trade patterns

Eddy Bekkers
Hryhorii Kalachyhin
Robert Teh
World Trade Organization

ABSTRACT: We employ the WTO Global Trade Model (GTM) to generate quantitative projections on the expected long-run impact of digitalization on global trade patterns. Five trends are modelled: (i) adoption of artificial intelligence which raises productivity growth; (ii) digitalization reducing trade costs, (iii) the shift to online sales (e-commerce), (iv) the reduced need for physical face-to-face interaction leading to lower trade costs; and (v) changes in data policies in response to these technologies which also impacts trade costs. We distinguish between a convergence scenario with larger productivity growth and trade cost reductions for low-income economies and a core scenario with uniform changes. The simulations generate three main sets of findings. First, digitalization is expected to provide a strong boost to global trade growth and a shift from merchandise trade towards services, and in particular, digitally deliverable services (DDS). With digitalization, global trade growth rises from 2.3% in the baseline to 4.2% annually between 2018-2040. The share of services trade will rise to 37.2% by 2040 with digitalization compared to 27% in the baseline, while the share of DDS in total trade rises to 17.4% by 2040 (compared to 12.4% in the baseline). Second, digitalization can be a force for inclusion, enabling low-income and lower-middle-income economies to raise their share in global trade and income. Trade growth in DDS is projected to be highest in low-income and lower-middle-income economies in the convergence scenario and the share of low-income and lower-middle-income economies in total trade would increase to 10.6% (compared to 8.2% in the baseline). Third, digitalization is projected to change the organization of production and patterns of revealed comparative advantage (RCA). The share of imported intermediates in exports rises in services but falls in manufacturing. In the convergence scenario, low-income economies will expand their RCA in DDS, although high-income economies will continue to retain a strong RCA in this sector.

Keywords: Dynamic CGE-Modelling, Structural Change, Digitalization

JEL codes: F14, F43, I25

Disclaimer: The opinions expressed in this article should be attributed to its authors. They are not meant to represent the positions or opinions of the WTO and its Members and are without prejudice to Members' rights and obligations under the WTO.

1 Introduction

In the last 35 years, technological advancements in information and telecommunication technologies (ICT), including internet access, have significantly impacted the way in which goods, services, and information are bought, sold, and exchanged by bringing electronic or digital markets and platforms into being. More and more cross-border trade is now digital in nature, a trend likely to continue in the future. We have also seen a significant increase in the

use of robots in industry across many parts of the globe. More recently, the dramatic interest spawned by large language models like ChatGPT may augur a new stage in society's deployment and use of artificial intelligence (AI), an important component of digitalization.

Qualitative analysis can be useful in identifying the ways in which new technologies and digitalization could affect international trade. In this paper, we complement this qualitative analysis with quantitative projections on changes in the size and patterns of international trade using the WTO Global Trade Model (GTM), a recursive dynamic computable general equilibrium (CGE) model with multiple sectors and production factors, intermediate linkages, non-homothetic preferences, and investment linkages between economies. Such a quantitative exercise serves three important goals. First, it disciplines qualitative predictions, as it forces to translate narratives into quantitative shocks in a micro-founded economic model. Second, the use of a consistent general equilibrium model implies that the indirect effects of shocks are all taken into account. Third, the fact that the model is computable makes it possible to go beyond qualitative predictions and provide quantitative projections on the magnitude of the effects of new technologies on international trade.

The GTM is used to explore the impact of five trends related to digitalization. First, we consider the productivity effects of AI based on projections in the literature. AI is projected to affect the organization of production in three main ways: (i) the replacement of labor by (broad) capital; (ii) increased productivity of labor and capital; (iii) the creation of new tasks (Briggs and Kodnani 2023; Acemoglu 2024). We follow the projections in Briggs and Kodnani (2023) who focus on the productivity effects of the first two channels.

Second, we examine the impact of digitalization on trade costs. Digital technologies are expected to reduce trade costs along various channels. In particular, we focus on the improvement of customs procedures, rising the efficiency of logistics, falling communication costs because of AI, and falling contract enforcement costs because of new technologies such as blockchain and improved broadband and bandwidth. We regress inferred trade costs based on trade and production data used for the simulations on variables capturing the different channels described, as well as control variables such as distance.

Third, we consider the impact of the growth of e-commerce on trade costs based on studies showing that trade costs are lower for online trade than for offline trade (Lendle et al. (2016)). We use these estimates on the differences in trade costs together with scenarios for the rise of e-commerce (domestic and international) to project reductions in trade costs as a result of the rising importance of e-commerce.

Fourth, we analyze the impact of digitalization through tools like tele- and video conferencing to increasingly substitute for and reduce the need for physical or face-to-face interactions (Baldwin, 2017). This can reduce trade costs in sectors with a need for physical face-to-face interaction. Inferred trade costs are regressed on face-to-face intensity. The impact of face-to-face intensity on trade costs is assumed to fall as a result of digitalization.

Fifth, digitalization and the expanded use of AI will make data policies even more relevant. Economies could either choose to agree on data policies based on safeguards that would reduce trade costs in economies that currently have more restrictive policies or decide to introduce more restrictive data policies based on ad hoc authorization because of security concerns. Projected trade cost changes are based on gravity estimation with the digital services trade restrictiveness index (DSTRI) combined with insights from business questionnaires (WTO-OECD, 2024).

In the simulations, we distinguish between a convergence scenario with larger productivity growth and trade cost reductions for low-income economies and a core scenario with uniform changes across regions. This enables us to determine the importance of policies promoting the catching up of low-income economies.

We first construct a baseline scenario for the world economy as a benchmark. We combine baseline data on the world economy from the GTAP 11 database with the base year 2017 (Aguiar, Chepeliev, et al. 2022) with projections of growth in different variables, such as GDP

per capita, population and labor force and skill levels from various sources (IMF, OECD, UN, IIASA). Furthermore, we add variation in productivity growth across sectors to capture the phenomenon of structural change. We also include baseline trade cost changes related to several trade policy developments that occurred after 2017, such as the US-China trade conflict, Brexit, and implementation of the WTO Trade Facilitation Agreement.[1] Finally, savings rates change based on empirical projections based on demographic developments (Fouré, Bénassy-Quéré, and Fontagné 2013).

With these ingredients, the value share of services in output is projected to rise in the baseline, whereas the shares of manufacturing and agriculture are projected to fall. The sectoral distribution of trade follows a structural change in production. Hence, the share of services trade is projected to rise at the expense of manufacturing trade. Finally, the geographic distribution of trade changes, with the share of high-income economies falling. Low-income and lower-middle-income economies are projected to increase their share of global trade to 10.4% – more than doubling their share compared to the initial share (5.1%). However, more than half of global exports is still projected to come from high-income economies in the baseline.

The simulations generate three main sets of findings. First, digitalization is expected to provide a strong boost to global trade growth and shift from merchandise trade towards services and in particular digitally deliverable services (DDS). With AI and digitalization, global trade growth rises from 2.3% in the baseline to 4.2% annually between 2018-2040. The share of services trade will rise to 37.2% by 2040 with digitalization compared to 27% in the baseline, whereas the share of DDS in total trade rises to 17.4% by 2040 (compared to 12.4% in the baseline). Second, digitalization can be a force for inclusion, enabling low-income and lower-middle-income economies to raise their share in global trade and income. In the convergence scenario, the highest DDS trade growth is projected for low-income and lower-middle-income economies. Furthermore, the income of low- and lower-middle-income regions grows faster than high-income economies. Third, digitalization is projected to change the organization of production and patterns of revealed comparative advantage (RCA). The share of imported intermediates in exports rises in services but falls in manufacturing. In the convergence scenario, low-income economies will expand their RCA in DDS, although high-income economies will maintain a strong RCA in this sector.

This paper makes an important contribution to the literature on the long-run outlook for global trade patterns by carefully modeling five changes associated with one of the main trends in the global economy (besides geopolitical tensions and climate change): digitalization. Part of this exercise is the development of empirical estimates of trade costs changes - and the correspondent ad valorem equivalents (AVEs) - as a result of digitalization, e-commerce, and diminishing face-to-face intensity. Second, we shed light on the important policy-relevant question to what extent digitalization can contribute to the convergence of incomes between economies. Third, we provide insights into the expected shift from merchandise to services trade and the expected rise of digitally deliverable services.

The paper is structured as follows. Section 2 describes the WTO GTM that is used to project the future impacts of these technologies on global trade. It also presents our baseline scenario for the world economy. In Section 3, we describe how the five trends related to digitalization are modeled. Section 4 presents the simulation results. Section 5 concludes.

[1]We do not incorporate potential across-the-board trade cost increases as a result of geoeconomic fragmentation unrelated to data policies. Such a worsening trade policy environment is discussed, for example, in Góes and Bekkers (2022) who conclude that the welfare losses for the global economy of decoupling are huge, particularly for low-income economies, as they would lose out from technology spillovers from richer economies. Hence, such a scenario would slow down the catch-up of low-income economies. However, it is not expected that the comparison of the core and convergence scenario interact with geoeconomic fragmentation.

2 Model and baseline construction

2.1 WTO Global Trade Model

We use the WTO Global Trade Model (GTM) for the baseline projections and experiments. The GTM is a recursive dynamic CGE model containing multiple sectors, multiple factors of production, and four types of demand (private demand, government demand, investment demand, and intermediate demand by firms), intermediate linkages, non-homothetic preferences for private households, a host of taxes, and a global transport sector (see for the model documentation Aguiar, Erwin, et al. (2019) and for a formal description of the model Bekkers, Jhunjhunwala, et al. (forthcoming)). Each region features a representative agent earning factor income and collecting tax revenues who maximizes utility by spending income plus tax revenues on private consumption, government consumption, as well as savings. These savings are collected by a hypothetical global trust, which invests these across different regions. In the simulations the allocation of foreign investment responds to differences in rates of return.

Firms are profit-maximizing and choose the optimal mix of factor inputs and intermediate inputs. There are five production factors: high-skilled and low-skilled labor, capital, sector-specific natural resources, and land.[2] Capital accumulation is a recursive dynamic. Hence, the current period capital stock is equal to the capital stock in the previous period minus depreciation plus investment. As stated earlier, investment flows to regions with higher rates of return. Capturing many features of the global economy in a detailed way requires us to abstract from one important feature: agents are not forward-looking, and different periods are only connected in a recursive dynamic way through the adjustment of the stock of capital.

The model is calibrated to the GTAP database, Version 11, which has 160 regions and 65 sectors. Baseline shares in the base year, 2017, are equal to actual shares. [3] We use an aggregation with 27 sectors and 24 regions, as displayed in Table 1.[4] We report simulation results for aggregate regions by income level: low-income (LI), lower middle-income (LMI), upper-middle-income (UMI), and high-income economies (HI). The sectoral aggregation includes the sectors of interest related to the digitalization of the economy, such as telecommunications, business services, and electronic equipment. We report simulations results for digitally-deliverable services (DDS) and other services based on the list of DDS in IMF et al. (2023). [5] Because of the broad definition employed, the reported value of DDS can be considered as an upper-bound estimate of DDS.

2.2 Construction of the baseline

Before exploring the impact of AI and digitalization, we first construct a baseline scenario for the world economy. This is done by starting with data in 2017, introducing trade policy changes that have taken place since then, and using projections on GDP per capita growth, population, labor force, and skills to determine the trajectory of the world economy until 2040. The growth in GDP per capita, population, labor force, and skills are imposed on the projections by endogenizing labor productivity growth and allowing for endogenous capital accumulation based on recursive dynamics.

GDP per capita growth is based on actual IMF data until 2022 and IMF World Economic Outlook (April 2023) until 2027.[6] From 2028 onwards, we use the OECD Shared Socioeconomic

[2]Since we have only one agricultural sector, land is immobile. In the basic model, land is imperfectly mobile across different agricultural sectors.

[3]Although GTAP11 contains 160 regions and 65 sectors, we use data aggregated to 141 regions and 65 sectors for regressions and AVE calculations.

[4]To better capture the impact of digitalization, we include ICT services as a separate sector in the simulations employing Splitcom. See Appendix A.2 for more details.

[5]Definitions of groups of economies by income level and aggregate sectors are in Appendix A.2.

[6]We use yearly averages for this period to avoid spikes or plunges.

Table 1: Overview of regions and sectors

	Regions		Sectors
AUS	Australia	AGR	Agriculture
OAS	Other Asian economies	OIL	Oil
CHN	China	ONR	Other natural resources
JPN	Japan	PRF	Processed Food
KOR	Korea	TWL	Textiles, wearing apparel and leather
SEA	ASEAN	P_C	Petroleum, coal products
ASL	Asian LDCs	CHE	Chemicals and Petrochemicals
IND	India	PRP	Pharmaceuticals, rubber and plastic products
IDN	Indonesia	OTG	Other Goods
CAN	Canada	MET	Metals
USA	USA	EEQ	Electronic Equipment
MEX	Mexico	ELE	Computer, electronic and optical products
BRA	Brazil	OME	Other Machinery
LAC	Latin America	MVH	Motorvehicles
E27	EU-27	OTN	Transport equipment nec
GBR	United Kingdom	UTC	Utilities and Construction
EFT	EFTA economies	TRD	Trade
ROW	Rest of World	TRP	Transport
RUS	Russian Federation	AFS	Accommodation, Food and service activities
MIN	Middle East and North Africa	WHS	Warehousing and support activities
TUR	Turkiye	CMN	Communication
SSA	Sub-Saharan Africa	OBS	Business Services
SSL	Sub-Saharan LDCs	FIN	Financial Services
ZAF	South Africa	INS	Insurance
		OTS	Other Services
		EDH	Education and human health
		ROS	Recreational and other services

Pathways projections of GDP per capita, SSP2 (Dellink et al. 2017). Population and labor force growth come from the UN population projections, medium variant for 2015 (UN 2015). Changes in the number of skilled and unskilled workers are inferred from projections on education levels by IIASA (Kc and Lutz 2017). In particular, we use changes in the share of tertiary educated as a proxy for changes in the share of skilled workers. Table 2 contains the average yearly growth rates of GDP per capita, population, and labor force by skill category.

The table shows that projected GDP per capita growth in the baseline varies considerably from an average of 4% in Asian LDCs to 0.74% in Canada. Population growth is low across many regions and turns negative in some notable parts of the world, e.g. in East Asia. Based on the skill data from IIASA, the number of unskilled workers falls in many regions, whereas the number of skilled workers grows strongly in most regions. To allow for changes in the amount of land and natural resources employed, we introduce isoelastic supply functions for these two production factors with supply elasticities equal to 1. We also increase the parameter of the flexibility of the expected net rate of return on the capital stock with respect to investment (from 10 to 50 percent). We do that to reduce the tendency of international investment flows to respond to changes in expected rates of return to achieve smoother simulations. All the other parameters are set at standard values provided by the GTAP11 database.[7]

Besides the standard features described, we model two types of structural change in the economy. First, we allow for differential productivity growth across sectors based on historical data to model classical structural change in the economy (a rising share of services output in total output and falling shares of agriculture and manufacturing). In our baseline, productivity

[7]The details can be verified from the replication files, which are available upon request.

Table 2: Average annual growth rate of main macroeconomic variables from 2017 to 2040, and gross savings rates in 2017 and 2040

Region	GDP per capita	Population	Unskilled labor force	Skilled labor force	Savings rate 2017	Savings rate 2040
ASL	4.00	0.71	0.96	2.41	0.22	0.21
AUS	1.03	1.04	0.70	1.69	0.25	0.27
BRA	1.35	0.55	0.27	1.36	0.16	0.17
CAN	0.74	0.97	0.31	1.05	0.20	0.20
CHN	3.68	-0.13	-0.53	1.27	0.44	0.39
E27	1.42	0.09	-0.51	0.74	0.24	0.24
EFT	0.86	0.64	0.02	1.10	0.30	0.32
GBR	0.91	0.45	-0.08	1.06	0.13	0.12
IDN	3.56	0.59	1.12	2.77	0.34	0.29
IND	3.85	0.81	0.75	2.21	0.26	0.28
JPN	0.89	-0.41	-1.16	0.29	0.25	0.26
KOR	2.07	-0.09	-1.23	0.77	0.39	0.33
LAC	1.75	0.81	0.79	2.04	0.18	0.19
MEX	1.26	0.68	0.79	2.20	0.23	0.22
MIN	1.78	1.25	1.10	2.64	0.26	0.24
OAS	1.87	0.89	1.21	1.90	0.19	0.19
ROW	2.59	-0.71	0.37	1.35	0.22	0.23
RUS	1.93	-0.22	-0.37	0.47	0.29	0.29
SEA	2.85	0.69	0.51	2.00	0.29	0.26
SSL	2.69	2.13	2.89	4.39	0.18	0.22
SSO	2.52	2.00	2.52	4.20	0.19	0.23
TUR	2.27	0.77	0.63	2.11	0.26	0.20
USA	1.07	0.58	0.17	0.96	0.18	0.17
ZAF	1.19	0.84	0.87	1.93	0.23	0.26

growth in primary and secondary sectors is, on average, larger than in services. However, in contrast to previous work, which differentiates only between these three broad categories (see, for example Mensbrugghe (2005)), we differentiate between different services sectors since historical data show that there has been considerable heterogeneity in productivity growth between services sectors. A detailed description of the estimations based on historical data is presented in Bekkers, Corong, et al. (2023). Table 3 displays the assumptions on differential total factor productivity (TFP) growth imposed on the model.

Second, gross savings rates change over time based on an empirical life-cycle framework. In particular, we follow the approach in Fouré, Bénassy-Quéré, and Fontagné (2013) and model the gross savings rate as a function of GDP, demographic variables, GDP per capita relative to the US, and GDP per capita growth. Without this additional feature, savings rates would stay virtually constant with savings a Cobb-Douglas share of income of the representative agent. Further details are in Bekkers, Corong, et al. (2023). [8] Table 2 also displays the savings rates in 2017 and 2040 in the model, showing that in most regions the savings rate decreases from 2017 to 2040. However, some developing economies such as India and South Africa are projected to see an increase in their savings rates.

Finally, we incorporate trade policy changes since 2017. First, we introduce iceberg trade cost reductions due to the implementation of the Trade Facilitation Agreement (TFA), based on WTO's calculations of AVEs of the OECD Trade Facilitation Indicators by Moïsé and Sorescu

[8] Targeting the savings rates to the projections from a macroeconomic model makes the model more realistic and also helps the model to get closer to a steady state with converging rates of return, given that the base year (2017) savings rates are too large for a steady-state with constant rates of return, especially in economies like China.

Table 3: Difference between sectoral and average total factor productivity growth

Sector	Differential TFP
Agriculture	2.49
Mining and extraction	0.00
Manufacturing	1.51
Construction	-1.40
Utilities	-1.10
Trade	0.77
Transport	0.00
Accommodation	-1.40
Communication	1.30
Financial services and insurance	1.02
Real estate	0.78
Other business services	-1.44
Public services	-0.55

(2013).[9] Second, we increase tariff rates between China and the US as a reflection of increasing trade tensions. Third, we increase iceberg trade costs between EU-27 and the UK due to Brexit. Fourth, we introduce a reduction in tariffs and NTMs because of preferential trade agreements signed until 2019. The tariff part is based on the ITC database of forward-looking bilateral and sector-specific ad valorem tariffs (ITC 2024), while the NTMs part is estimated by using the DESTA depth indexes database (Dür, Baccini, and Elsig 2014). For Brexit and NTM effects from new PTAs, we calculate ad valorem equivalents based on Egger et al. (2015)'s gravity-based coefficient estimates of the impact of the depth of FTAs on trade costs. Beyond these developments, we assume that geopolitical conflicts and trade fragmentation do not worsen further in the baseline. Scenario analysis on future trade policy cooperation can be found in Métivier et al. (2023).

