Artificial Intelligence and the Globalisation of Services*

Saskia Meuchelböck† Sarah Schroeder‡

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Abstract

Information and communication technologies made many knowledge-intensive services tradable across borders. Artificial intelligence changes the production of these services themselves, raising a central question for the next phase of globalisation: will AI substitute for services previously traded internationally, or deepen specialisation and demand for complementary inputs? We examine how exposure to advances in frontier AI capabilities is associated with firms' imports and exports of digitally deliverable services (DDS). We link Danish service transactions by firm, partner, and service type to employer–employee and firm registers. Firm exposure combines advances in AI capabilities with occupational employment shares fixed before those advances, capturing technological exposure rather than realised adoption. Firms with larger increases in exposure experience larger increases in total DDS imports over time, with positive estimates across specifications. Export estimates are also positive but substantially less precise. Across service categories, product-related services provide the clearest positive association for both flows. Heterogeneity by task offshorability further suggests that AI can either complement or substitute for foreign service inputs depending on firms' task composition, while we find little systematic heterogeneity by workforce education. Overall, the results show that greater exposure to potentially task-replacing technologies can coexist with deeper international sourcing of services and that the relationship between AI and services trade varies across types of tasks and service inputs.

Keywords: artificial intelligence; trade in services; digitally deliverable services; firms; tasks
JEL codes: F14, F16, O33, J24

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†Aarhus University and Kiel Institute for the World Economy. Address: Department of Economics and Business Economics, Aarhus University, Universitetsbyen 51, 8000 Aarhus C, Denmark. Email: sameu@econ.au.dk.

‡Aarhus University and Ratio Institute, Stockholm. Address: Department of Economics and Business Economics, Aarhus University, Universitetsbyen 51, 8000 Aarhus C, Denmark. Email: sschroeder@econ.au.dk.

1 Introduction

Digital technologies have extended the international division of labour into knowledge work. By reducing the cost of transmitting information and coordinating production across distance, they have enabled firms to source and sell coding, design, accounting, research, and other knowledge-intensive services across borders. Recent advances in artificial intelligence may transform this process further by changing how information-intensive tasks are performed and by expanding the capabilities of the firms and workers that supply them. This raises a central question for the next stage of globalisation: does AI substitute for internationally traded services, or deepen the cross-border specialisation that digital technologies made possible?

For imports, these forces operate in opposing directions. AI may allow firms to perform internally tasks that they previously purchased from foreign suppliers. Alternatively, it may increase demand for complementary software, data, intellectual property, research, and specialised expertise, deepening firms' reliance on foreign service inputs. For exports, AI may lower production costs, improve quality, and expand the scale or range of services that firms can provide abroad. Yet it may also erode the value of replicable outputs and intensify competition from foreign producers. The aggregate response is therefore theoretically ambiguous, and its composition matters: movements across service categories may offset one another, while imports and exports capture distinct margins of firms' international adjustment.

We answer this question by linking Danish survey-based records of international service transactions to employer–employee registers. The transaction data identify the firm, partner country, service type, and direction of trade, allowing us to observe firms' purchases from foreign suppliers and sales to foreign customers separately. Our analysis concentrates on digitally deliverable services (DDS), i.e. services that can in principle be delivered cross-border over computer networks. We combine these records with the dynamic AI occupation exposure index (DAIOE) by (Engberg et al., 2024). The measure maps advances in frontier AI capabilities into occupations according to their task and ability content. We then aggregate these occupation-level advances to the firm using occupational employment shares fixed before the subsequent capability changes. Variation in firm exposure therefore arises because firms entered the period with different workforce structures and those workforces were differentially exposed to common advances at the AI frontier.

Our main specification relates longer-run changes in firms' imports and exports of digitally deliverable services over 2014–2024 to changes in firm-level AI exposure. The long-difference approach is intended to capture structural changes in firms' international services trade rather than short-run fluctuations. Holding occupational weights fixed prevents subsequent workforce adjustment from mechanically changing measured exposure. It does not make initial occupational composition random: firms with different workforces may also differ in other determinants of trade growth. The estimates therefore capture conditional associations between technological exposure and subsequent trade adjustment rather than the causal effect of AI adoption. This distinction is central because the exposure measure records changes in what AI can do in relation to a firm's pre-existing tasks, rather than whether or how intensively the firm implements the technology.