3 Modelling the impact of digitalization: five trends

We model five trends related to digitalization: (i) the adoption of AI fostering productivity; (ii) digitalization lowering trade costs; (iii) rising shares of e-commerce reducing trade costs; (iv) reduced need for physical face-to-face interaction in economic transactions reducing trade costs; (v) digitalization and AI leading to an increased importance of data policies impacting trade costs. For each of the five trends, we develop a core scenario and a convergence scenario. The core scenario contains lower productivity growth related to AI in economies with a lower AI readiness, identical trade cost reductions related to digitalization, and rising trade costs as a result of more restrictive data policies associated with geopolitical tensions. Under the convergence scenario, sectoral AI productivity shocks are identical, there is an acceleration of trade cost reductions related to digitalization in laggard economies and a convergence of data policies towards an approach based on safeguards and trust leading to lower trade costs.[10] For each of the trends, we first describe the economic rationale behind its inclusion, and then turn to the design of the shock (theoretical framework and calibration). A summary of the scenarios can be found in Table 10 below.

[9] Moïsé and Sorescu (2013) provide data for primary, secondary, and tertiary sectors. We scale them down based on rates of TFA implementation by members from WTO (2020).

[10] Shocks associated with the introduction of e-commerce and the reduced importance of physical face-to-face intensity are the same in the core and convergence scenarios.

3.1 The adoption of AI fostering productivity

Artificial intelligence (AI) refers to the ability of a digital computer or computer-controlled robot to perform tasks commonly associated with humans, such as the ability to reason, discover meaning, generalize, or learn from past experience (Britannica 2024). It can be seen as a form of automation in which the computing ability of machines is substituted for human intelligence and expertise (Aghion, B. F. Jones, and C. I. Jones 2017).

3.1.1 Design of the shock

AI is projected to affect the organization of production in three main ways: (i) the replacement of labor by (broad) capital; (ii) increased productivity of labor and capital; (iii) the creation of new tasks (Briggs and Kodnani 2023; Acemoglu 2024). We follow the projections in Briggs and Kodnani (2023) who focus on the productivity effects of the first two channels. They employ the United States Department of Labor's O*NET tasks database to study the extent of AI exposure by occupation in the United States and the possible productivity effects of AI adoption.[11] They estimate that roughly two-thirds of US occupations are exposed to some degree to AI. They project that widespread adoption of generative AI could reduce the employment of some workers who will be replaced by such applications but will also raise the productivity of those workers who remain in their jobs. Their calculations suggest that about 7% of the United States workers could be replaced by AI. But those workers who remain in their jobs and work with AI tools could see their productivity rise by as much as 3.1% (average over different studies). Adding up the various effects, AI adoption is projected to increase the United States labor productivity growth by 1.5% per year over a 10-year horizon (Briggs and Kodnani 2023).

In our simulations, we introduce the AI shock in 2027.[12] In the convergence scenario we assume that sectoral productivity growth is identical across economies based on the productivity shocks for the US generating an average productivity growth of 1.5% per year for this economy.[13]. The projected productivity growth varies across sectors based on the calculated AI exposure of occupations mapped to sectors using employment data. The same sectoral productivity growth data are also applied to other economies. However, since other economies do not have the same sectoral or industrial structure as the United States, productivity gains will differ across economies. For example, since productivity growth is projected to be larger in business services, most economies will have a lower average productivity growth than the United States, which has a high share of business services.

It is worth noticing that a similar approach is used in WTO (2024) with one main difference in the sectoral variation in AI productivity shocks derived from the occupational variation in AI exposure. In WTO (2024), the authors use variation based on occupation tasks exposure in Eloundou et al. (2023). In this paper, we do not employ this additional complication and follow the variation in productivity shocks in Briggs and Kodnani (2023) based on occupational group level variation.

In the core scenario, we allow for variation in the ability of economies to harness AI adoption benefits based on the replicated AI Preparedness Index (AIPI) proposed in Cazzaniga et al. (2024). This index ranges from 0 to 1 and captures various determinants of AI adoption: digital infrastructure, human capital, technological innovation and legal frameworks.[14] We normalize

[11] The database offers comprehensive information on both worker attributes and job characteristics across the United States occupations. See O*Net (2024).

[12] We use 2027 as a starting year for AI shock for two reasons. First, we use conservative predictions by Bughin et al. (2018) that the net impact of AI will take off after ten years. According to Waters (2017), 2016-2017 are the years when AI started to conspicuously transform the technology industry. Therefore, we use it as a starting point for the 10-year cooling-off period. Second, Bughin et al. (2018) mention that "absorption of AI might reach today's s level of digital absorption by 2027."

[13] This shock is phased in over 14 years, which corresponds with an annual growth rate of 1.06% per year

[14] As this index was not publicly available when the simulations were prepared, we replicated it using the

economies' AIPI values relative to the US value and multiply our economy-sector AI shocks by the normalized index. Hence, the less an economy is prepared for AI adoption, the smaller the projected productivity increase.

In contrast to the estimate from Briggs and Kodnani (2023), Acemoglu (2024) calculates the increase in total factor productivity from AI adoption to be no more than 0.71% over ten years. This is less than half the projected TFP gain from Briggs and Kodnani (2023). The main reason for this lower productivity effect is that Acemoglu (2024) estimates that only about 19.9% of tasks in the United States would be exposed to AI competition based on Eloundou (2023). Furthermore, Acemoglu (2024) scales projected productivity gains down assuming that less than 25% of the potential productivity gains coming from Eloundou's AI exposure would be profitable, based on Svansberg (2024). For comparison, Briggs and Kodnani (2023) estimates that roughly two-thirds of the United States occupations will be exposed to some degree to AI, and that a significant share of the workload can be replaced of the occupations exposed. Even further, Acemoglu (2024) argues that TFP gains may even be as low as 0.55% over ten years because some future returns will have to come from hard-to-learn tasks and may require new institutions, policies, and regulations to fully harness the benefits. Given these differences in estimates of TFP gains, our calculations should be seen as an upper bound of the productivity gains from AI.

3.1.2 Projected productivity changes

The last column of Table 4 displays the productivity shocks in the different sectors, which is identical across all regions. The table makes clear that the largest productivity increases are expected for the business services sectors such as finance (OFI), insurance (INS), communications (CMN) and other business services (OBS), whereas the smallest productivity gains are projected to occur for sectors such as motor vehicles (MVH) and processed food (PRF). Column 2 shows the AI Preparedness Index across regions. The United States of America scores highest in terms of AI preparedness and low-income Sub-Saharan Africa scores (SSL) lowest. Combining these data implies average productivity growth in the convergence scenario (not considering AI preparedness) and the divergence scenario (considering AI preparedness). Differences in the convergence scenario are driven by sectoral output shares across economies with regions with a larger share of business services in output projected to incur larger productivity gains. In the divergence scenario, differences are more pronounced because of differences in AI preparedness.

Allowing for variation in the AI productivity shock by the economy will lead to divergence since low-income economies have the lowest AI preparedness. More generally, this means that the convergence scenario should be understood as implying more convergence or less divergence compared to the core scenario, not necessarily as generating convergence by itself.

3.2 Digitalization lowering trade costs

Digital technologies have the potential to reduce trade costs in multiple ways. They can help improve customs procedures, raise the efficiency of logistics, reduce communication costs between people speaking different languages, reduce contract enforcement costs, and reduce communication costs in general if broadband coverage is improved and internet speed is raised.

3.2.1 Design of the shock

To determine the potential for trade cost reductions because of digital technologies, we proceed in two steps. First, we regress inferred trade costs on a set of determinants which are projected to change because of digitalization. Inferred trade costs are calculated based on the approach

methodology implemented by Cazzaniga et al. (2024). See Appendix A.6 for more details.

Table 4: Various characteristics of the implemented AI productivity shock

#	Region	AI Preparedness Index	Average (production weighted) productivity shock (convergence)	#	Sector	AI productivity shock (convergence)
1	ASL	0.44	0.88	1	AGR	0.85
2	AUS	0.90	1.01	2	OIL	0.76
3	BRA	0.54	0.99	3	ONR	0.66
4	CAN	0.92	1.01	4	PRF	0.69
5	CHN	0.76	0.96	5	P_C	0.81
6	E27	0.82	1.00	6	CHM	0.86
7	EFT	0.95	1.02	7	PRP	0.88
8	GBR	0.96	1.05	8	TWL	0.68
9	IDN	0.62	0.92	9	OTG	0.79
10	IND	0.59	0.95	10	MET	0.70
11	JPN	0.92	1.01	11	EEQ	0.86
12	KOR	0.93	1.01	12	ELE	1.10
13	LAC	0.53	0.97	13	OME	0.94
14	MEX	0.64	0.95	14	MVH	0.63
15	MIN	0.63	0.91	15	OTN	0.93
16	OAS	0.68	0.99	16	UTC	0.71
17	ROW	0.60	0.93	17	TRD	1.08
18	RUS	0.65	0.94	18	AFS	0.62
19	SEA	0.73	0.98	19	TRP	0.79
20	SSL	0.39	0.91	20	WHS	0.72
21	SSO	0.51	0.91	21	CMN	1.31
22	TUR	0.63	0.92	22	OFI	1.64
23	USA	1.00	1.06	23	INS	1.60
24	ZAF	0.55	1.01	24	OBS	1.35
				25	ROS	0.98
				26	OTS	0.86
				27	EDH	1.28

Source: Own calculations based on the approach by Cazzaniga et al. (2024)
Notes: The table presents the summary characteristics of the applied AI productivity shock. The first column shows the values of the AI preparedness index, calculated based on Cazzaniga et al. (2024) approach. The values are normalized with respect to the US index. The second column shows the values for average production-weighted AI productivity shock in the convergence scenario, i.e., without the impact of the AI Preparedness Index, on a regional level. The third column represents the average AI productivity shock in the convergence scenario on a sectoral level. For mapping to region and sector names, see Table 1.

originally proposed by Head and Ries (2001) as well as Chen and Novy (2011) and applied by Novy (2013), among others. Hence, iceberg trade costs between the economy i and j in sector s, τ_{ijs}, can be expressed as the ratio of international relative to intra-national trade flows in trade models with CES-preferences such as the Armington model used in the simulations:

$$\tau_{ijs} = \left(\frac{X_{ijs} X_{jis}}{X_{iis} X_{jjs}} \right)^{\frac{1}{2(\sigma_s - 1)}} \tag{1}$$

X_{ijs} is the value of sales from economy i to j in sector s and σ_s the substitution elasticity between goods of different origin in sector s. We refer to this measure of trade costs as the Head and Ries (HR) Index.

We regress the HR Index in equation (1) on seven variables related to digitalization for the three aggregate sectors primary (agriculture and extraction), secondary (manufacturing),

and tertiary (services):[15] (i) lead time to import as a measure of customs procedures ($LEAD_TIME$); (ii) the liner shipping connectivity index as a measure of logistics efficiency ($LSCI$); (iii) the depth of credit information index ($CREDIT$) and an enforcing contracts indicator ($CONTRACT$) as a measure of the quality of the credit and contract environment; (iv) the existence of a common language ($LANG$) as a measure of the importance of language differences, (v) one principal component of log-linearised fixed and mobile broadband subscriptions per capita ($COMP_BROAD$), (vi) bandwidth speed per user ($BAND$) and (vii) importer-specific WB-WTO Services Trade Restrictiveness Index [16] ($STRI$):

$$\ln \tau_{ij} = \alpha + \beta_l \ln LSCI_{ij} + \beta_t \ln LEAD_TIME_{ij} + \beta_e \ln CONTRACT_{ij} + \beta_c \ln CREDIT_{ij} + \beta_b COMP_BROAD_{ij} + \beta_b BAND_{ij} + \beta_b STRI_j + \gamma LANG_{ij} + X'\theta + \epsilon_{ij} \quad (2)$$

The dependent variable is calculated based on GTAP Data for 2017. The explanatory variables are based on data from the WTO, the World Bank, CEPII and the International Telecommunication Union (ITU). We also include gravity variables from CEPII as control variables, such as distance, the existence of an FTA, and colonial linkages. The estimation results are in Appendix A.3. [17]

As a second step, we develop a scenario for trade cost reductions based on projected changes in the determinants of trade costs as a result of digitalization. More specifically, in the convergence scenario, we assume that economies with lower scores of the determinants of digitalization converge partially to the level of the economy with the 75% best performance. We assume that laggard economies close half of the gap with the 75% best-performing economies.[18] In line with this approach, the negative impact of common language on trade costs is assumed to fall by half. [19]

The size of the shocks in the core scenario is based on the size of the shocks in the convergence scenario. In particular, in the core scenario, trade cost reductions are identical across regions for the different sectors, such that the global trade-weighted average reduction in trade costs is identical to the global reduction in the convergence scenario.

3.2.2 Projected trade cost changes

The ad valorem equivalent trade cost reductions are mapped to yearly changes such that trade costs fall as projected by the empirical estimates over the course of 23 years. Appendix A.4 provides the details. Tables 5 and 6 display the trade-weighted annual reductions in trade costs for importing regions and sectors. Analyzing the variation across sectors, the average yearly reduction in trade costs varies between 0.09% for computer, electronic and optical equipment (ELE) and 1.28% for warehousing (WHS). This variation is driven by the fact the tertiary sector is estimated to have the largest trade cost reductions and the fact that the largest trade cost reductions across regions occur in lower income regions covering a small share of global exports of sectors like ELE. Comparing the shocks across regions shows that the largest reductions are projected in the convergence scenario are projected for the least-developed regions such as SSL (1.58%), whereas the smallest reduction is projected for high and middle-income economies.

[15] We estimate for the three broad sectors, because we do not have sufficient information at the detailed sectoral level.

[16] We adjust WB-WTO values for intra-EEA pairs using the ratio of OECD intra-EEA STRI related to OECD STRI.

[17] More details on the measurement of the different variables are also in Appendix A.3.

[18] For economies already above 75% best performance, no trade costs changes are projected in the convergence scenario.

[19] We calculate the ad valorem equivalents of these changes for all the economies available in the databases used and aggregate them up to the level of our 24 aggregate regions using bilateral trade-weighted averages per sector.

Mexico (MEX) has the lowest projected reduction in trade costs, which can be explained by the fact that this the economy already scores above the 75% quartile for most indicators.

Table 5: Annual ad valorem equivalent trade cost reductions as a result of technological change in convergence scenario. Averages across importers

Region	Total	Common Language	Lead	LSCI	STRI	Contract and Credit	Broadband and Bandwidth
ASL	-0.95	-0.19	-0.06	-0.11	0.00	-0.42	-0.18
AUS	-0.22	-0.15	0.00	-0.02	0.00	-0.04	-0.02
BRA	-0.57	-0.35	-0.10	-0.03	-0.01	-0.06	-0.03
CAN	-0.21	-0.06	-0.08	-0.01	0.00	-0.05	-0.01
CHN	-0.37	-0.21	-0.10	0.00	-0.01	-0.02	-0.03
E27	-0.43	-0.27	-0.03	-0.02	0.00	-0.10	-0.01
EFT	-0.48	-0.30	-0.01	-0.05	-0.01	-0.10	-0.02
GBR	-0.36	-0.25	-0.04	-0.01	0.00	-0.04	-0.02
IDN	-0.38	-0.21	-0.07	-0.01	-0.01	-0.01	-0.07
IND	-0.56	-0.13	-0.04	-0.01	-0.01	-0.07	-0.30
JPN	-0.39	-0.27	-0.04	0.00	0.00	-0.07	-0.01
KOR	-0.20	-0.13	-0.04	0.00	0.00	-0.01	-0.01
LAC	-0.49	-0.16	-0.08	-0.09	0.00	-0.12	-0.05
MEX	-0.14	-0.07	-0.05	0.00	0.00	-0.01	-0.01
MIN	-0.48	-0.22	-0.07	-0.03	0.00	-0.10	-0.05
OAS	-0.33	-0.15	-0.07	-0.02	0.00	-0.05	-0.05
ROW	-0.55	-0.26	-0.06	-0.10	0.00	-0.05	-0.07
RUS	-0.51	-0.30	-0.11	-0.03	-0.01	-0.04	-0.02
SEA	-0.26	-0.16	-0.03	-0.01	0.00	-0.03	-0.04
SSL	-1.58	-0.25	-0.19	-0.09	-0.02	-0.50	-0.56
SSO	-0.83	-0.17	-0.04	-0.06	-0.01	-0.10	-0.45
TUR	-0.30	-0.19	-0.03	-0.01	0.00	-0.03	-0.03
USA	-0.21	-0.13	-0.02	-0.01	0.00	-0.03	-0.02
ZAF	-0.41	-0.15	-0.04	-0.02	0.00	-0.05	-0.15

Source: Own calculations

Notes: The table shows the projected annual (phased-in for 23 years) AVE trade cost reductions from digitalization in a convergence scenario, i.e. when lagging economies close their gap to the 75th percentile by half. For mapping to region names, see Table 1.

3.3 E-commerce

More and more consumers and firms are turning to online markets and platforms to make their purchases. It is estimated that global e-commerce transactions in 2016 amounted to about $28 trillion, up 44 percent from 2012 (USITC 2017). Online shopping became a lifeline for hundreds of millions during the COVID-19 pandemic. E-commerce transactions between businesses (B2B) are estimated to be six times larger than e-commerce purchases of consumers from businesses (B2C). While cross-border e-commerce transactions were only about 15% of the total e-commerce market (Express 2017), it is estimated to be around 22% in 2022 (Statista 2022), reaching 33% by 2028 (Juniper 2023).

By reducing search costs, the internet and e-commerce platforms can facilitate market transactions, including cross-border trade (see, e.g. Cairncross (2001), Borenstein and Saloner (2001)). This is borne out by the empirical literature, which finds that e-commerce reduces distance-related trade costs (Freund and Weinhold 2004; Clarke 2008; Hortaçsu, Martínez-Jerez, and Douglas 2009; Ahn, Khandelwal, and Wei 2011; Lendle et al. 2016). E-commerce shrinks the distance between buyer and seller by nearly a third according to Lendle et al. (2016), thereby facilitating more exchange.