Our central finding is that firms more exposed to advances in AI capabilities subsequently

expanded their sourcing of digitally deliverable services from abroad. Across four specifications, the coefficient on AI exposure is positive and statistically significant, ranging from 0.160 to 0.243. The estimate remains broadly stable as we progressively account for baseline firm characteristics, foreign ownership and trade activity, workforce education, and exposure to robotics and software technologies. The corresponding export coefficients are consistently positive, ranging from 0.058 to 0.111, but none is statistically distinguishable from zero.

Among the category-level results, product-related services constitute the clearest common result: AI exposure is positively and significantly associated with both their imports and their exports. We additionally find a positive association with imports of enterprise-related services and exports of intellectual-property services. For ICT, financial and insurance, and personal services, the estimated associations are statistically imprecise. Taken together, the evidence is strongest for an expansion of foreign service sourcing, with more limited evidence that greater AI exposure is accompanied by an expansion of firms' foreign service sales.

To investigate the mechanisms behind these patterns, we ask whether the relationship between AI exposure and services trade depends on firms' task structure and workforce composition. The clearest heterogeneity appears on the import side and is related to task offshorability. For product-related services, such as R&D, engineering, and technical services, the positive association between AI exposure and imports is strongest among firms with less offshorable tasks and weakens as tasks become more easily offshored. Intellectual-property-related services show a similar relationship, while ICT services move in the opposite direction: the negative association between AI exposure and imports becomes weaker as offshorability rises. These results are consistent with AI complementing foreign knowledge and technical inputs in some production environments while substituting for externally sourced tasks in others. By contrast, we find no similarly systematic heterogeneity by the share of highly educated workers, suggesting that the nature of firms' tasks matters more for these adjustment patterns than workforce education alone.

The paper contributes to research on technology and the international organisation of production. The trade-in-tasks literature shows how reductions in the cost of separating activities across countries can reorganise production and alter the gains from international specialisation (Grossman and Rossi-Hansberg, 2008). Research on services trade similarly demonstrates how communication technologies increased the scope for cross-border exchange (Freund and Weinhold, 2002; Herman and Oliver, 2023), while firm-level evidence documents substantial heterogeneity in participation and trade values across service traders (Eppinger, 2019; Ariu et al., 2020). We add a new technological margin to this literature. Advances in AI can change the cost of performing tradable tasks, the capabilities of service suppliers, and firms' demand for complementary expertise. By observing imports and exports separately and distinguishing service categories, we locate the firm-level trade margins associated with differential exposure to these advances.

The paper also contributes to the growing empirical literature on the economic effects of AI. Existing studies examine how AI affects labour demand (Acemoglu et al., 2022), worker productivity (Brynjolfsson et al., 2025), and firm growth and product innovation (Babina et al., 2024). We extend the outcome of interest beyond adjustment within the firm to the cross-border

relationships through which firms obtain and sell knowledge-intensive services. Most closely related, Bastos and Nayyar (2026) study AI and bilateral services trade at the US sector level; Betai and Chen (2026) examine cross-border outsourcing on an online labour platform around the arrival of generative AI; and Ide and Talamàs (2025) develop a theory of AI, offshoring, and comparative advantage in knowledge work. Our contribution is to connect workforce-based exposure to broad advances in AI capabilities with reported foreign purchases and sales at the firm level across multiple service groups. This linkage reveals an international dimension of technological adjustment that is concealed by sector aggregates and cannot be recovered from a single contracting platform.

The remainder of the paper proceeds as follows. Section 2 describes the transaction and worker data, develops the exposure measure, and presents three stylised facts. Section 3 introduces the long-difference framework and its interpretation. Section 4 presents the results for total DDS trade and individual service categories. Section 5 examines heterogeneity by task offshorability and workforce skills. Section 6 discusses the implications and directions for future research.

2 Data, Measurement, and Stylised Facts

2.1 Data

International services trade and linked register data. We use confidential firm-level data on Danish international trade in services from Statistics Denmark's International Trade in Services survey, covering 2014–2024. The data contain information on services transactions with non-residents at the firm–country–service type level. Purchases from a non-resident are recorded as imports and measure services obtained from foreign suppliers; sales to a non-resident are recorded as exports and measure services supplied to foreign customers. The survey provides comprehensive coverage of Denmark's largest services-trading enterprises, which report their cross-border services activities at monthly frequency. In addition, annual or quarterly reports are collected from a stratified random sample of small and medium-sized enterprises. The sampling population is constructed using, among other sources, information from the Danish Business Register, VAT records, and EU sales records. Firms with estimated services trade below DKK 1 million (around USD 150,000) are generally not sampled. Overall, the firm-level microdata account for approximately 80% of the value of total services imports and exports reported in the aggregate Balance of Payments statistics.

We focus our analysis on digitally deliverable services (DDS), i.e. services that can in principle be delivered cross-border over computer networks. These include, for example, computer and information services, professional and management consulting, research and development, engineering and technical services, financial services, and charges for the use of intellectual property. We identify DDS based on the EBOPS 2010 classification following IMF, OECD, UNCTAD and WTO (2023); the detailed mapping is reported in Appendix Table A1. We depart slightly from the standard definition by excluding trade-related services (EBOPS 10.3.4) and insurance services directly related to goods trade. As these services are closely tied to merchandise transactions, changes in their imports and exports may primarily reflect changes

in firms' goods-trading activity. Our baseline measure therefore focuses on DDS whose cross-border provision is less mechanically linked to goods trade.

Our empirical analysis focuses on balanced panels of 421 DDS importers and 322 DDS exporters. Given the survey design, the absence of a firm from the microdata in a particular year does not necessarily imply zero services trade, but may instead reflect changes in survey participation. To avoid interpreting changes in recorded services trade as actual entry or exit, we restrict the analysis to firms observed throughout the sample period. Our estimation sample therefore disproportionately consists of relatively large and persistent services traders, while small and occasional services traders are less likely to be represented. Nevertheless, the firms in our balanced panels account for around 80% of the value of DDS trade recorded in the microdata. We aggregate the services transactions to the firm-level for exports and imports separately and link them to other Danish administrative information on firms and workers through the firm identifier. The linked records provide employer–employee relationships, occupational composition, education, firm accounts, ownership, and goods-trade activity. All monetary values are deflated using the consumer price index (CPI) and expressed in constant 2015 DKK.

Occupational and firm exposure to advances in AI. We measure technological exposure using the Dynamic AI Occupational Exposure (DAIOE) index developed by Engberg et al. (2024). DAIOE tracks advances in frontier performance across a broad set of AI application domains and maps those advances to occupations according to the abilities required to perform their tasks, building on the approach of Felten et al. (2018). An occupation's exposure therefore increases when AI capabilities improve in domains that are relevant to its work. Unlike static occupational indices, DAIOE varies across both occupations and time, allowing us to measure how changes in the technological frontier alter the set of tasks potentially affected by AI.

We aggregate occupational exposure to the firm level using employment shares fixed in 2013:

$$AIExposure_{it} = \sum_{o \in \mathcal{O}} \omega_{io,2013} DAIOE_{ot}, \tag{1}$$

where $\omega_{io,2013}$ denotes the share of firm i's 2013 workforce employed in occupation o, and $DAIOE_{ot}$ is the corresponding occupation–year exposure index. The exposure measure is currently available through 2021.[1] Our main regressor is the long difference in this firm-level measure. Because the occupational weights are fixed, changes in firm exposure arise from subsequent advances in AI capabilities interacting with differences in firms' initial workforce composition. Later changes in employment or occupational structure therefore cannot mechanically affect measured exposure.

This measure is particularly well suited to our question. First, its time variation captures the uneven evolution of AI capabilities rather than assigning occupations a fixed ranking throughout the sample period. Second, it maps a common technological frontier into heterogeneous firm-level exposure through workforce structures observed before the subsequent changes in AI capabilities and trade. Third, it does not condition on realised adoption, which is an organisational choice that may be jointly determined with firms' sourcing and foreign-sales decisions.

[1] We are in the process of extending the *DAIOE* through 2024 to capture recent advances in AI capabilities and to align the exposure period with our 2014–2024 services-trade sample.

Direct adoption measures are appropriate for estimating the consequences of implementation; DAIOE instead captures how strongly developments at the technological frontier bear on the tasks initially performed inside each firm.

A separate validation exercise using nationally representative Danish firm surveys supports the empirical relevance of this measure. Comparing five widely used occupational exposure indices, Pulito et al. (2026) find that DAIOE has the strongest association with firms' reported AI adoption and outperforms patent-based and large-language-model-focused alternatives. This evidence provides criterion validity for the measure: firms whose initial workforces are more exposed according to DAIOE are more likely subsequently to report adopting AI. It does not imply that exposure and adoption are equivalent. Firms may be highly exposed without adopting AI, and firms with similar exposure may differ in the timing and intensity of implementation. Moreover, baseline workforce composition may be correlated with other determinants of trade growth. We therefore interpret the measure as exposure to advances in AI capabilities through the firm's pre-existing task structure, and the resulting estimates as conditional associations rather than causal effects of AI adoption.