Table 6: Annual ad valorem equivalent trade cost reductions as a result of technological change in convergence scenario. Averages across sectors

Sector	Total	Common Language	Lead	LSCI	STRI	Contract and Credit	Broadband and Bandwidth
AFS	-1.18	-0.64	-0.19	-0.04	-0.01	-0.17	-0.15
AGR	-0.31	-0.13	-0.06	-0.02	0.00	-0.05	-0.05
CHM	-0.16	-0.09	-0.02	-0.01	0.00	-0.03	-0.01
CMN	-1.15	-0.66	-0.12	-0.04	-0.01	-0.19	-0.14
EDH	-1.19	-0.65	-0.20	-0.03	-0.03	-0.13	-0.17
EEQ	-0.11	-0.07	-0.01	-0.01	0.00	-0.02	0.00
ELE	-0.09	-0.06	-0.02	0.00	0.00	-0.01	0.00
INS	-1.08	-0.62	-0.10	-0.12	-0.01	-0.14	-0.10
MET	-0.16	-0.08	-0.02	-0.01	0.00	-0.03	-0.01
MVH	-0.17	-0.11	-0.02	-0.01	0.00	-0.03	0.00
OBS	-1.04	-0.63	-0.11	-0.03	-0.01	-0.16	-0.11
OFI	-1.14	-0.62	-0.09	-0.04	0.00	-0.34	-0.06
OIL	-0.13	-0.04	-0.02	0.00	0.00	-0.03	-0.02
OME	-0.12	-0.07	-0.01	-0.01	0.00	-0.02	0.00
ONR	-0.50	-0.24	-0.10	-0.01	0.00	-0.06	-0.09
OTG	-0.16	-0.09	-0.02	-0.01	0.00	-0.03	-0.01
OTN	-0.14	-0.07	-0.01	-0.02	0.00	-0.04	-0.01
OTS	-1.25	-0.69	-0.16	-0.05	-0.01	-0.19	-0.16
P_C	-0.35	-0.14	-0.03	-0.05	0.00	-0.08	-0.05
PRF	-0.35	-0.16	-0.03	-0.05	0.00	-0.08	-0.04
PRP	-0.16	-0.09	-0.01	-0.01	0.00	-0.03	-0.01
ROS	-1.27	-0.67	-0.20	-0.04	-0.02	-0.19	-0.16
TRD	-1.12	-0.64	-0.13	-0.04	0.00	-0.22	-0.10
TRP	-1.24	-0.68	-0.18	-0.04	-0.01	-0.19	-0.15
TWL	-0.18	-0.09	-0.02	-0.01	0.00	-0.04	-0.02
UTC	-1.25	-0.59	-0.19	-0.05	-0.02	-0.21	-0.20
WHS	-1.28	-0.70	-0.17	-0.05	-0.01	-0.22	-0.15

Source: Own calculations
Notes: The table shows the projected annual (phased-in for 23 years) AVE trade cost reductions from digitalization in a convergence scenario, i.e. when lagging economies close their gap to the 75th percentile by half. For mapping to sector names, see Table 1.

3.3.1 Design of the shock

Our database does not distinguish between goods traded online and offline. With such a distinction we could employ projections about the changing share of online traded goods to project the impact of the rising importance of e-commerce in the global economy. Therefore, we follow an indirect approach combining projections on the total share of goods and services sold online (both domestic and international) with data on the difference in online and offline trade costs. Through a composition effect, a rising share of online goods and services will reduce the trade costs on all goods and services (online and offline) traded. Appendix A.5 contains a formal description of the projected AVE trade cost reduction describing how projections for the rising online share in goods and services are obtained and how the difference in trade costs between online and offline is estimated.

3.3.2 Projected trade costs changes

Table 8 displays the average yearly reduction in trade costs for the different sectors. Differences between economies and sectors are driven by differences in GDP per capita growth, which determines the predicted increase in the share of online trade, and by differences in the estimated

impact of GDP per capita on the share of online trade. Two scenarios are implemented, with and without a decreasing role for a common language. In the former scenario, it is assumed that the impact of having no common language on the difference in trade costs between online and offline trade falls by 50%, in line with the convergence scenario for the fall in trade costs.

3.4 Reduced need for physical face-to-face interactions

Face-to-face interactions represent an important way in which economic agents can work on tasks together, negotiate and settle disputes, or conduct market transactions. However, it is possible that technological developments will allow such interactions or transactions to occur without the need for physical or face-to-face encounters. There are those who have predicted a new wave of globalization that will enable workers from one economy to perform service tasks in another without the need to be physically present there (Baldwin 2016). The work-from-home phenomenon we experienced during the pandemic provides evidence that the future alluded to by Baldwin (2016) is probably closer than we think.

3.4.1 Design of shock

For the purpose of our simulation, we assume that the need for face-to-face task interaction increases the costs of conducting transactions. The development of new technologies that does away with the need for face-to-face interaction will, therefore, reduce trade costs.

As in Section 3.2, trade costs are represented by the HR Index. To calculate this index, we employ data from the most recent GTAP 11 database for the year 2017. Furthermore, for easier comparability, we set the substitution elasticity equal across all sectors.[20]

We further calculate the intensity of face-to-face interactions for different sectors using the United States Department of Labor's O*NET database. This dataset contains measures indicating the importance of certain tasks for different occupations on a scale from 0 –100. Following Blinder (2009), we use four task indicators, which are likely to capture the importance of face-to-face interactions. These are "Establishing and maintaining personal relationships", "Assisting and caring for others", "Performing for or working directly with the public," as well as "Selling or influencing others." These variables are available at the occupational level and therefore must be mapped to the industry level. In doing so, we follow the methodology in Oldenski (2012) by using data on the shares of occupations used in each industry from the United States Bureau of Labor Statistics Occupational Employment Statistics (2007, 2010). Unfortunately, it was impossible to match the task-based occupation data to certain agricultural and natural resource sectors, which fall out of the sample. However, we omit all natural resource sectors, as face-to-face interactions are unlikely to play a role in their context. Lastly, we construct a composite measure, referred to as the Face-to-face Index, by taking the average of the four task-related variables at the sectoral level. A larger value of the index indicates a stronger intensity of face-to-face interactions in a certain sector.

The first insights can already be inferred from Figure 1, which plots our measure of trade costs, the HR Index, against the intensity of face-to-face interactions. We see that a stronger intensity of face-to-face meetings is associated with larger trade costs in general. Furthermore, compared to goods sectors, the Face-to-face Index seems to be larger for service sectors (rhomb markers), which tend to appear on the right part of the figure. The sector with the lowest trade cost is non-ferrous metals (NFM) while the sector with the highest trade cost is accommodation, food, and service activities (AFS).

To further explore this relationship, we also estimate OLS regressions with three specifications, displayed in Table 7. As our Face-to-face Index varies only at the sectoral

[20] In calculating the AVEs associated with a reduced need for physical face-to-face interaction, we correct the variation in substitution elasticities to ensure that the AVEs are consistent with the elasticities employed in the simulations.

Figure 1: The intensity of face-to-face interactions and trade costs

Source: Own calculations
Note: The figure shows the relationship between the calculated face-to-face intensity in the X axis and the log of the HRM index representing trade costs in the Y axis. The circle markers represent aggregated commodity sectors, and the rhomb markers - represent services sectors. For mapping to sector names, see Table 1.

level, we conduct the analysis with data averaged across economy pairs (i.e., it only contains sectoral variation) and importer and exporter fixed effects that absorb other unobserved characteristics.

Table 7: Face-to-face Interactions and Trade Costs

	(1)	(2)	(3)
	log_hrm	log_hrm	log_hrm
Services	0.317***		0.160***
	(262.13)		(81.89)
Face_raw_av		1.188***	0.723***
		(270.23)	(101.21)
_cons	0.578***	-0.217***	0.0845***
	(1005.85)	(-66.43)	(17.24)
Importer and exporter fixed effects	Yes	Yes	Yes
N	275533	275533	275533

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

On their own, both the services variable as well as the Face-to-face Index are highly significant and associated with larger trade costs in all samples. Nevertheless, as specification 3 shows, once both variables are included in the regressions, the effect of being in a service sector is strongly reduced by approximately half. The same effect is observed for the Face-to-face Index. Therefore, these results indicate that face-to-face interactions are strong drivers of trade costs and that the channel driving the higher trade costs for service sectors seems to be the importance of face-to-face meetings.

3.4.2 Projected trade costs changes

In the simulations, we project that face-to-face intensity will fall in laggard sectors by reaching the sector with the lowest score for face-to-face intensity, non-ferrous metals (NFM). As a result, there is no economy-specific heterogeneity in the shock and, thus also no difference in the shocks between the core and convergence scenarios. The projected average yearly reduction in trade costs from diminished face-to-face intensity is presented for the different sectors in Table 8.

Table 8: Projected average yearly ad valorem equivalent trade cost reduction from E-commerce, diminished face-to-face intensity and data policies in convergence scenario by sector

Sector	E-commerce		Face-to-face	Data Policies
	With language	No language		
AFS	-0.12	-0.09	-4.61	-0.15
AGR	-0.19	-0.12	0.00	-0.04
CHM	-0.09	-0.06	-0.22	-0.07
CMN	-0.15	-0.10	-2.75	-0.13
EDH	-0.08	-0.05	-3.22	-0.13
EEQ	-0.08	-0.05	-0.16	-0.03
ELE	-0.09	-0.05	-0.27	-0.02
INS	-0.06	-0.04	-2.72	-0.08
MET	-0.09	-0.06	-0.07	-0.07
MVH	-0.11	-0.06	-0.66	-0.03
OBS	-0.06	-0.04	-2.75	-0.15
OFI	-0.05	-0.03	-3.46	-0.07
OIL	0.00	0.00	0.00	-0.16
OME	-0.08	-0.05	-0.13	-0.05
ONR	0.00	0.00	-0.12	-0.08
OTG	-0.11	-0.07	-0.90	-0.09
OTN	-0.07	-0.05	-0.07	-0.04
OTS	-0.08	-0.05	-1.26	-0.15
P_C	-0.17	-0.11	-0.42	-0.14
PRF	-0.18	-0.12	-0.29	-0.10
PRP	-0.09	-0.06	-0.26	-0.05
ROS	-0.11	-0.08	-3.26	-0.11
TRD	-0.15	-0.10	-4.77	-0.07
TRP	-0.28	-0.18	-2.43	-0.10
TWL	-0.13	-0.07	-0.58	-0.10
UTC	-0.06	-0.03	-1.37	-0.28
WHS	-0.28	-0.18	-2.44	-0.09

Source: Own calculations
Notes: The table shows the projected annual AVE trade cost reductions from E-commerce, diminished face-to-face intensity, and "moving-to-the-middle" evolution of data policies. For mapping to sector names, see Table 1.

3.5 Data policies

Digitalization has led to the introduction of data policies in most economies. Such data policies consist, on the one hand, of regulations on the cross-border movement of data and, on the other hand, of regulations on the localization of data. Future data policies can take different directions. Following the stylized scenarios in OECD/WTO (2024), we distinguish between a Moving-to-the-Middle Scenario characterized by convergence to data policies based on safeguards that are incorporated in the convergence scenario and a Geoeconomic Fragmentation Scenario characterized by restrictive data policies for trade between economies in different geopolitical blocks which is incorporated in the core scenario.

3.5.1 Design of shock

The shocks associated with data policies are designed based on OECD/WTO (2024). We only consider the shocks related to data flow regulations, since the impact of data localization policies is small. In the Geoeconomic Fragmentation Scenario (included in the core scenario), there are three geopolitical blocks (Eastern, Western, and Neutral) and economies in the Eastern and Western Geopolitical Blocks apply restrictive cross-border data policies based on an ad hoc authorization approach to data flows from the opposite block. The shocks between the blocks are asymmetric because they are based on the economies' current data transfer regimes. Iceberg trade costs increase because companies need to employ additional resources to comply with these policies.

In the Moving-to-the-Middle Scenario, regions with cross-border data policies based on ad hoc authorization would benefit from reductions in trade costs associated with moving to a safeguards approach. The size of the trade cost changes in both scenarios is based on gravity estimation regressing trade flows on OECD's Digital Services Trade Restrictiveness Index (DSTRI) combined with information about cross-border data policies in place in the DSTRI.

3.5.2 Projected trade costs changes

Table 8) shows that reductions in trade costs related to data policy reforms are largest in services sectors such as utilities (UTC), accommodation, food and services activities (AFS), and communications (CMN). Table 9 displays the average trade cost reduction per importer under the core and convergence scenarios related to data policies.

In the convergence scenario, trade cost changes tend to fall for a small number of economies with stringent data policies. At the same time, the majority of the other regions experience trade cost increases in the core scenario as a result of a shift to more stringent data policies. [21]

3.6 Overview of shocks

Table 10 provides an overview of the five trends modeled. Two trends are identical in the core and convergence scenario: E-commerce and Face-to-Face. These trends are modeled as sector-specific without variation between economies. The other trends vary between the two scenarios. The sectoral AI shocks are the same in all economies in the convergence scenario, whereas they vary by AI preparedness in the core scenario. In terms of trade cost reductions related to digitalization, convergence corresponds with a larger drop in trade costs for lagging (lower-income) economies. For changes in data policies the distinction between the core and convergence scenario is more subtle again. Under the convergence scenario, larger reductions in trade costs are expected in low-income economies because these economies tend to have either no data policies or restrictive policies.[22]

Figures 2 and 3 illustrate the cumulative AVE trade cost reductions among sectors and importers, respectively, in the convergence scenario. Comparing the drivers of trade cost changes, the reduced importance of face-to-face intensity is projected to generate the largest trade cost reduction, followed by the reduced impact of common language on trade costs. Comparing trade cost changes across sectors indicates that the largest trade cost reductions are projected to occur in the services sectors. Finally, the comparison across regions shows

[21] For two regions (ASL and ZAF) trade costs are not projected to change, because information is not available about their data policies in the indicator employed, the OECD DSTRI.

[22] The trends modeled are sometimes interconnected. For example, broadband is physical infrastructure whose impact will cut across many of the technological trends we consider, from logistics to e-commerce, and face-to-face interaction. Improvements in customs and trade procedures from digitalization will positively impact international e-commerce. In the analysis, we abstract from these interactions, which could both increase or decrease projected trade cost changes.

Table 9: Projected average yearly ad valorem equivalent trade cost reduction from data policies by importer

Importer	Core	Convergence
ASL	0.00	0.00
AUS	0.13	0.00
BRA	0.05	0.00
CAN	0.05	0.00
CHN	0.00	-0.34
E27	0.04	0.00
EFT	0.04	0.00
GBR	0.04	0.00
IDN	0.00	-0.38
IND	0.00	-0.36
JPN	0.09	0.00
KOR	0.09	0.00
LAC	0.08	0.00
MEX	0.05	0.00
MIN	0.02	-0.35
OAS	0.23	0.00
ROW	0.00	-0.42
RUS	0.00	-0.45
SEA	0.02	0.00
SSL	0.01	0.00
SSO	0.01	-0.24
TUR	0.00	-0.33
USA	0.12	0.00
ZAF	0.00	0.00

Source: Own calculations
Notes: The table shows the projected annual AVE trade cost reductions from data policies in core and convergence scenarios. For mapping to region names, see Table 1.

Table 10: Overview of trends modeled in the two scenarios

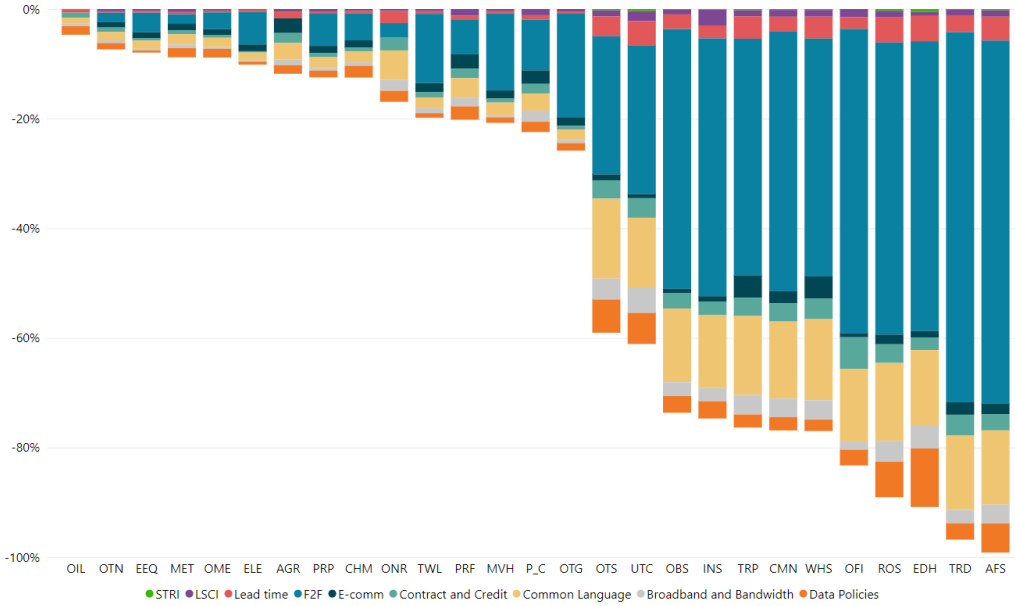
	Scenarios	
Trends	Core	Convergence
The adoption of AI fostering productivity	Different productivity growth by sector and region as a function of sectoral composition of economy and the AI preparedness index.	Different productivity growth by sector and region as a function of sectoral composition of an economy
Digitalization reducing trade costs	Reductions in iceberg trade costs as a result of new technologies. Identical reductions across different regions	Reductions in iceberg trade costs as a result of new technologies. Trade costs in lagging pairs catch up by half to 25% best performing pairs
Rising E-commerce shares reducing trade costs	Reductions in iceberg trade costs due to the expansion of online sales.	Reductions in iceberg trade costs due to the expansion of online sales.
Reduced need for physical face-to-face interactions	Lower iceberg trade costs due to reduced need for physical face-to-face interactions	Lower iceberg trade costs due to reduced need for physical face-to-face interactions
Changes in data policies modifying trade costs	Rising trade costs because of the introduction of ad hoc authorization policies related to geopolitical tensions	Falling trade costs because of convergence to safeguard based data policies reflecting convergence of policies

that Sub-Saharan Africa and Asian LDCs (SSL and ASL) are projected to see the largest trade cost reductions in the convergence scenario, explained by the scope to catch up and raise, for example, logistics performance more than other regions. However, also the sectoral structure matters. For example, the EFTA economies (EFT) are projected to benefit substantially from

trade cost reductions because of their sectoral specialization in services.

Figure 4 displays these insights more concisely, comparing the contribution of Digitalization, E-commerce, Face-to-Face and Digital Policies to changes in trade costs across four main sectors and four groups of economies by income group. The largest contribution comes from Digital Policies and Face-to-Face, while the impact of e-commerce on trade costs is relatively small.[23] The projected changes are the largest in digitally deliverable services and other services sectors, while the main beneficiaries are low-income economies.

Figure 2: Cumulative AVE trade cost reductions in 2018-40 among sectors



Source: own calculations.
Notes: the figure depicts the relative sizes of the cumulative AVE trade cost reductions in the observing period at the sectoral level. The percentage changes are not additive. For mapping to sector names, see Table 1.

4 Simulation results

4.1 Baseline projections results

The baseline projections generate three main insights. First, the value share of services in output rises in the baseline, whereas the share of manufacturing falls across all regions (Figure 6). This is a result of both shifting preferences as economies grow richer and the higher productivity growth in the manufacturing sector relative to the rest of the economy, making services relatively more expensive and raising its value share because of the limited scope for substitution.[24]

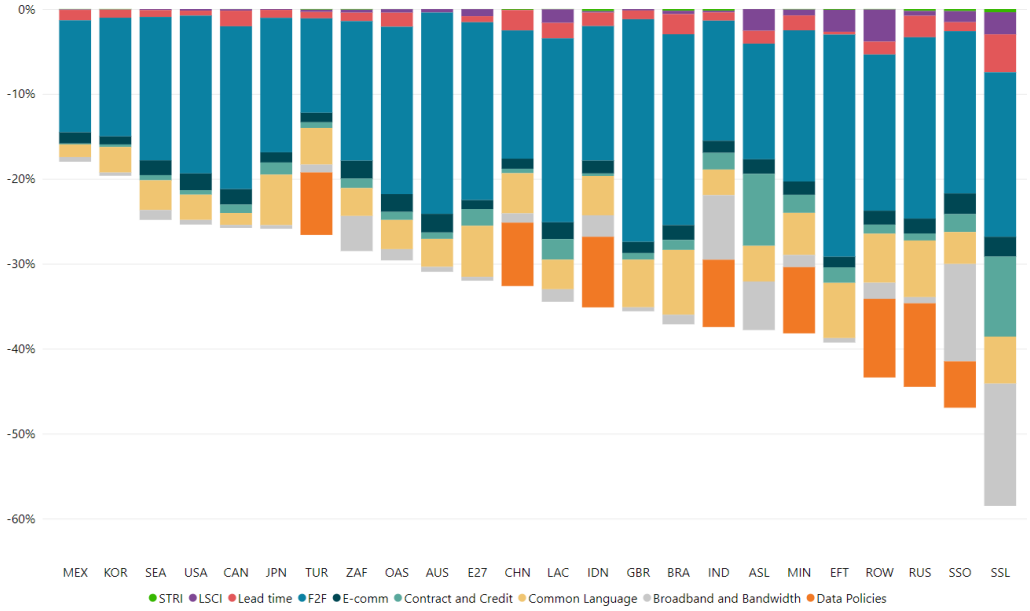
Second and related, the share of services in total trade rises between 2018 and 2040, although the manufacturing sector remains dominant in global trade (Figure 7).