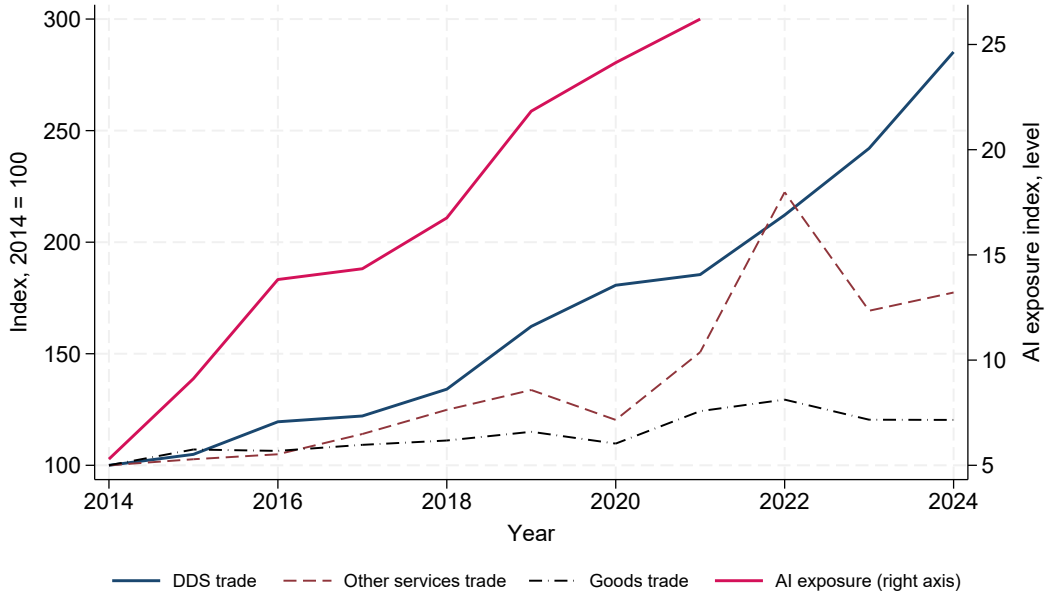
2.2 Stylised Facts

The following facts establish the scale, timing, and firm-level motivation for the analysis. They are descriptive patterns and do not identify causal effects.

Fact 1: The rapid expansion of digitally deliverable services coincides with advances in frontier AI capabilities. Figure 1 documents a clear parallel development: digitally deliverable services expand markedly over 2014–2024, alongside substantial advances in frontier AI capabilities. Notably, DDS trade is by far the fastest-growing component of Danish trade over our sample period, increasing to almost three times its 2014 level by 2024. Goods trade grows only moderately, while other services trade remains below twice its 2014 level over the period shown, despite a temporary spike around 2021–2022.[2] This pattern is not unique to Denmark: globally, digitally delivered services have also been the fastest-growing segment of international trade, outpacing both goods and other services. Over the same period, our measure of AI exposure rises substantially as frontier AI capabilities improve. This aggregate co-movement motivates us to examine what lies behind it at the firm level, i.e. whether firms that are more exposed to advances in AI capabilities also experience systematically different changes in DDS trade.

[2]The sharp increase in other services is largely driven by transportation services, which account for a substantial share of Danish services trade. During the COVID-19 pandemic, freight rates rose sharply in 2021 and 2022, increasing the value of transportation services trade. This increase was temporary and reversed as freight rates normalized.