Third, the export-to-GDP ratio is projected to fall slightly in the baseline between 2018 and 2040 (Figure 8). This reflects the falling share of manufacturing and rising share of services in total output combined with a smaller initial share of services exports in trade. The shift towards services in the economy, a sector that is less tradable than manufacturing, leads to a

[23] Note that AI is assumed to only affect productivity in the scenarios and does not affect trade costs.

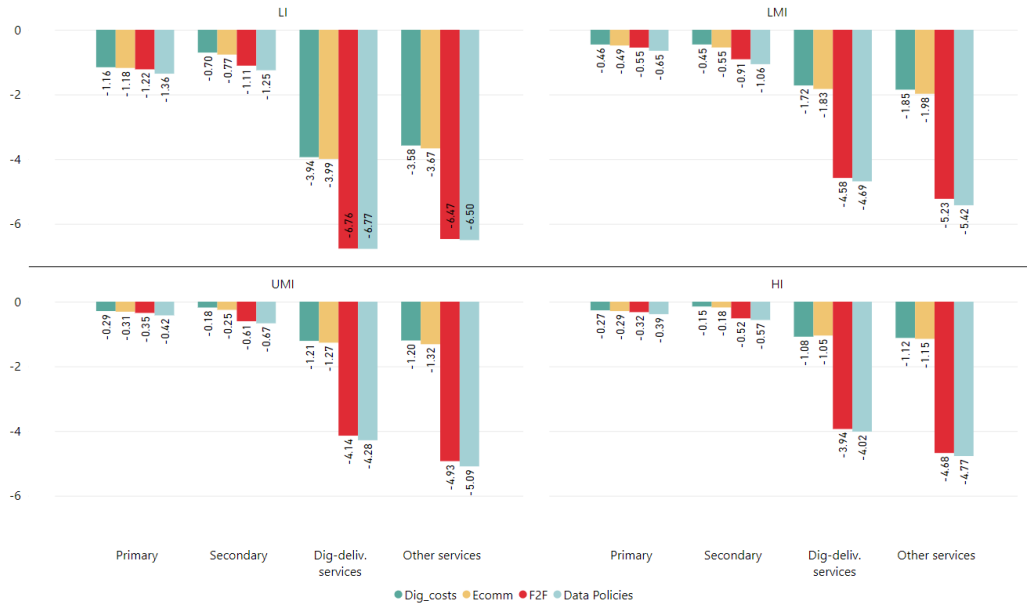
[24] This reflects the Baumol effect in which a sector whose productivity growth lags that of another sector ultimately hoovers up more resources, thus taking up a larger share of the economy at the expense of the more productive sector.

Figure 3: Cumulative AVE trade cost reductions in 2018-40 among importers



Source: Calculated based on own simulations.
Notes: the figure depicts the relative sizes of the cumulative AVE trade cost reductions in the observing period at the regional level. The percentage changes are not additive. For mapping to region names, see Table 1.

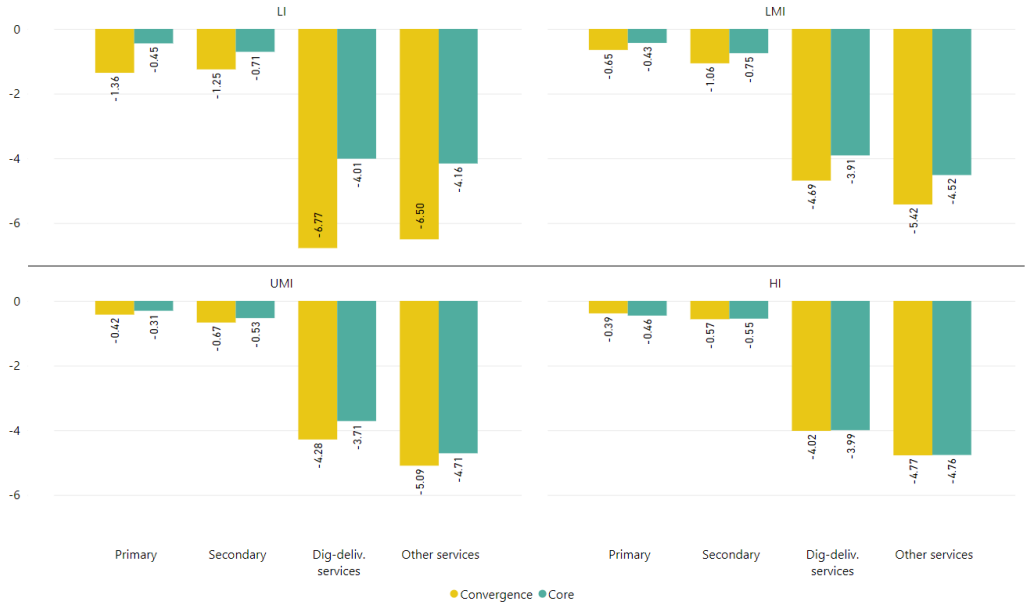
Figure 4: Iceberg trade cost reduction in main sectors across regional groups in four convergence scenarios



Source: own calculations.
Notes: the figure demonstrates the difference in projected iceberg trade costs reduction in four convergence scenarios among sectors and regional groups. For mapping to aggregate sectors and regional groups, see Tables A.1 and A.2, respectively.

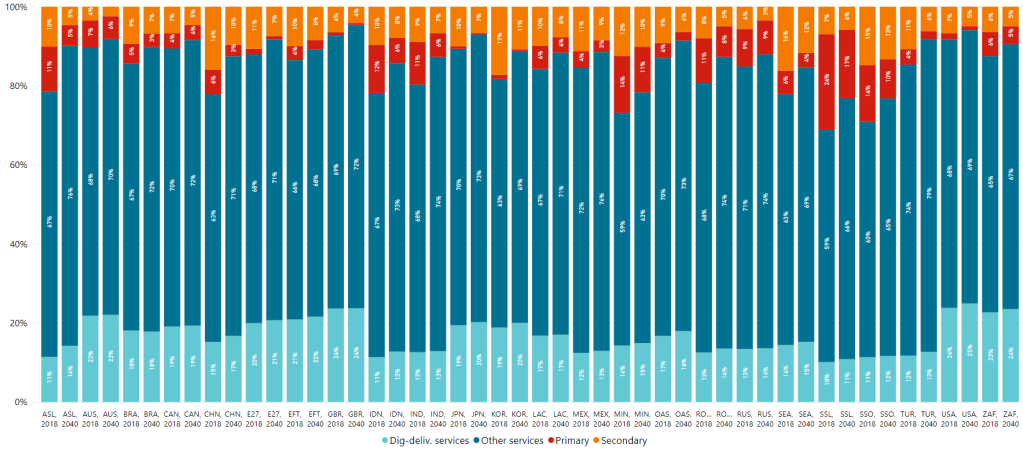
fall in exports relative to GDP as a result. At the same time, it is notable that in the baseline, the trend is projected to be the opposite for some high-income (EFTA and Australia) and

Figure 5: Iceberg trade cost reduction in main sectors across regional groups



Source: own calculations.
Notes: the figure demonstrates the difference in projected iceberg trade costs reduction in core and convergence scenarios among sectors and regional groups. For mapping to aggregate sectors and regional groups, see Tables A.1 and A.2, respectively.

Figure 6: The value added share of manufacturing (upper panel) and services (lower panel) in 2018 and 2040 in the baseline



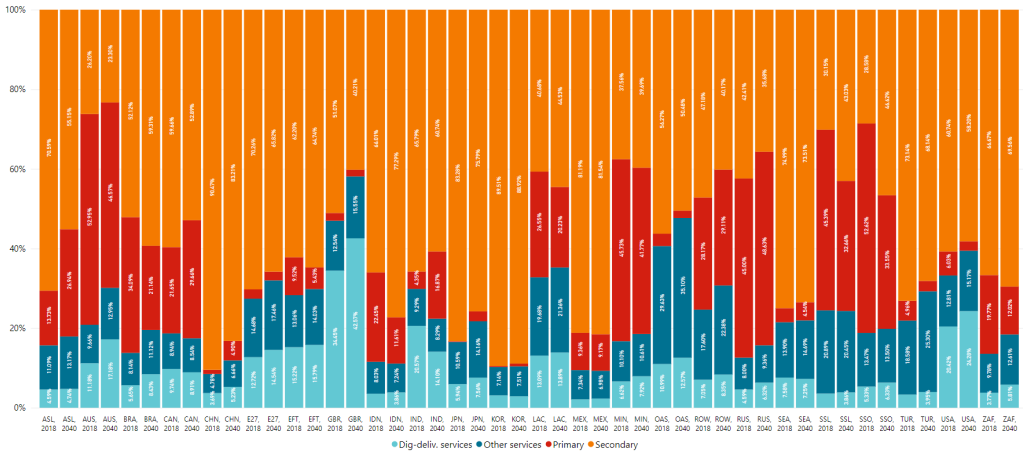
Source: simulations' results.
Notes: the figure demonstrates the change in value added in manufacturing and services sectors in aggregated regions between 2018 and 2040 in the baseline scenario, i.e., without the impact of digitalization developments. For mapping to region names, see Table 1.

low-income (Sub-Saharan Africa and LAC) regions.

4.2 The impact of digitalization

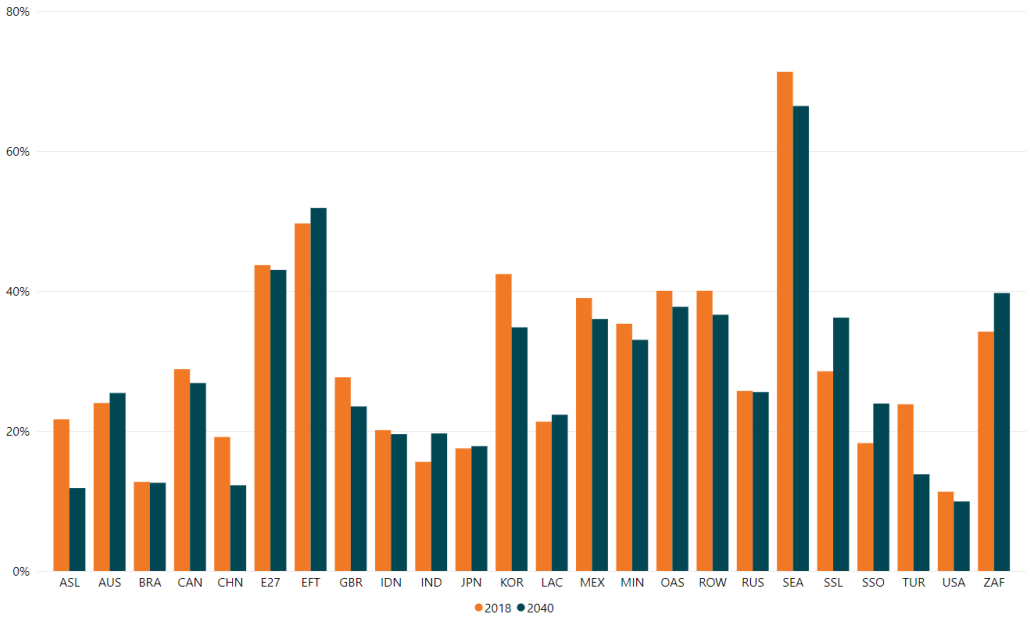
In this section, we analyze the impact of digitalization on (i) global trade growth; (ii) the importance of total services and DDS trade globally and for different regions; (iii) the share of different regions in total trade, services trade and DDS; (iv) changes in revealed comparative

Figure 7: Export shares of aggregate sectors in 2018 and 2040 in different regions on baseline scenario



Source: simulations' results.
Notes: the figure demonstrates the development of export shares of primary and secondary industries, as well as digitally-deliverable and other services of the aggregated regions between 2018 and 2040 in the baseline scenario, i.e., without the impact of digitalization. For mapping to region names, see Table 1. For mapping to aggregate sectors see Table A.1

Figure 8: The ratio of exports to GDP in 2018 and 2040 in different regions in the baseline scenario



Source: simulations' results.
Notes: the figure demonstrates the change in exports to GDP ratios among the aggregated regions between 2018 and 2040 in the baseline scenario, i.e., without the impact of digitalization. For mapping to region names, see Table 1.

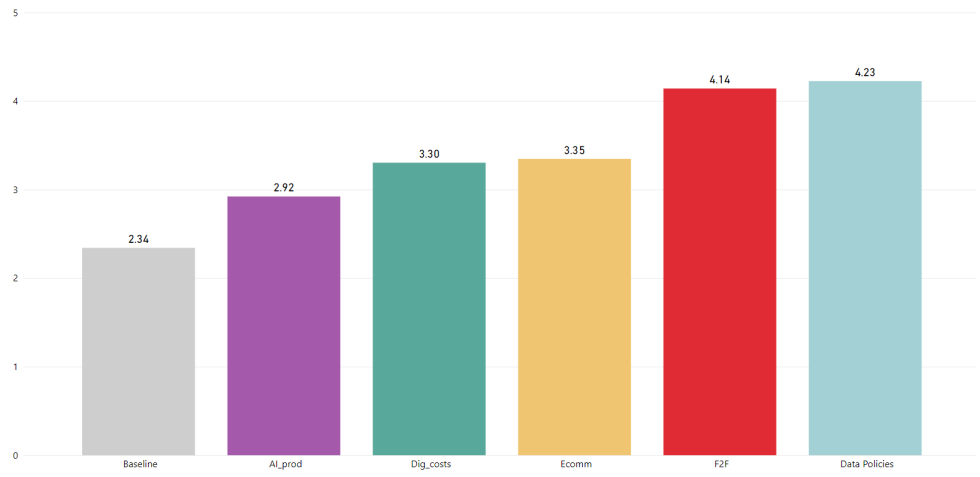
advantage; (v) the scope for income convergence between economies; (vi) the organization of value chain production. For both the core and convergence scenarios, we analyze the effect of

each trend related individually as well as their cumulative effects.[25]

4.2.1 Global trade growth

Figure 9 shows the global average annual trade growth in the baseline and convergence scenarios from 2018 until 2040, adding the different trends related to digitalization cumulatively. In the baseline global trade is projected to rise by an annual average of 2.3% until 2040. The AI-related productivity increase will enhance trade growth to an annual average of 2.9% until 2040. Adding the remaining trends, trade growth will reach an annual average of 4.2%. The two main contributors to global trade growth are increased productivity through AI and the diminishing role of face-to-face interaction. The other drivers are less important.

Figure 9: Global average annual trade growth (%)



Source: Own simulations.
Note: the figure demonstrates the global annual trade growth in p.p. between 2018 and 2040 in the baseline and convergence scenarios.

4.2.2 Trade in services and digitally-deliverable services

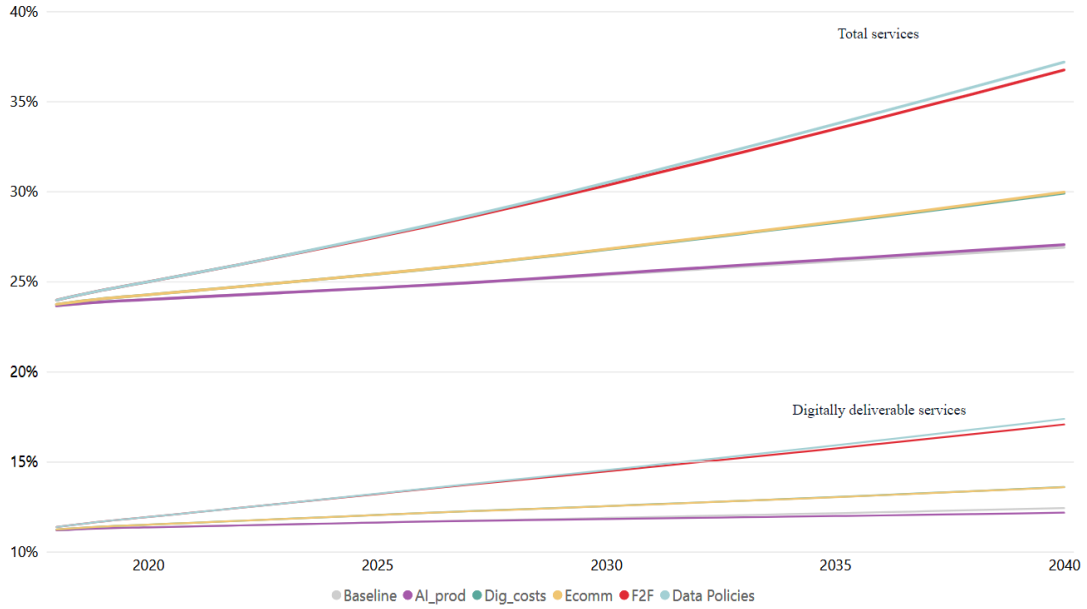
Figure 10 shows that in the baseline, the shares of DDS and total services are projected to increase from respectively 11.5% in 2022 to 12.4% in 2040 and from 24.3% to 26.9%. All digitalization trends would increase the share of DDS further to 17.4% by 2040 and the share of services in trade to 37.2%. The reduction of trade costs related to digitalization (Dig_costs) and the diminishing need for face-to-face interaction (F2F) are the main drivers of the increase in the share of both DDS and all services trade with face-to-face playing the most important role. The other trends hardly affect the share of services and DDS trade. AI adoption is even projected to slightly reduce the value share of digitally-deliverable services in total trade. The reason is that AI will raise productivity more in digitally-deliverable services than in other sectors. With limited scope for substitution between sectors, this will reduce the value share of digitally-deliverable services in output (Baumol effect).[26]

Figure 11 provides further details on the projected change in the global share of the different DDS sectors in all trade. First, the shares of all DDS sectors rise with digitalization, despite

[25]This means we add up the effects of the trends introduced: the reduction in face-to-face intensity, digitalization of logistics and customs procedures, shift to e-commerce, AI-related increases in productivity, and changes in data policies.

[26]Measured in quantities, the changes in shares would most likely be different, and the share of DDS would rise with the AI productivity shock, but this is not displayed.