Figure 1: Aggregate Danish trade and AI exposure over time



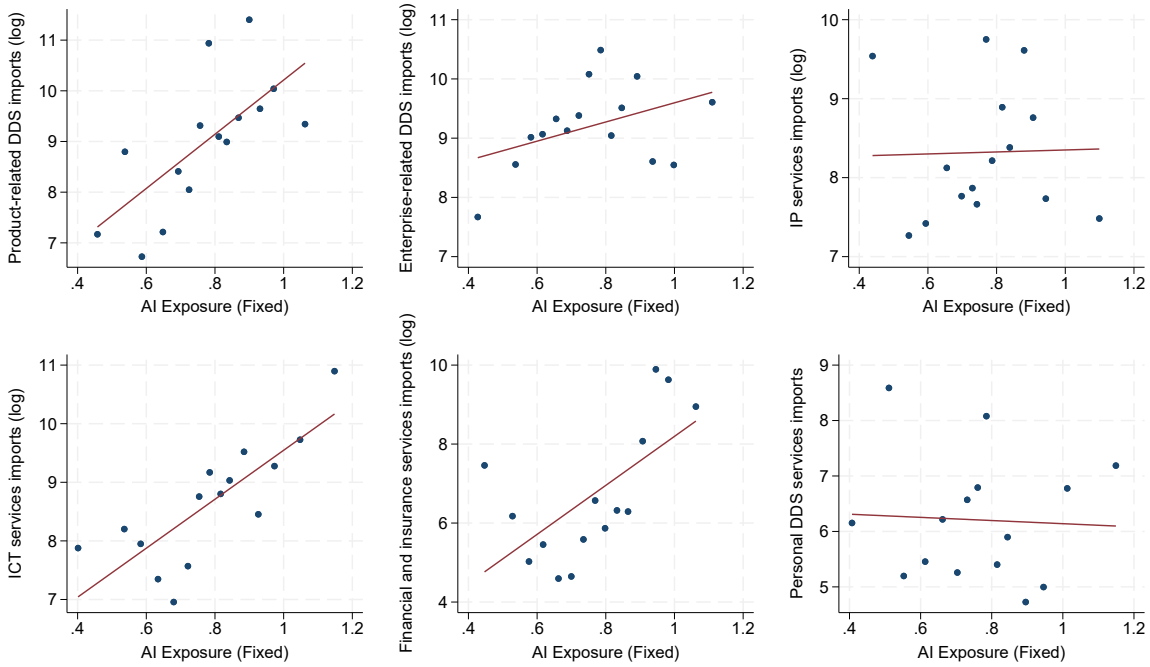
Notes: The trade series displayed from 2014–2024 are constructed by aggregating microdata on goods and services trade. They measure total trade, defined as exports plus imports. Trade values are expressed in constant 2015 DKK and each series is normalized to 100 in 2014. The AI exposure series aggregates firm-level AI exposure across all Danish firms for which the measure can be constructed, rather than only firms in our services-trade sample. The AI exposure index is shown in levels on the right-hand axis. The AI exposure measure is currently available through 2021.

Fact 2: Two-way traders dominate international services trade. Using the firms in our balanced import and export samples, we classify firms by their trading status, distinguishing between importers only, exporters only, and firms that engage in both directions of services trade. Among the 464 firms with service imports and/or exports, 285 firms, or 61.4%, both import and export services, while 140 firms import only and 39 export only. At the beginning of our sample period, two-way traders account for 88.1% of total service imports and 96.1% of total service exports, and this pattern remains broadly stable over time. Hence, imports and exports are not activities undertaken by distinct populations of firms; most service-trade value is accounted for by firms operating on both sides of the international market. For firms exposed to advances in AI capabilities, imports and exports therefore represent two distinct margins of adjustment: AI may change firms' demand for foreign service inputs as well as their ability to supply services to foreign customers. We consequently study both sides of services trade separately rather than summarising firms' international engagement through net trade.

Fact 3: The association between firm AI exposure and services trade differs markedly across DDS categories. To examine the composition of services trade, we group digitally deliverable services into six broad categories—product-related, enterprise-related, intellectual-property-related, ICT, financial and insurance, and personal services—following the service classification Biewen and Meinusch (2023). The detailed service types included in each category are reported in Table A2. Figure 2 provides descriptive evidence for the import side by relating firm-level AI exposure to imports within each category. The positive association

is clearest for product-related services and is also visible for ICT and financial and insurance services. It is more modest for enterprise-related services and absent for intellectual-property-related and personal services.

Figure 2: AI Exposure and Imported Digitally Deliverable Services, by Category



Notes: The figure presents binned scatterplots of firm-level services imports against firm-level AI exposure. Each panel corresponds to one broad category of digitally deliverable services. The detailed service types included in each category are reported in Table A2.

Taken together, these stylized facts establish the growing importance of DDS trade, its concentration in two-way traders, its temporal overlap with progress across frontier AI capabilities, and pronounced heterogeneity by service categories. These descriptive patterns motivate and guide our empirical analysis at the firm-level introduced in Section 3.