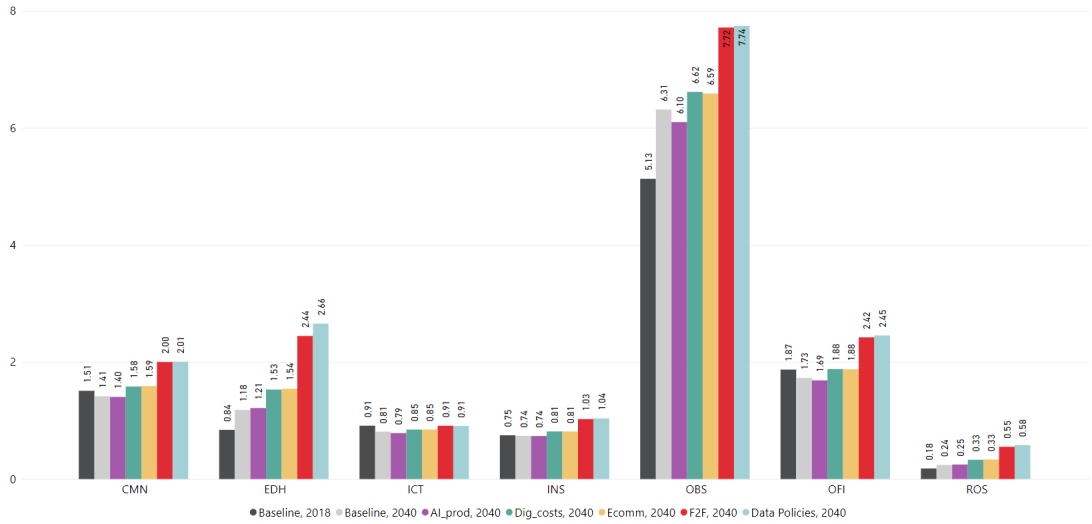
Figure 10: Global shares of services sectors in exports



Source: Calculated based on own simulations.
Notes: the figure demonstrates the dynamics of increased shares of digitally deliverable and total services in global exports over 2018-2040 in the baseline and convergence scenarios.

the fact that the value share of sectors with high productivity growth is projected to fall in the baseline (for example, in communication (CMN), ICT and other financial services (OFI)). Second, the largest increases in value shares are projected to occur in education and health care (EDH) and other business services (OBS). Other business services is currently the largest services sector and is projected to remain the largest by 2040.

Figure 11: Global shares of digitally deliverable services in total exports

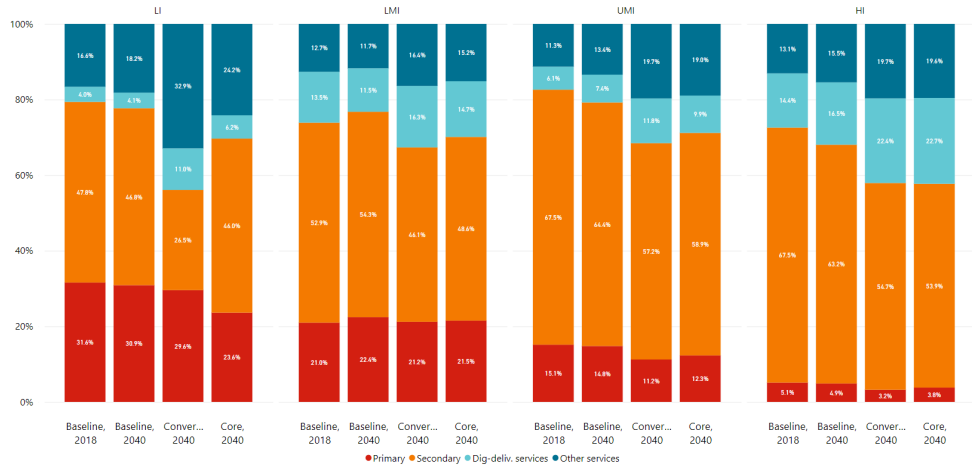


Source: Calculated based on own simulations.
Notes: the figure demonstrates the share of various digitally-deliverable services in global exports in the baseline scenario in 2018, as well as baseline and convergence scenarios in 2040. For mapping to sector names, see Table 1.

4.2.3 Shifts in the sectoral composition of exports by income group

Figure 12 explores the shifts in the sectoral composition of exports by economy groups. Across all income groups, digitalization results in an increase in the value share of services in exports. Further, across all income groups, this shift comes mostly at the expense of the secondary rather than the primary sector. Interestingly, the largest change occurs in low-income regions. In the baseline scenario, digitally-deliverable and other services make up less than 22.3% of their exports by 2040, whereas in the core scenario services reach around 30% of their exports and in the convergence scenario services are projected to make up almost half of the total exports of low income regions (43.9%). In particular, the share of other services rises strongly for low-income economies (mostly transport and accommodation, food and services activities)

Figure 12: Shares of main sectors in exports of regional groups



Source: Calculated based on own simulations.
Notes: The figure demonstrates the sectoral structure of regional groups' exports in the baseline scenario in 2018, as well as baseline, core and convergence scenarios in 2040. For mapping to aggregate sectors and regional groups, see Tables A.1 and A.2, respectively.

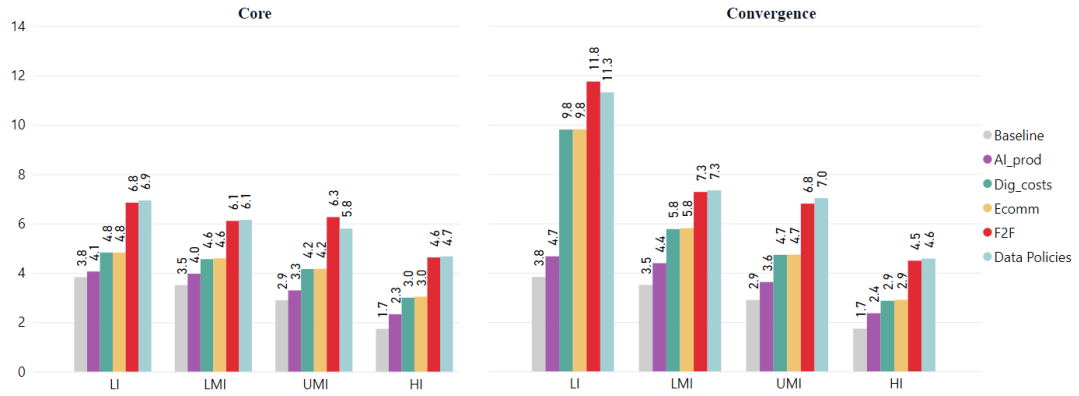
4.2.4 Trade growth in DDS by income group

Figure 13 displays the annual growth of real exports of DDS by income groups. Both in the baseline and with the different digitalization trends, DDS trade of low-income economies grows fastest and of high-income economies slowest. In the core scenario, growth rates rise similarly for all income groups, whereas in the convergence scenario, growth rates increase most for lower-income regions.

4.2.5 The share of different income groups in DDS trade

Figure 14 shows the implications for the shares of the different income groups in global exports of DDS. The figure reflects the differences in growth rates in Figure 13. The share of high-income regions falls substantially from 74.9% to 63.7%. This reduction is driven by baseline trends, falling trade costs related to digitalization, face-to-face, and the convergence of data policies. In the upper-middle-income regions, all trends contribute to rising shares, whereas in lower-middle-income economies, it is the opposite in the case of the diminishing role of face-to-face interaction and liberalization in data policies. The reason lies in the response of other services sectors to these shocks. Also, for the low-income regions, the entire increase comes from falling trade costs related to digitalization. This illustrates the importance of trade-related digitalization policies,

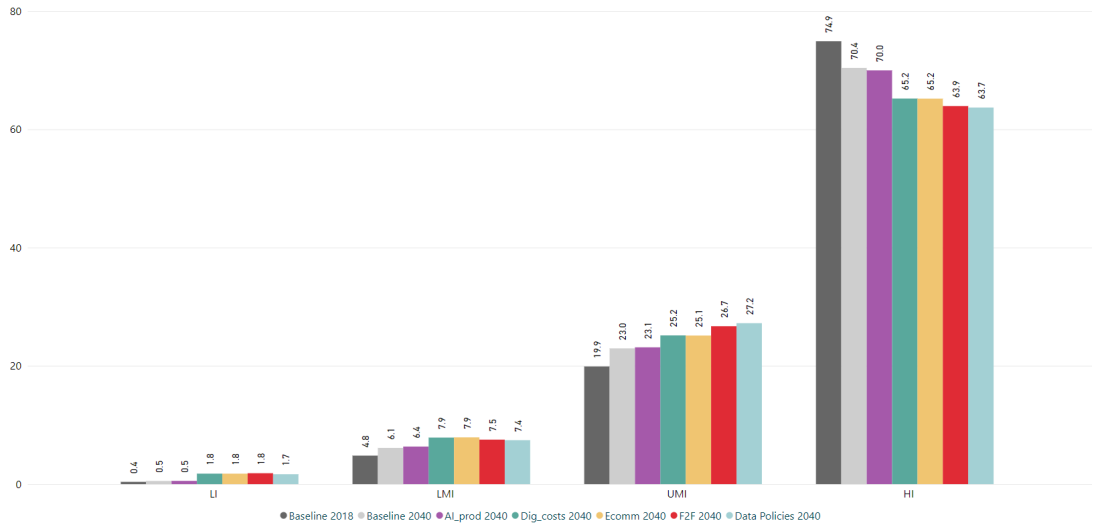
Figure 13: Average annual trade growth (%) of digitally-deliverable services in income groups in core and convergence scenarios



Source: Calculated based on own simulations.
Notes: the figure demonstrates the average annual trade growth in p.p. of digitally deliverable services in regional groups between 2018 and 2040 in various core and convergence scenarios. For mapping to aggregate sectors and regional groups, see Tables A.1 and A.2, respectively.

such as improved internet access for the participation of low-income regions in the global market for digitally deliverable services.[27]

Figure 14: Share of regional groups in exports of digitally deliverable services



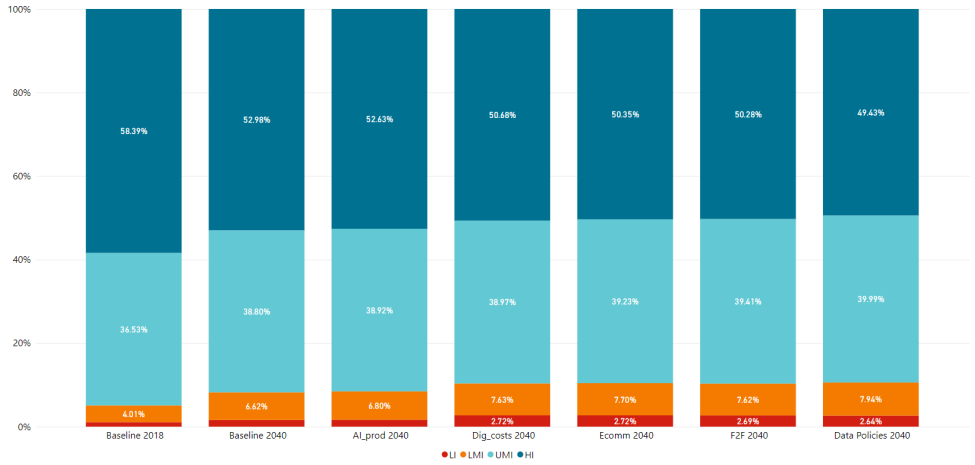
Source: Calculated based on own simulations.
Notes: the figure demonstrates the share of regional groups in global exports of digitally deliverable services in the baseline scenario in 2018, as well as baseline and convergence scenarios in 2040. For mapping to regional groups, see Table A.2.

4.2.6 The share of different income groups in total trade

Before turning to changes in specialization patterns and revealed comparative advantage (RCA), we analyze changes in the contribution of different regions to total trade in Figure 15.

[27]Figure A.2 in the annex confirms that low-income economies' share of the exports of digitally deliverable services expands much more in the convergence than in the core scenario, mostly because of the reduction in digitalization-related trade costs.

Figure 15: Share of regional groups in total exports



Source: Own simulations.
Notes: the figure demonstrates the regional structure of global exports in the baseline scenario 2018, as well as baseline and convergence scenarios in 2040. For mapping to aggregate regional groups, see Table A.2.

Low-income, lower-middle-income, and upper-middle-income economies are all projected to increase their share of trade relative to the baseline because of digitalization. However, the trends do not have a uniform impact on the shares. For instance, trade cost reductions related to digitalization and e-commerce expansion are projected to raise the share of low-income and lower-middle-income economies in global trade. However, the reduced need for face-to-face interaction decreases their share of global trade. This is because high-income and upper-middle-income economies benefit more from the reduced need for face-to-face interaction, thereby increasing their share in global exports. While high-income economies preserve their leading role in global exports, digitalization decreases this share. In the baseline scenario, their share of global trade falls from 58.4% in 2018 to 53% in 2040. In the convergence scenario, digitalization decreases this share further to less than half at 49.4% by 2040.[28]

4.2.7 Digitalization, specialization patterns and revealed comparative advantage

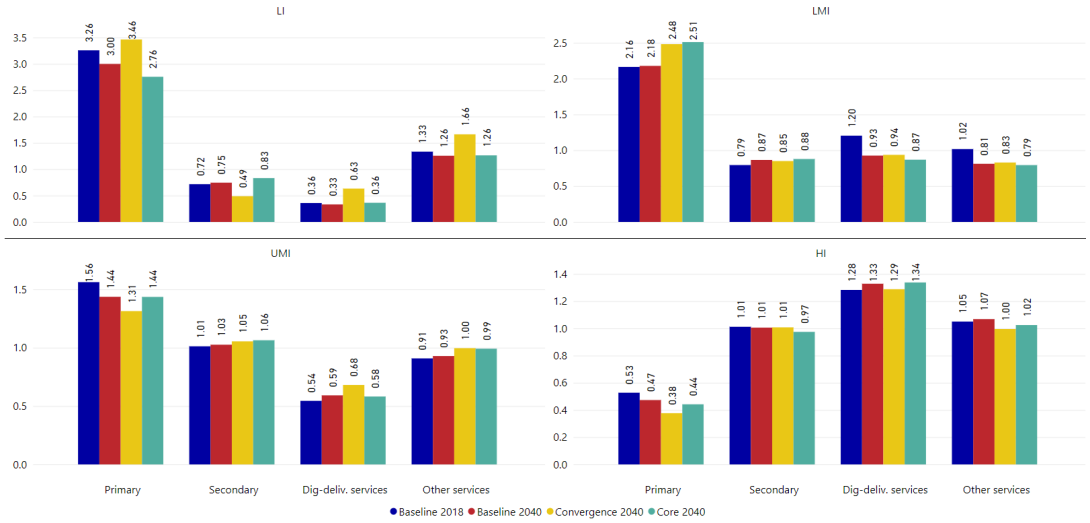
To analyze changes in specialization patterns, Figure 16 displays the revealed comparative advantage (RCA) by income groups in the baseline, core and convergence scenarios, generating two main findings. First, the RCA in DDS increases substantially in the low and upper-middle-income economies in the convergence scenario. Second, despite the shifts in specialization, the patterns of comparative advantage display a large degree of inertia with high income economies maintaining a revealed comparative advantage in DDS and low and middle-income economies maintaining their RCA in primary goods.

More into detail, low-income economies start with a comparative disadvantage in the secondary and DDS sectors and a strong comparative advantage in the primary sector and, to a lesser extent, in other services. In the baseline, little changes to this specialization pattern. In the convergence scenario, low-income economies expand their RCA in DDS, other services, and also primary at the expense of the secondary sector, whereas in the core scenario, low-income economies expand their RCA in manufacturing (the secondary sector) at the expense of the other sectors.

[28]Figure A.3 shows that low-income and lower-middle-income economies are projected to have the highest rate of trade growth in all sectors in the convergence scenario. Instead, high-income economies have a higher trade growth rate for DDS in the core scenario compared to the convergence. However, it is still less than in low-income and lower-middle-income economies.

In the middle income economies, projected changes in RCAs are limited. In the lower-middle-income economies, the fall in RCA in DDS from 1.2 to 0.9 is barely affected in the convergence scenario, whereas in the upper-middle-income economies, the increase in RCA in DDS from 0.5 to 0.6 rises further to 0.7 in the convergence scenario. Finally, among the high-income regions, RCA is projected to increase in the services sectors at the expense of the primary sector in the baseline scenario. The convergence scenario brings a correction to this trend, with the RCA in DDS dropping a bit.

Figure 16: Revealed comparative advantage of regional groups in main sectors



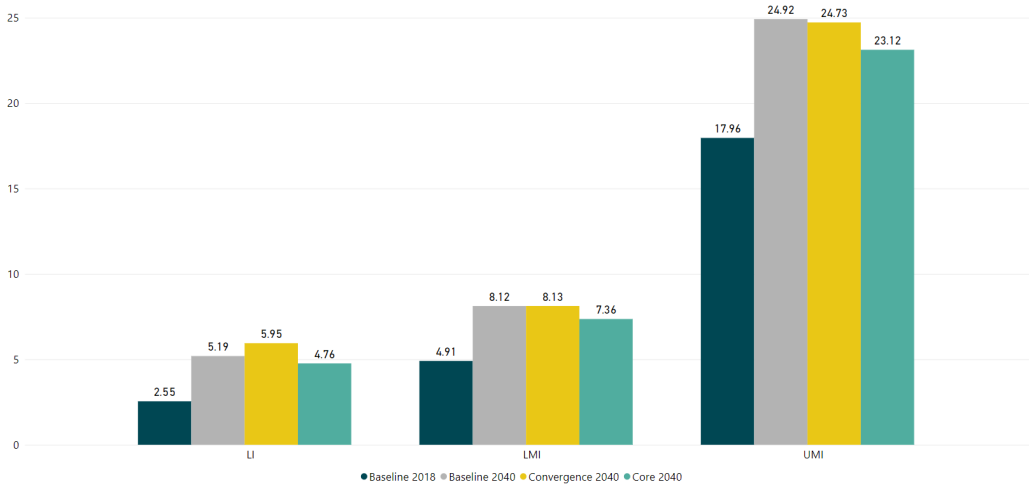
Source: Calculated based on own simulations.
Notes: The figure shows the revealed comparative advantage of regional groups in main sectors in the baseline scenario in 2018, as well as baseline, core and convergence scenarios in 2040. Every graph has its own axis to detect differences. For mapping to aggregate sectors and regional groups, see Tables A.1 and A.2, respectively.

4.2.8 The potential of digitalization to contribute to income convergence

The question is what these changes in trade and specialization patterns imply for income convergence between economies? Figure 17 displays the average share of GDP per capita in low-income (LI), lower-middle-income (LMI), and upper-middle-income (UMI) economies relative to high-income economies in the initial situation, the baseline in 2040, and the core and convergence scenarios. The figure makes clear that in the baseline, low- and middle-income economies are projected to reduce the income gap with high-income economies. However, in the convergence scenario, low-income economies would even catch up more than in the baseline, whereas in the core scenario, low-income economies would get further away from the high-income economies compared to the baseline. For upper-middle-income economies the picture is somewhat different. They would catch up less with the high-income economies in both the core and convergence scenarios than in the baseline. The reason is that the impact of diverging forces in the core scenario (and convergence scenario for middle-income economies) dominates the converging forces. The diverging forces in the simulations consist of high-income economies benefiting more from AI-related productivity growth and face-to-face related trade cost reductions due to their larger production shares in sectors where AI and face-to-face presence are most prominent.[29]

[29] One caveat is that the simulations do not consider potential dynamic productivity effects from specialization, which could foster the scope for catch-up of low-income economies in the convergence scenario if specialization in DDS would entail dynamic productivity effects.

Figure 17: Share of GDP per capita in different income groups relative to high-income regions in the baseline and the core and convergence scenario

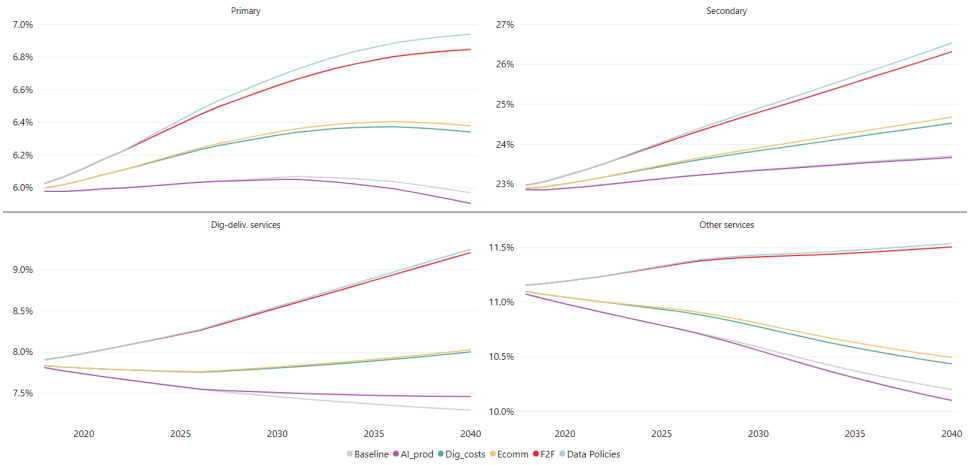


Source: Calculated based on own simulations.
Note: this figure demonstrates the ratio of GDP per capita of income groups relative to GDP per capita in high-income regions.

4.2.9 Value chain organization: imported intermediate inputs in output

Figure 18 shows the development of the share of imported intermediates in gross output for the different trends. In the baseline, the imported intermediate shares fall for all aggregate sectors except for the secondary sector (manufacturing).

Figure 18: Share of imported intermediates in global gross output of main sectors



Source: Calculated based on own simulations.
Notes: the figure demonstrates the dynamics of shares of imported intermediates in the global gross output of main sectors over 2018-2040 in the baseline and convergence scenarios. Every graph has its own axis to detect changes. For mapping to aggregate sectors, see Table A.1.

However, the digitalization trends boost the intermediate import shares. In the secondary sector, all the digitalization trends tend to increase the share of imported intermediate inputs in gross output.[30] Hence, digitalization comes with more openness in the production process. AI-related productivity reduces intermediate import shares in all sectors except for digitally

[30]Figure A.4 displays the share of imported services in manufacturing gross output for the four income groups.

deliverable services. The reason is that higher productivity expands gross output more than intermediate inputs.

5 Concluding remarks

In this paper, we examined the expected impact of new digital technologies on international trade until 2040. We employed a dynamic recursive CGE model to generate a baseline trajectory of the world economy based on GDP, population, labor force, and skill projections from different international agencies. We complemented this with our own empirically underpinned predictions on differential productivity changes by sector (structural change), changes in preferences, and the evolution of trade relative to output as well as trade policy developments after 2017. The baseline simulation involved projecting the evolution of the global economy up to 2040 and showed significant structural change occurring with a rising share of services in production and a falling share of manufacturing and agriculture.

We identified and modeled five technological trends that we believe are likely to affect the size and pattern of international trade: the adoption of AI fostering productivity; the fall in trade costs due to the impact of digitalization on logistics and customs procedures; the increase in e-commerce and the reduced intensity of face-to-face interactions, which both reduce trade costs; and changes in trade costs related to the increased importance of data policies. We constructed a core and a convergence scenario of these trends, where in the latter scenario, we assumed lagging regions catching up with the top one-fourth of economies in digitalization.

The simulations produce the following findings. First, digitalization and AI are expected to provide a strong boost to global trade growth, which would rise from an annual average of 2.3% between 2018-2040 in the baseline scenario to 4.2%. Second, low-income and lower-middle-income economies are projected to increase their share of global trade to 10.6% compared to their share of 8.2% in the baseline scenario. This is a result of both falling trade costs and the more intensive use of digitally-deliverable services as well as more digital-friendly policies. Third, the share of services trade will rise to 37% by 2040, while the share of digitally deliverable services in total trade is expected to rise from 11.2% to 17.4% by 2040, significantly higher than the projected 12.4% share in the baseline. Fourth, the highest growth of trade in digitally-deliverable services is projected to occur in low-income and lower-middle-income economies. This outcome shows that digitalization can be a force for trade inclusion, enabling low-income and lower-middle-income regions to capture a larger share of trade growth. Still, high-income economies will continue to have a strong comparative advantage in digitally-deliverable services. Fifth, using the share of imported intermediates in global exports as a measure of global value chains or offshoring, digitalization appears to have differing effects on the role of GVCs, depending on the sector concerned.

Our findings about how digitalization can be a force for trade inclusion suggest the importance of promoting the adoption of digital technologies in low-income and middle-income economies through a combination of infrastructure provision (e.g., in telecommunications and power), the establishment of a predictable regulatory environment and investments in education and training to create a digitally-ready workforce.

As we noted in the paper, one assumption we make is that geopolitical tensions do not lead to a worsening of trade relations among major economies. This, of course, cannot be guaranteed. Furthermore, we did not explicitly model how AI adoption could reduce trade costs, an issue that has not been seriously considered in the trade literature.

Finally, we think that considering how future trade and industrial policy scenarios could unfold, as well as explicitly modeling and quantifying how AI adoption could affect trade costs offer fruitful areas for future research.

In line with the results for total gross output, the share of imported services rises in all regions, and all drivers contribute to this rising share, except for AI adoption.

References

Acemoglu, Daron (2024). *The Simple Macroeconomics of AI*. Pre-published.

Aghion, Philippe, Benjamin F. Jones, and Charles I. Jones (Oct. 2017). "Artificial Intelligence and Economic Growth". In: *NBER Working Papers* 23928. URL: https://ideas.repec.org//p/nbr/nberwo/23928.html (visited on 03/10/2024).

Aguiar, Angel, Maksym Chepeliev, et al. (2022). "The Global Trade Analysis Project (GTAP) Data Base: Version 11". In: *Journal of Global Economic Analysis* 7.2 (2). ISSN: 2377-2999. DOI: 10.21642/JGEA.070201AF. URL: https://jgea.org/ojs/index.php/jgea/article/view/181 (visited on 10/08/2023).

Aguiar, Angel, Corong Erwin, et al. (Nov. 8, 2019). *The WTO Global Trade Model: Technical Documentation*. DOI: 10.30875/337f4736-en. URL: https://www.wto-ilibrary.org/content/papers/25189808/242 (visited on 06/10/2024). Pre-published.

Ahn, JaeBin, Amit Khandelwal, and Shang-Jin Wei (2011). "The Role of Intermediaries in Facilitating Trade". In: *Journal of International Economics* 84.1, pp. 73–85. ISSN: 0022-1996. URL: https://econpapers.repec.org/article/eeeinecon/v_3a84_3ay_3a2011_3ai_3a1_3ap_3a73-85.htm (visited on 03/10/2024).

Baldwin, Richard E., ed. (2016). *The Great Convergence: Information Technology and the New Globalization*. Cambridge, Massachusetts: The Belknap Press of Harvard University Press. 329 pp.

Bekkers, Eddy, Erwin L. Corong, et al. (2023). *How Will Global Trade Patterns Evolve in the Long Run?* Working Paper ERSD-2023-03. WTO Staff Working Paper. DOI: 10.30875/25189808-2023-3. URL: https://www.econstor.eu/handle/10419/268613 (visited on 03/10/2024).

Bekkers, Eddy, Kirti Jhunjhunwala, et al. (forthcoming). *Global Trade Policy Reform and Gender Inequality in the Labour Market*. Pre-published.

Borenstein, Severin and Garth Saloner (Feb. 1, 2001). "Economics and Electronic Commerce". In: *Journal of Economic Perspectives* 15.1, pp. 3–12. ISSN: 0895-3309. DOI: 10.1257/jep.15.1.3. URL: https://pubs.aeaweb.org/doi/10.1257/jep.15.1.3 (visited on 03/10/2024).

Briggs, Joseph and Devesh Kodnani (2023). *The Potentially Large Effects of Artificial Intelligence on Economic Growth*. Goldman Sachs. URL: https://www.gspublishing.com/content/research/en/reports/2023/03/27/d64e052b-0f6e-45d7-967b-d7be35fabd16.html (visited on 03/10/2024).

Britannica (2024). *Artificial Intelligence (AI) — Definition, Examples, Types, Applications, Companies, & Facts*. URL: https://www.britannica.com/technology/artificial-intelligence (visited on 03/10/2024).

Bughin, Jacques et al. (2018). *Notes from the Ai Frontier Modeling the Impact of Ai on the World Economy*. URL: https://www.mckinsey.com/~/media/McKinsey/Featured%20Insights/Artificial%20Intelligence/Notes%20from%20the%20frontier%20Modeling%20the%20impact%20of%20AI%20on%20the%20world%20economy/MGI-Notes-from-the-AI-frontier-Modeling-the-impact-of-AI-on-the-world-economy-September-2018.ashx (visited on 03/17/2024). Pre-published.

Cairncross, Frances (2001). *The Death of Distance: How the Communications Revolution Is Changing Our Lives*. Harvard Business School Press. 342 pp. ISBN: 978-1-57851-438-0.

Cazzaniga, Prepared Mauro et al. (Jan. 14, 2024). "Gen-AI: Artificial Intelligence and the Future of Work". In: *Staff Discussion Notes No. 2024/001*, p. 41. ISSN: 2617-6750.

Chen, Natalie and Dennis Novy (Nov. 1, 2011). "Gravity, Trade Integration, and Heterogeneity across Industries". In: *Journal of International Economics* 85.2, pp. 206–221. ISSN: 0022-1996. DOI: 10.1016/j.jinteco.2011.07.005. URL: https://www.sciencedirect.com/science/article/pii/S0022199611000821 (visited on 03/10/2024).

Clarke, George R. G. (Mar. 1, 2008). "Has the Internet Increased Exports for Firms from Low and Middle-Income Countries?" In: *Information Economics and Policy* 20.1, pp. 16–37. ISSN: 0167-6245. DOI: 10.1016/j.infoecopol.2007.06.006. URL: https://www.sciencedirect.com/science/article/pii/S0167624507000418 (visited on 03/10/2024).

Dellink, Rob et al. (Jan. 1, 2017). "Long-Term Economic Growth Projections in the Shared Socioeconomic Pathways". In: *Global Environmental Change* 42, pp. 200–214. ISSN: 0959-3780. DOI: 10.1016/j.gloenvcha.2015.06.004. URL: https://www.sciencedirect.com/science/article/pii/S0959378015000837 (visited on 03/10/2024).

Dür, Andreas, Leonardo Baccini, and Manfred Elsig (2014). "The Design of International Trade Agreements: Introducing a New Dataset". In: *Review of International Organizations* 9.3, pp. 353–375. ISSN: 15597431. DOI: 10.1007/s11558-013-9179-8.

Egger, Peter et al. (July 2015). "Non-Tariff Barriers, Integration and the Transatlantic Economy". In: *Economic Policy* 30.83, pp. 539–584. ISSN: 0266-4658, 1468-0327. DOI: 10.1093/epolic/eiv008. URL: https://academic.oup.com/economicpolicy/article-lookup/doi/10.1093/epolic/eiv008 (visited on 07/17/2023).

Eloundou, Tyna et al. (Aug. 21, 2023). *GPTs Are GPTs: An Early Look at the Labor Market Impact Potential of Large Language Models*. arXiv: 2303.10130 [cs, econ, q-fin]. URL: http://arxiv.org/abs/2303.10130 (visited on 07/05/2024). Pre-published.

Express, DHL (2017). *The 21st Century Spice Trade – A Guide to the Cross-border E-commerce Opportunity*.

Fouré, Jean, Agnès Bénassy-Quéré, and Lionel Fontagné (2013). "Modelling the World Economy at the 2050 Horizon". In: *Economics of Transition* 21.4, pp. 617–654. ISSN: 1468-0351. DOI: 10.1111/ecot.12023. URL: https://onlinelibrary.wiley.com/doi/abs/10.1111/ecot.12023 (visited on 03/10/2024).

Freund, Caroline L and Diana Weinhold (Jan. 1, 2004). "The Effect of the Internet on International Trade". In: *Journal of International Economics* 62.1, pp. 171–189. ISSN: 0022-1996. DOI: 10.1016/S0022-1996(03)00059-X. URL: https://www.sciencedirect.com/science/article/pii/S002219960300059X (visited on 03/10/2024).

Góes, Carlos and Eddy Bekkers (2022). "The Impact of Geopolitical Conflicts on Trade, Growth, and Innovation". In: *WTO Staff Working Papers* ERSD-2022-9. URL: https://ideas.repec.org//p/zbw/wtowps/ersd20229.html (visited on 03/10/2024).

Head, Keith and John Ries (Sept. 2001). "Increasing Returns versus National Product Differentiation as an Explanation for the Pattern of U.S.-Canada Trade". In: *American Economic Review* 91.4, pp. 858–876. ISSN: 0002-8282. DOI: 10.1257/aer.91.4.858. URL: https://www.aeaweb.org/articles?id=10.1257/aer.91.4.858 (visited on 03/10/2024).

Hortaçsu, Ali, F. Asís Martínez-Jerez, and Jason Douglas (Feb. 2009). "The Geography of Trade in Online Transactions: Evidence from eBay and MercadoLibre". In: *American Economic Journal: Microeconomics* 1.1, pp. 53–74. ISSN: 1945-7669. DOI: 10.1257/mic.1.1.53. URL: https://www.aeaweb.org/articles?id=10.1257/mic.1.1.53 (visited on 03/10/2024).

IMF et al. (2023). *Handbook on Measuring Digital Trade, Second Edition*. URL: https://www.oecd-ilibrary.org/content/publication/ac99e6d3-en.

ITC (2024). *Market Access Map*. URL: https://www.macmap.org/ (visited on 03/10/2024).

Juniper (July 2023). *33% of eCommerce Spend to Be Cross-border by 2028 Globally — Press*. URL: https://www.juniperresearch.com/press/33-of-ecommerce-spend-to-be-cross-border-by-2028/ (visited on 03/10/2024).

Kc, Samir and Wolfgang Lutz (Jan. 1, 2017). "The Human Core of the Shared Socioeconomic Pathways: Population Scenarios by Age, Sex and Level of Education for All Countries to 2100". In: *Global Environmental Change* 42, pp. 181–192. ISSN: 0959-3780. DOI: 10.1016/j.gloenvcha.2014.06.004. URL: https://www.sciencedirect.com/science/article/pii/S0959378014001095 (visited on 03/10/2024).

Lendle, Andreas et al. (Mar. 2016). "There Goes Gravity: eBay and the Death of Distance". In: *The Economic Journal* 126.591, pp. 406–441. ISSN: 00130133. DOI: 10.1111/ecoj.12286. URL: https://academic.oup.com/ej/article/126/591/406-441/5077424 (visited on 03/10/2024).

Mensbrugghe, D. (2005). "LINKAGE Technical Reference Document". In: URL: https://www.semanticscholar.org/paper/LINKAGE-Technical-Reference-Document-Mensbrugghe/c6b6fc51ca3c3ec3ddd5b0996a6b7a76c4149234 (visited on 03/10/2024).

Métivier, Jeanne et al. (July 2023). "International Trade Cooperation's Impact on the World Economy". In: *Journal of Policy Modeling* 45.4, pp. 713–744. ISSN: 01618938. DOI: 10.1016/j.jpolmod.2023.06.007. URL: https://linkinghub.elsevier.com/retrieve/pii/S016189382300073X (visited on 12/02/2024).

Moïsé, Evdokia and Silvia Sorescu (Mar. 4, 2013). "Trade Facilitation Indicators: The Potential Impact of Trade Facilitation on Developing Countries' Trade". In: *OECD Trade Policy Papers* 144. URL: https://ideas.repec.org//p/oec/traaab/144-en.html (visited on 06/13/2024).

Novy, Dennis (2013). "Gravity Redux: Measuring International Trade Costs with Panel Data". In: *Economic Inquiry* 51.1, pp. 101–121. ISSN: 1465-7295. DOI: 10.1111/j.1465-7295.2011.00439.x. URL: https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1465-7295.2011.00439.x (visited on 03/10/2024).

O*Net (2024). *About O*NET at O*NET Resource Center*. URL: https://www.onetcenter.org/overview.html (visited on 03/10/2024).

Statista (2022). *Global Cross-Border e-Commerce Share 2022*. Statista. URL: https://www.statista.com/statistics/867991/cross-border-e-commerce-share-world/ (visited on 03/10/2024).

UN (2015). *The World Population Prospects: 2015 Revision*. Report. URL: https://www.un.org/en/development/desa/publications/world-population-prospects-2015-revision.html (visited on 03/10/2024).

USITC (2017). *Global Digital Trade 1: Market Opportunities and Key Foreign Trade Restrictions*. URL: https://www.usitc.gov/publications/industry_econ_analysis_332/2017/global_digital_trade_1_market_opportunities_and.htm (visited on 03/10/2024).

Waters, Richard (Jan. 2, 2017). "AI's Year for Showing It Can Live up to the Hype". In: URL: https://www.ft.com/content/b0f63ae4-b8ac-11e6-961e-a1acd97f622d (visited on 03/07/2024).

WTO (2020). *Trade Facilitation Agreement Database*. URL: https://tfadatabase.org/en/implementation/progress-by-member (visited on 06/13/2024).

— (2024). *Trading with Intelligence. How AI Shapes and Is Shaped by International Trade*. URL: https://www.wto.org/english/res_e/booksp_e/trading_with_intelligence_e.pdf (visited on 11/29/2024).

Appendix A Details simulations

Appendix A.1 Disaggregated sectors and regions

Table A.1: Disaggregated sectors

Aggregated Sectors	Sectors	GTAP65 Sectors
Primary	Agriculture	Paddy rice, Wheat, Cereal grains nec, Vegetables, fruit, nuts, Oil seeds, Sugar cane, sugar beet, Plant-based fibers, Crops nec, Bovine cattle, sheep and goats, Animal products nec, Raw milk, Wool, silk-worm cocoons, Forestry and Fishing
	Oil	Oil
	Other natural resources	Coal, Gas, Other extraction
Secondary	Processed Food	Bovine meat products, Meat products nec, Vegetable oils and fats, Dairy products, Processed rice, Sugar, Food products nec, Beverages and tobacco products
	Petroleum, coal products	Petroleum, coal products
	Chemicals	Chemical products
	Pharmaceuticals, rubber and plastic products	Basic pharmaceutical products, Rubber and plastic products
	Textiles, apparel, leather	Textiles, Wearing apparel and Leather products
	Metals	Ferrous metals, Metals nec and Metal products
	Computer, electrical equipment	Computer, electronic and optic
	Electrical equipment	Electrical equipment
	Machinery and equipment	Machinery and equipment nec
	Motor vehicles	Motor vehicles and parts
	Transport equipment	Transport equipment nec
	Other Goods	Wood products, Paper products, publishing, Mineral products nec, Manufactures nec
Digitally Deliverable Services	Finance	Financial services nec
	Insurance	Insurance
	Business Services	Business services nec
	Communication	Communication
	Education and human health	Education, Human health and social work activities
Other Services	Utilities and Construction	Electricity, Gas manufacture, distribution, Water, Construction
	Trade	Trade
	Accommodation	Accommodation, Food and service activities
	Transport	Transport nec, Water transport, Air transport,
	Warehousing and support activities	Warehousing and support activities
	Recreational and other services	Recreational and other services
	Other Services	Public Administration and defense, Real estate activities, Dwellings

Table A.2: Disaggregated regions

Regional Groups	Regions	Disaggregated Regions
High-Income	Australia	Australia
	Canada	Canada
	United Kingdom	United Kingdom
	EFTA economies	Switzerland, Norway and Rest of EFTA
	Japan	Japan
	Korea	Korea
	USA	United States of America
	European Union (27)	Austria, Belgium, Bulgaria, Croatia, Cyprus, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Poland, Portugal, Romania, Slovakia, Slovenia, Spain and Sweden
Upper-Middle-Income	Brazil	Brazil
	China	China
	Indonesia	Indonesia
	Mexico	Mexico
	Russian Federation	Russian Federation
	South Africa	South Africa
	Türkiye	Türkiye
	Latin America	Rest of North America, Argentina, Bolivia (Plurinational State of), Chile, Paraguay, Peru, Uruguay, Venezuela (Bolivarian Republic of), Rest of South America, Costa Rica, Guatemala, Honduras, Nicaragua, Panama, El Salvador, Rest of Central America, Dominican Republic, Haiti, Jamaica, Puerto Rico, Trinidad and Tobago and Rest of Caribbean
	Middle East and North Africa	Saudi Arabia (Kingdom of), Bahrain (Kingdom of), Iran (Islamic Republic of), Iraq, Israel, Jordan, Kuwait, Lebanon, Oman, Palestinian Territory, Occupied, Qatar, Syrian Arab Republic, United Arab Emirates, Rest of Western Asia, Algeria, Egypt, Morocco, Tunisia, Rest of North Africa
Low- Middle-Income	India	India
	ASEAN	Viet Nam, Brunei Darussalam, Malaysia, Philippines, Singapore, Thailand
	Other Asian economies	Mongolia, Hong Kong, China, Chinese Taipei, New Zealand, Rest of Oceania, Afghanistan, Rest of East Asia, Pakistan, Sri Lanka, Rest of South Asia
	Rest of World	Albania, Serbia, Belarus, Ukraine, Rest of Eastern Europe, Rest of Europe, Kazakhstan, Kyrgyzstan, Tajikistan, Uzbekistan, Rest of Former Soviet Union, Armenia, Azerbaijan, Georgia, Rest of the World
Low-Income	Asian LDCs	Cambodia, Lao People's Democratic Republic, Rest of Southeast Asia, Bangladesh, Nepal
	Sub-Saharan Africa	Cameroon, Côte d'Ivoire, Ghana, Nigeria, Senegal, Kenya, Mauritius, Botswana, Eswatini, Namibia, Rest of South African Customs Union
	Sub-Saharan LDCs	Benin, Burkina Faso, Mali, Niger, Togo, Rest of Western Africa, Chad, Congo, Democratic Republic of the Congo, Equatorial Guinea, Guinea, Gabon, Rest of South and Central Africa, Comoros, Ethiopia, Madagascar, Malawi, Sudan, Tanzania, United Republic of, Uganda, Zambia, Zimbabwe, Mozambique, Rwanda, Central African Republic, Rest of Eastern Africa

Appendix A.2 Splitting up ICT-services

The GTAP-sector "Other business services: real estate, renting and business activities" is split up into two sectors, as it consists of many other services besides ICT-related services. To be able to focus better on the effects of digitalization, the program Splitcom is employed together with WIOD data to split up this sector into "programming and consultancy" and remaining business services. In particular, employing WIOD dat the share of sector J62 J63 in the J and M sectors (except for telecommunications (J61), which is a separate sector in GTAP) is used to calculate the share of the new sector Information technology and consultancy. Specifically, the share of sector J62 J63 in sectors J59 J60, J62 J63, and M69 M70, M71, M72, M73, M74 M75 is employed. This is done to discipline the share of programming and consultancy for each region in production, exports, and imports.

Appendix A.3 Digitalization and trade cost reductions: description of data used and estimation results

In order to study how digitalization affects trade costs, we include several variables sourced from WTO, ITU, World Bank, OECD and CEPII. Table A.3 presents the list of the independent variables used, while Table A.4 displays summary statistics of the dependent variable, HR Index.

Tables A.5 and A.6 present estimation results. They differ in terms of the sample considered. In the baseline, all the 141 regions present in GTAP are included, while in the reduced sample, the set of GTAP regions representing the "rest of the world" [31] are excluded, for a total of 121 regions included. The results are mostly consistent between the two samples, however, the reduced sample provides more anticipated outcomes and coefficients. Therefore, we use the latter coefficients for AVEs calculations. At the same time, we acknowledge that some coefficients are counter-intuitive:

1. The Coefficient for contract environment in the primary sector is positive, and the coefficient for bandwidth in the secondary sector is negative. In these cases, we use zeros in our AVEs calculations, so the iceberg trade costs are not affected.

2. Although the coefficient for bandwidth in the tertiary sector Column (4) is positive, no lower bounds on the implied AVEs related to bandwidth are imposed as the change of sign is the result of the interaction term with STRI.[32]

[31] For example, "Rest of Oceania, Rest of Southeast Asia", etc.

[32] At the same time, it is worth noting that the AVE of STRI depends on three features: (i) coefficient of STRI and interaction terms; (ii) the value of STRI for a particular economy-pair; the values of bandwidth and broadband for a particular economy pair. As a result, some of the obtained AVE of STRI might be positive. However, no lower bound on the implied AVEs is imposed.

Appendix A.4 Calculating ad valorem equivalents technology trade cost reductions

We can write iceberg trade costs at the GTAP commodity level k corresponding to the aggregate sector s as follows:

$$\tau_{ijk} = \exp \ln \left(\frac{X_{ijs} X_{jis}}{X_{iis} X_{jjs}} \right)^{\frac{1}{2(\sigma-1)} \frac{\sigma-1}{\sigma_k - 1}} = \exp \left\{ \frac{\sigma - 1}{\sigma_k - 1} \ln \tau_{ijs} \right\} \tag{A.1}$$

Equation (A.1) implies for the percentage change in iceberg trade costs from τ^0_{ijk} to τ^1_{ijk}:

$$AVE_{ijk} = \frac{\tau^1_{ijk}}{\tau^0_{ijk}} - 1 = \frac{\exp \frac{\sigma-1}{\sigma_k - 1} \ln \tau^1_{ijs}}{\exp \frac{\sigma-1}{\sigma_k - 1} \ln \tau^0_{ijs}} - 1 = \exp \left\{ \frac{\sigma - 1}{\sigma_k - 1} \left[\alpha_s \left(\ln z^1_{ij} - \ln z^0_{ij} \right) + \beta_s \left(y^1_{ij} - y^0_{ij} \right) \right] \right\} - 1 \tag{A.2}$$

We need the AVE on a yearly basis (with superscript y) and moreover we need ams, which is the percentage increase in technology of international trade:

$$AVE^y_{ijk} = \frac{\tau^{1,y}_{ijk}}{\tau^{0,y}_{ijk}} - 1 = 100 * \left\{ (1 + AVE_{ijk})^{\frac{1}{T}} - 1 \right\} \tag{A.3}$$

$$ams^y_{ijk} = \frac{a^{1y}_{ijk} - a^{0y}_{ijk}}{a^{0y}_{ijk}} = \frac{\frac{1}{\tau^{1y}_{ijk}} - \frac{1}{\tau^{0y}_{ijk}}}{\frac{1}{\tau^{0y}_{ijk}}} = \frac{\tau^{0,y}_{ijk}}{\tau^{1,y}_{ijk}} - 1 = 100 * \left\{ (1 + AVE_{ijk})^{-\frac{1}{T}} - 1 \right\} \tag{A.4}$$

T is the number of years and a_{ijk} is the level of technology in international trade. We assume that economies are catching up in terms of reductions in trade costs to the median or to the best 75%, τ_{ijk}. In particular, we assume that economies close only a fraction α of the gap (for example, half). The new iceberg trade costs, τ^1_{ijk}, will then be given by:

$$\tau^1_{ijk} = \tau^0_{ijk} - \alpha \left(\tau^0_{ijk} - \tau^{75}_{ijk} \right) \tag{A.5}$$

With τ^{75}_{ijk} the iceberg trade cost of the 75-th percentile best performing economy. We calculate the corresponding ad valorem equivalent iceberg trade cost reduction as follows:

$$AVE^{75}_{ijk} = \frac{\tau^1_{ijk}}{\tau^0_{ijk}} - 1 = 1 - \alpha \frac{\tau^0_{ijk} - \tau^{75}_{ijk}}{\tau^0_{ijk}} - 1 = \alpha \left(\frac{\tau^{75}_{ijk}}{\tau^0_{ijk}} - 1 \right) \tag{A.6}$$

Hence, the fraction by which the gap is closed simply scales down the AVE reduction in iceberg trade costs. The expression for ams with partial convergence is given by:

$$ams^{y,75}_{ijk} = \frac{\tau^{0y}_{ijk}}{\tau^{1y}_{ijk}} - 1 = \frac{\tau^{0y}_{ijk}}{\tau^{0y}_{ijk} - \alpha \left(\tau^{0y}_{ijk} - \tau^{75y}_{ijk} \right)} - 1 = \frac{1}{1 - \alpha \frac{\tau^{0y}_{ijk} - \tau^{75y}_{ijk}}{\tau^{0y}_{ijk}}} - 1 = \frac{1}{1 + \alpha AVE^{75y}_{ijk}} - 1$$

$$= \frac{1}{1 + \alpha \left\{ \left(1 + AVE^{75}_{ijk} \right)^{\frac{1}{T}} - 1 \right\}} - 1$$

Table A.3: Indicators used in gravity estimation, their measurement and sources

Indicator	Measurement	Source
Lead time to import	The median time (the value for 50% of shipments) from port of discharge to arrival at the consignee	World Bank
The liner shipping connectivity index (LSCI)	Captures how well economies are connected to global shipping networks. Takes values in relation to values in 2004 (=100).	
The depth of credit information index	Index (0-8) that measures rules affecting the scope, accessibility, and quality of credit information available through public or private credit registries.	
Enforcing contracts indicator	Time required to enforce a contract is the number of calendar days	
Geographical distance	Population-weighted distance between most populated cities (harmonic mean)	CEPII
The existence of an FTA	1 if there is an FTA in a economy-pair and 0 otherwise	
Colonial linkages	1 if economies share a common colonizer post 1945 and 0 otherwise	
Common language	1 if economies share common official or primary language and 0 otherwise	
Fixed broadband subscriptions per capita	Number of subscription per capita (takes value from 0 to 1)	ITU
Mobile broadband subscriptions per capita	Number of subscription per capita (may exceed the value of 1)	
International bandwidth speed	Average usage of all international links including fiber-optic cables, radio links and traffic processed by satellite ground stations and teleports to orbital satellites (expressed in Mbit/s)	
STRI	Captures the restrictiveness of an economy's regulatory and policy framework with respect to trade in services. Takes values from 0 to 100 (the lower, the less restrictive)	WB-WTO, OECD

Note: ITU - International Telecommunication Union; WB - World Bank; UPU - Universal Postal Union; WEF - World Economic Forum; ILO - International Labour Organization; FI - Fraser Institute; UN - United Nations

Table A.4: Summary Statistics

$Ln(\tau_{ij})$	Primary Sector	Secondary Sector	Tertiary Sector
Mean	1.068	1.457	3.266
Std. Dev.	0.373	0.504	0.596
Min	0.173	0.244	1.238
Max	2.837	4.377	5.524

Table A.5: Trade Costs Analysis. Baseline: Full Sample.

	(1)	(2)	(3)	(4)
	Primary sector	Secondary sector	Tertiary sector	Tertiary sector
fta_wto	-0.0301***	-0.0449***	0.0409***	0.0485***
	(-251.67)	(-692.69)	(180.14)	(211.25)
comcol	-0.0597***	-0.0579***	0.0759***	0.0779***
	(-261.41)	(-352.16)	(128.93)	(132.56)
col45	-0.0275***	0.000715***	0.0158***	0.0191***
	(-63.54)	(4.57)	(32.32)	(39.10)
log_dist	0.0681***	0.0726***	0.175***	0.174***
	(1019.97)	(2398.72)	(1521.36)	(1508.20)
landlocked	-0.0567***	-0.463***	-0.385***	-0.376***
	(-79.93)	(-1310.07)	(-353.21)	(-344.24)
contig	-0.0652***	-0.136***	-0.109***	-0.109***
	(-391.91)	(-1812.86)	(-385.74)	(-385.65)
log_credit	0.0389***	-0.0893***	-0.00789***	-0.0100***
	(209.19)	(-608.26)	(-16.11)	(-20.56)
log_contract	-0.0363***	0.0363***	0.0600***	0.0644***
	(-187.09)	(342.35)	(158.02)	(169.67)
comlang_ethno	-0.0497***	-0.0567***	-0.226***	-0.228***
	(-387.54)	(-878.44)	(-1080.78)	(-1093.35)
log_lsci	-0.0637***	-0.127***	-0.141***	-0.140***
	(-498.88)	(-1919.36)	(-682.52)	(-677.84)
log_leadtime	0.0360***	0.0268***	0.179***	0.171***
	(247.83)	(330.80)	(627.78)	(590.24)
log_bandwidth_user	-0.00208***	0.0160***	-0.0509***	0.0763***
	(-27.19)	(419.39)	(-434.95)	(125.19)
comp_broad	-0.0212***	-0.0683***	-0.106***	-0.122***
	(-329.81)	(-1595.77)	(-690.11)	(-84.48)
log_STRI			0.0156***	0.428***
			(85.76)	(220.23)
c.comp_broad#c.log_STRI				0.00526***
				(14.11)
c.log_STRI#c.log_bandwidth_user				-0.0363***
				(-212.81)
_cons	0.335***	0.506***	1.504***	0.0414***
	(198.71)	(494.66)	(421.71)	(5.30)
N	5747137	26357456	8500304	8500304

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.6: Trade Costs Analysis. Baseline: Reduced Sample.

	(1)	(2)	(3)	(4)
	Primary sector	Secondary sector	Tertiary sector	Tertiary sector
fta_wto	-0.0311***	-0.0493***	0.0447***	0.0531***
	(-264.69)	(-778.17)	(203.01)	(238.75)
comcol	-0.0700***	-0.0607***	0.0639***	0.0661***
	(-310.56)	(-374.54)	(111.17)	(115.48)
col45	0.0330***	0.000139	0.0235***	0.0273***
	(73.11)	(0.91)	(49.32)	(57.44)
log_dist	0.0666***	0.0709***	0.182***	0.181***
	(995.20)	(2381.06)	(1609.30)	(1598.92)
landlocked	-0.0386***	-0.549***	-0.506***	-0.492***
	(-43.54)	(-1444.07)	(-428.12)	(-414.36)
contig	-0.0675***	-0.137***	-0.105***	-0.104***
	(-409.91)	(-1873.79)	(-383.99)	(-382.98)
log_credit	-0.225***	-0.147***	-0.249***	-0.254***
	(-452.06)	(-751.95)	(-337.66)	(-344.68)
log_contract	-0.0343***	0.0296***	0.0611***	0.0663***
	(-175.77)	(283.02)	(162.94)	(177.12)
comlang_ethno	-0.0403***	-0.0514***	-0.211***	-0.214***
	(-314.95)	(-811.78)	(-1035.14)	(-1047.79)
log_lsci	-0.0452***	-0.139***	-0.136***	-0.133***
	(-319.86)	(-2042.43)	(-636.75)	(-627.01)
log_leadtime	0.0438***	0.0321***	0.207***	0.200***
	(292.21)	(397.81)	(721.13)	(681.98)
log_bandwidth_user	-0.00544***	0.0147***	-0.0542***	0.0779***
	(-69.47)	(390.07)	(-470.70)	(132.71)
comp_broad	-0.0254***	-0.0677***	-0.117***	-0.0949***
	(-370.68)	(-1575.81)	(-756.81)	(-65.88)
log_STRI			0.0129***	0.459***
			(72.55)	(244.20)
c.comp_broad#c.log_STRI				-0.00453***
				(-12.15)
c.log_STRI#c.log_bandwidth_user				-0.0379***
				(-229.75)
_cons	0.855***	0.745***	1.964***	0.376***
	(455.30)	(708.89)	(537.70)	(49.27)
N	4976381	25405159	8151656	8151656

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Appendix A.5 Detailed description of the E-commerce shock design

The value of trade between i and j in sector s is equal to the sum of online and offline trade:

$$X_{ijs} = X_{ijs}^{off} + X_{ijs}^{on} \tag{A.7}$$

In the employed model, trade follows an Armington structure with product differentiation by sourcing economy. Following this structure for both types of trade, total trade can be written as follows with c_{is} the price of input bundles, τ_{ijs} iceberg trade costs, P_{js} the price index, E_{js} expenditures, and σ_s the elasticity of substitution between varieties from different regions:

$$\begin{aligned}(c_{is}\tau_{ijs})^{1-\sigma_s} P_{js}^{\sigma_s-1} E_{js} &= \left(c_{is}\tau_{ij}^{off}\right)^{1-\sigma} \left(P_j^{off}\right)^{\sigma_s-1} E_j^{off} + \left(c_{is}\tau_{ijs}^{on}\right)^{1-\sigma_s} \left(P_{js}^{on}\right)^{\sigma_s-1} E_{js}^{on} \\ &= c_{is} P_{js}^{\sigma_s-1} E_{js} \left[sh_{js} \left(\tau_{ijs}^{off}\right)^{1-\sigma_s} + (1-sh_{js}) \left(\tau_{ijs}^{on}\right)^{1-\sigma_s}\right] \end{aligned} \tag{A.8}$$

sh_{js} is the price-index adjusted share spent offline in importer js, $sh_{js} = \frac{\left(P_{js}^{off}\right)^{\sigma_s-1} E_{js}^{off}}{(P_{js})^{\sigma_s-1} E_{js}}$. This share is equal to the spending share under the assumption that the price index is identical for the two types of trade, corresponding with the assumption of an integrated market.

Trade costs for total trade, τ_{ijs}, can now be written as a weighted average of trade costs on offline and trade costs on online trade:

$$\tau_{ijs} = \left[(1-sh_{js}^{on}) \left(t_{ijs}^{off}\right)^{1-\sigma_s} + \left(sh_{js}^{on}\right) \left(t_{ijs}^{on}\right)^{1-\sigma_s}\right]^{\frac{1}{1-\sigma_s}} \tag{A.9}$$

The percentage change in aggregate trade costs from period 0 to period 1, $\frac{\tau_{ijs}^1}{\tau_{ijs}^0} - 1$, of an increase in the share of goods and services traded online (the ad valorem equivalent trade cost reduction) can be expressed as follows, combining the difference in the estimated online and offline trade costs τ_{ijs}^{off} and τ_{ijs}^{on} and the the share of goods traded online in periods 0 and 1, $sh_{js}^{on,0}$ and $sh_{js}^{on,1}$:

$$\frac{\tau_{ijs}^1}{\tau_{ijs}^0} - 1 = \left[\frac{(1-sh_{js}^{on,1}) \left(\tau_{ijs}^{off}\right)^{1-\sigma_s} + \left(sh_j^{on,1}\right) \left(\tau_{ijs}^{on}\right)^{1-\sigma_s}}{(1-sh_{js}^{on,0}) \left(\tau_{ijs}^{off}\right)^{1-\sigma_s} + \left(sh_{js}^{on,0}\right) \left(\tau_{ijs}^{on}\right)^{1-\sigma_s}}\right]^{\frac{1}{1-\sigma_s}} - 1 \tag{A.10}$$

Differences in online and offline trade costs To estimate trade costs for online and offline trade, the same data of online trade through e-commerce and comparable offline trade as in Lendle et al. (2016) are employed. The following gravity equation is estimated for both online and offline trade using Poisson pseudo-maximum likelihood:

$$X_{ij}^m = \exp\left\{\mathbf{b}_d^m \mathbf{z}_{ij} + \eta_i^m + \kappa_j^m\right\} \varepsilon_{ij}^m; m = on, off \tag{A.11}$$

X_{ij}^m is the total value of trade for mode m, η_i^m and κ_j^m are exporter and importer fixed effects, and $\mathbf{z}_{ij}$ is a vector of trade cost variables consisting of distance and dummies for common language, a history of a colonial relation, common legal origin, and common border. In principle, the fixed effects could pick exporter- or importer-specific trade costs. However, given that no information is available on the role of trade costs in the fixed effects, differences in trade costs are inferred only from the bilateral regressors included in the gravity equation. In particular, combining the theoretical gravity equation in (A.8) with the empirical gravity equation in (A.11), iceberg trade costs can be written as $\left(\tau_{ijs}^m\right)^{1-\sigma_s} = \exp\left\{\mathbf{b}_d^{off} \mathbf{z}_{ij}\right\}$ and the ad valorem trade cost reduction in (A.10) can thus be written as:

$$\frac{\tau_{ijs}^1}{\tau_{ijs}^0} - 1 = \left[\frac{(1-sh_{js}^{on,1}) \exp\left\{\mathbf{b}_d^{off} \mathbf{z}_{ijs}\right\} + \left(sh_j^{on,1}\right) \left(\exp\left\{\mathbf{b}_d^{on} \mathbf{z}_{ij}\right\}\right)^{1-\sigma}}{(1-sh_{js}^{on,0}) \exp\left\{\mathbf{b}_d^{off} \mathbf{z}_{ijs}\right\} + \left(sh_j^{on,0}\right) \left(\exp\left\{\mathbf{b}_d^{on} \mathbf{z}_{ij}\right\}\right)^{1-\sigma}}\right]^{\frac{1}{1-\sigma}} - 1 \tag{A.12}$$

Share of goods and services sold online To project the share of goods sold online into the future for the 24 regions and 27 sectors employed in the model, data on the share of goods sold online from Eurostat are employed, more specifically the enterprises' total turnover from e-commerce as a percentage of total turnover.[33] The Eurostat data are available at the sectoral level for a total of 34 economies for the period 2009-2022 and in the estimates presented data for 2019 were utilized.[34]

To project future shares of goods sold online, the 2019 shares are regressed on GDP per capita for the 11 sectors in the database.[35] In order to avoid non-positive values for the share of goods sold online, a fractional logit transformation of the e-commerce share was conducted, before regressing the share on GDP per capita. The projections on GDP per capita also used for the baseline projections are in turn employed to generate projections for changes in the shares of online trade based on the coefficients estimated per sector.

Like in Lendle et al. (2016), the gravity equation in (A.11) is estimated pooling all types of goods traded online and goods in all comparable sectors traded offline, since there are not enough data available for many of the types of goods traded online. Table A.7 displays the estimation results, which are substituted into equation (A.12) to calculate projected changes in trade costs.

Table A.7 shows for example that the absence of a common language has a stronger negative impact on online trade than on offline trade. Focusing only on differences in the distance coefficient, would then overestimate the reduction in trade costs of online trade. Therefore, deviating from Lendle et al. (2016), all gravity regressors are taken into account in calculating trade costs for online and offline trade.

[33]We use the e-commerce Customer Relation Management and Secure Transaction Database, which relies on the annual Eurostat model questionnaires on ICT usage and e-commerce in enterprises.

[34]The data are available for the following economies: Austria, Belgium, Bosnia and Herzegovina, Bulgaria, Cyprus, Czechia, Germany, Denmark, Estonia, Greece, Spain, Finland, France, Croatia, Hungary, Ireland, Iceland, Italy, Lithuania, Luxembourg, Latvia, North Macedonia, Malta, Montenegro, Netherlands, Norway, Poland, Portugal, Romania, Serbia, Sweden, Slovenia, Slovakia and the United Kingdom.

[35]Data are available for 11 sectors and for the total economy, among which enterprises employing 10 persons or more were surveyed. The included sectors are: Manufacturing; Electricity, gas, steam, air conditioning and water supply; Construction; Wholesale and retail trade including repair of motor vehicles and motorcycles; Transportation and Storage; Accomodation; ICT Sector; Information and communication; Real Estate Activities; Professional, Scientific and Technical Activities and Administrative and Support Service Activities. These sectors were mapped into the GTAP sectors in the simulations.

Table A.7: Gravity estimation for online and offline trade flows

	(1)	(2)	(3)
	Online trade	Offline trade	Online and offline trade
Distance	-.43***	-.78***	-.78***
	(.069)	(.039)	(.039)
No common legal system	-.29***	-.37***	-.37***
	(.1)	(.061)	(.061)
No common border	-.79***	-.32***	-.32***
	(.15)	(.09)	(.09)
No common colony	-.15	.12	.12
	(.12)	(.11)	(.11)
No common language	-.95***	.15	.15
	(.14)	(.098)	(.098)
Distance online			.35***
			(.08)
No common legal system online			.087
			(.12)
No common border online			-.46***
			(.17)
No common colony online			-.28*
			(.16)
No common language online			-1.1***
			(.17)
Observations	4300	3942	8242
R^2	0.96	0.96	0.96

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix A.6 Details on replication of the AI Preparedness Index

The AI Preparedness Index was introduced by Cazzaniga et al. (2024). It is based on approximately 30 indicators that are grouped into four pillars/dimensions: (i) Digital infrastructure, (ii) Human capital and Labor Market Policies, (iii) Innovation and Economic Integration, (iv) Regulation and Ethics. Within each of the four pillars, the subindicators (x) - for the latest year with available data - are normalised on a 0-1 scale as follows:

$$\frac{(x - x_{min})}{(x_{max} - x_{min})} \tag{A.13}$$

After that, each pillar is calculated as a simple average of its normalized subcomponents, while the final AI Preparedness Index is then derived as the simple average of pillars' values.

As there is no public version of the AI Preparedness Index, we replicate it using their methodology. However, our replication has some differences as there are some unclarities about its compilation:

1. **Indicators.** (i) We use some alternative indicators to what is used by Cazzaniga et al. (2024). For instance, we use ITU data on population share that uses the internet instead of "Estimated internet users per 100 inhabitants." We do that because this seems to be the UN indicator for Millenium Goals, therefore it is calculated only until 2015. At the same time, our alternative indicator from ITU is of the same nature and has more recent data. (ii) Another issue is the absence of the mentioned indicators. Due to this reason, we do not have indicators such as "Number of wireless broadband subscriptions" and "Number of female STEM graduates" in our replication. [36] The full list of used indicators and their respective sources are shown in Table A.8.

2. **Data presence.** The root of this problem is that many economies do not have continuous data for some indicators. As a result, this problem has two dimensions: (i) Obsolete data for indicators. Unfortunately, there is no recent data for some indicators. For instance, the latest data on "Domestic credit to the private sector" for Canada is from 2008. We acknowledge that it can raise reliability concerns. (ii) How do you calculate 10-year averages if the latest data available is two decades old and/or if there are observations with 2/3/5-year gaps, etc.? Our solution for this problem is to identify the last available year for each economy and take the average for 10 years before that without distinction whether the data is missing within these 10 years or not.

3. **Missing data.** Initially, we combined a dataset with around 30 indicators for more than 190 economies. Therefore, the likelihood that at least some of the indicators in some economies would not be present at all, is high. To tackle this problem, we used the double threshold approach. More specifically, each economy has to have data points for at least 50% of all variables and for at least half of indicators per pillar, while each variable has to include observations for at least 50% of all economies.

Using the approaches described above, we calculated the index for 146 economies and mapped it into GTAP141 regions. The values for "Rest of" regions were calculated as a simple mean. Figure A.1 is the graphical representation of the index for selected economies.

As our productivity shocks are based on US data, to distinguish convergence and core scenarios, we standardize our indicator so that its value for the US equals 1, with respective changes for all other economies.

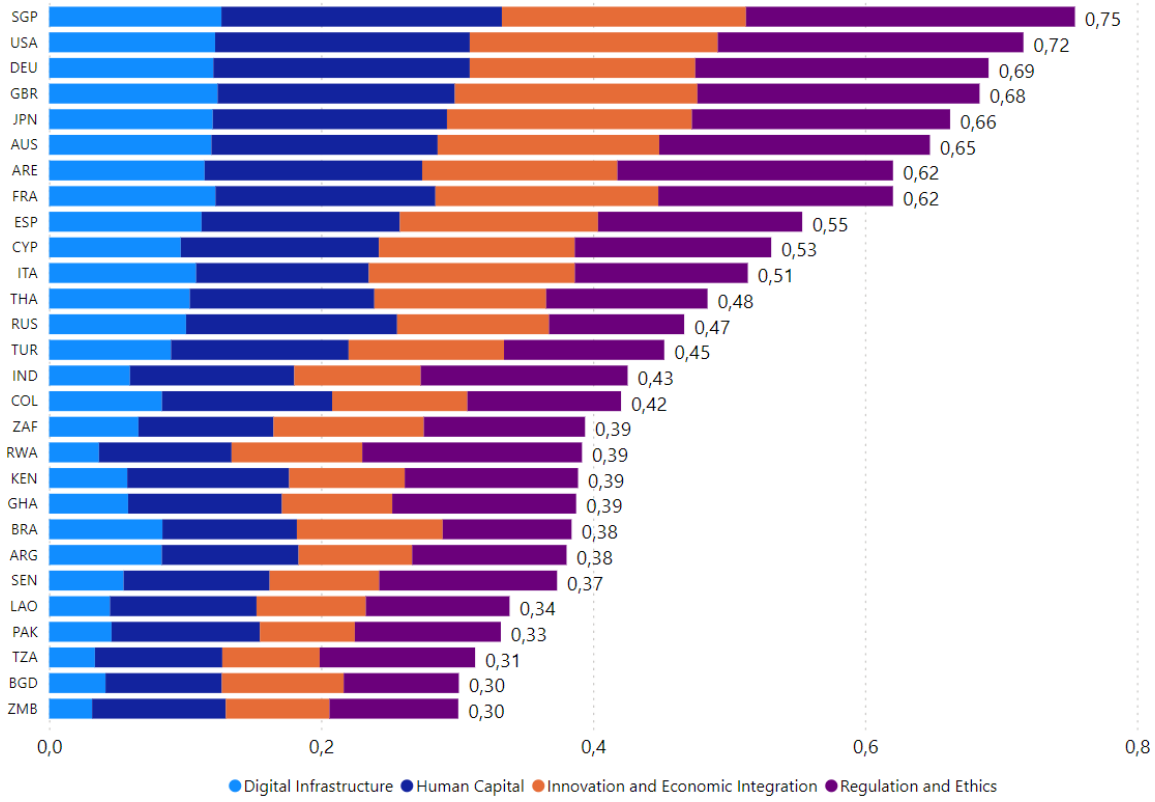
[36] However, we still use similar indicator for both sexes

Table A.8: Indicators used to replicate AI Preparedness Index

Dimension	Indicator	Source
Digital Infrastructure	Individuals using the internet (% of population)	ITU
	Fixed telephone lines per 100 inhabitants	ITU
	Mobile subscriptions per 100 inhabitants	ITU
	Fixed broadband subscriptions per 100 inhabitants	ITU
	ICT affordability (fixed-broadband and data-only mobile broadband) as %GNI in 2021	ITU
	Secure Internet servers (per 1 mln people)	ITU
	Postal reliability index	UPU
	Use of mobile phone or the internet to buy something online (% age 15+)	WB
	Online service index	UN
Human Capital and Labor Market Policies	Human capital index	UN
	Public education expenditure (10-year average, %GDP)	WB
	Skillset of graduates	WEF
	Digital skills among population	WEF
	Number of STEM graduates, both sexes (10-year average, % of total graduates)	WB
	Flexibility of wage determination	WEF
	Social protection (% covered by at least one social protection benefit)	ILO
	Internal labor market mobility	WEF
	Active labor market policies	WEF
	Pay and productivity	WEF
Innovation and Economic Integration	R&D expenditure (% of GDP)	WB
	Frontier technology readiness	WEF
	Domestic credit to private sector	WB
	Mean tariff rate	FI
	Non-tariff barriers	FI
	Free movement of capital and people	FI
Regulation and Ethics	Legal framework's adaptability to digital business models	WEF
	Worldwide governance indicators (average)	WB

Note: ITU - International Telecommunication Union; WB - World Bank; UPU - Universal Postal Union; WEF - World Economic Forum; ILO - International Labour Organization; FI - Fraser Institute; UN - United Nations

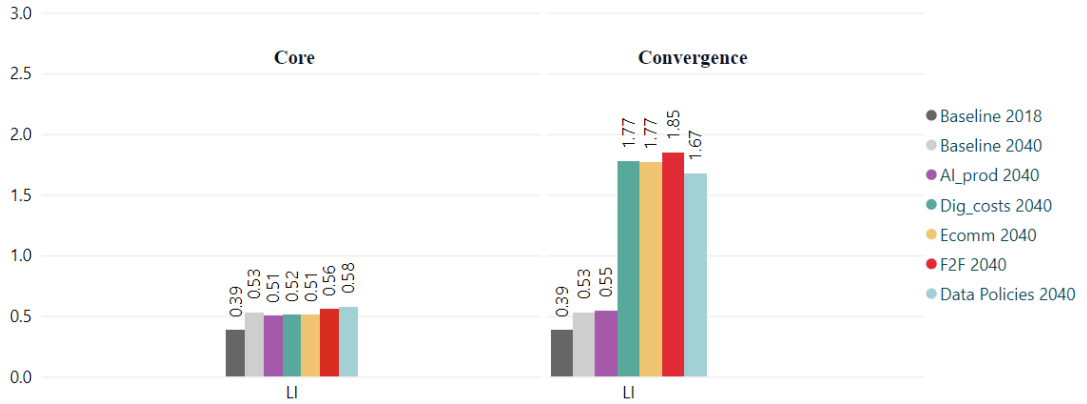
Figure A.1: Replicated AI Preparedness Index for selected economies



Source: Calculated based on the approach by Cazzaniga et al. (2024)
Notes: The figure shows the structure of the calculated non-normalized AI Preparedness Index for several economies. The index has four components: digital infrastructure, human capital, innovation and economic integration, regulation and ethics. For mapping to regional groups, see Table A.2.

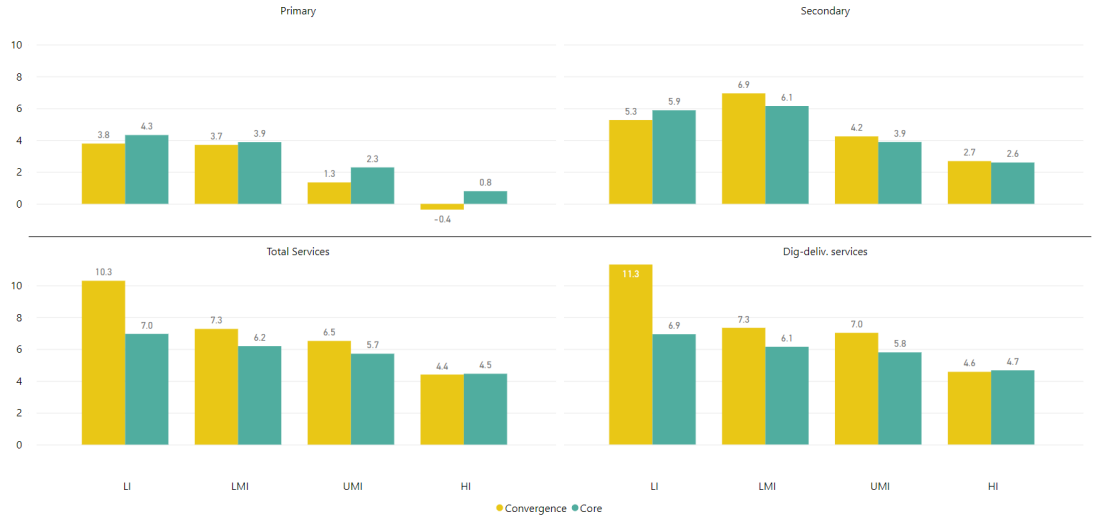
Appendix A.7 Additional Figures and Tables

Figure A.2: Share of low-income economies in exports of digitally deliverable services in core and convergence scnearios



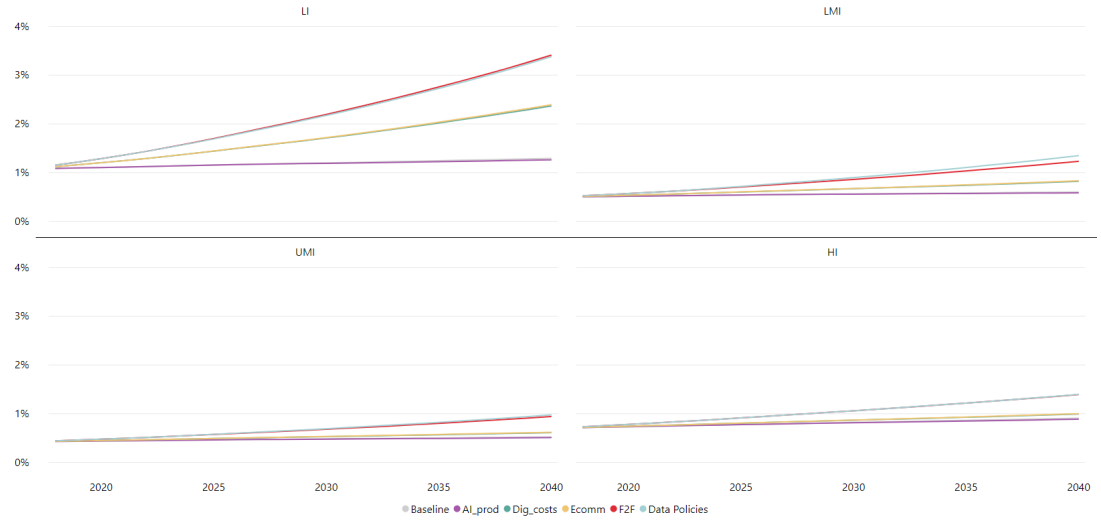
Source: Calculated based on own simulations.
Notes: the figure demonstrates the share of low-income economies in global exports of digitally deliverable services in the baseline scenario in 2018 and 2040 and various core and convergence scenarios in 2040. For mapping to regional groups, see Table A.2.

Figure A.3: Average annual trade growth (%) of main sectors in regional groups



Source: Own simulations.
Notes: the figure demonstrates the annual trade growth in p.p. of main sectors in regional groups between 2018 and 2040 in the core and convergence scenarios. For mapping to aggregate sectors and regional groups, see Tables A.1 and A.2, respectively.

Figure A.4: Share of imported services in manufacturing gross output of regional groups



Source: Calculated based on own simulations.
Notes: the figure demonstrates the dynamics of shares of imported services in the gross output of regional groups over 2018-2040 in the baseline and convergence scenarios. See Table A.2 for mapping to aggregate regional groups.