3 Empirical Framework

3.1 Long-difference specification

The main design relates longer-run changes in firms' occupational AI exposure to changes in their imports and exports of digitally deliverable services. For firm i, flow $f \in \{\text{imports}, \text{exports}\}$, and total DDS or service category s, the estimating equation is

$$\Delta_L \ln Y_{is}^f = \alpha_{f,s} + \beta_{f,s} \Delta_L AIExposure_i + X_{i,0}' \gamma_{f,s} + \lambda_{j(i)} + \mu_{r(i)} + \varepsilon_{is}^f, \tag{2}$$

where Δ_L denotes a long difference between the beginning and end of the respective observation period. For services trade, we average firm-level trade over 2014–15 and 2023–24 and define $\Delta_L \ln Y_{is}^f = \ln \overline{Y}_{is,2023\text{–}24}^f - \ln \overline{Y}_{is,2014\text{–}15}^f$. Using two-year averages reduces the influence of year-specific fluctuations in services trade. For AI exposure, the long difference is calculated

between average exposure in 2014–15 and exposure in 2021, the latest year currently available in the *DAIOE* measure.[3] The outcome Y_{is}^{f} is firm i's trade in service category s, measured separately for imports and exports, indexed by f. The vector $X_{i,0}$ contains the baseline controls described below. The terms $\lambda_{j(i)}$ and $\mu_{r(i)}$ denote industry and region fixed effects, respectively. They absorb systematic differences in longer-run trade growth across industries and regions, so that $\beta_{f,s}$ is identified from differences in AI-exposure growth after accounting for these common industry and regional components. Because the dependent variable is expressed as a change in log trade, $\beta_{f,s}$ measures the difference in trade growth associated with a one-unit increase in the change in occupational AI exposure.

Our baseline specification includes the beginning-of-period outcome, log employment, and firm age. We then add controls sequentially. Foreign ownership and goods-trade activity capture firms' broader international orientation, while the share of employees with a bachelor's degree or higher accounts for workforce education. The final specification additionally includes occupational exposure to robots and software based on the measures developed by Webb (2019). Webb constructs these indices by comparing verb–noun pairs extracted from patent texts in robotics and software with the corresponding language in O*NET occupational task descriptions. An occupation receives a higher score when patents in a given technology describe activities that closely overlap with the tasks performed in that occupation. We aggregate the occupation-level indices to the firm using fixed occupational employment shares, following the same aggregation principle as for firm-level AI exposure. The Webb indices capture potential exposure to task automation rather than firms' realised adoption of robots or software. Including them helps distinguish exposure to advances in AI capabilities from a broader susceptibility of the firm's initial task structure to technological automation.

3.2 Heterogeneity specifications

We further examine whether the association between AI exposure and services trade varies along two dimensions that are directly related to the organisation of knowledge-intensive production: The first moderator is firm-level task offshorability, constructed by aggregating the occupation-level offshorability measure of Autor and Dorn (2013) using the firm's occupational employment shares. It captures the extent to which the firm's workforce performs tasks that can, in principle, be delivered from another location. The second moderator is the share of the firm's employees with a bachelor's degree or higher. This variable captures workforce skill intensity and may proxy for the firm's capacity to integrate and use new technologies and specialised knowledge inputs.

For each moderator $M_{i,0}$, we estimate

$$\begin{aligned}\Delta_L \ln Y_{is}^{f} = \alpha_{f,s} + \beta_{f,s}\Delta_L AIExposure_i + \delta_{f,s}M_{i,0} \\ + \theta_{f,s}\left(\Delta_L AIExposure_i \times M_{i,0}\right) + X_{i,0}'\gamma_{f,s} + \lambda_{j(i)} + \mu_{r(i)} + \varepsilon_{is}^{f},\end{aligned} \tag{3}$$

where $M_{i,0}$ denotes either the firm's beginning-of-period task offshorability or the beginning-of-period share of workers with a bachelor's degree or higher. The specification includes the

[3] We are in the process of extending the AI exposure measure through 2024 to capture recent advances in AI capabilities and to align the exposure period with our 2014–2024 services-trade sample.

constituent terms of each interaction, the baseline controls, and industry and region fixed effects. The coefficient $\theta_{f,s}$ indicates whether the association between AI-exposure growth and trade growth varies with the moderator.

3.3 Empirical variation and interpretation

Because occupational employment shares are fixed in 2013, the long-difference change in firm-level AI exposure can be written as

$$\Delta_L AIExposure_i = \sum_{o \in \mathcal{O}} \omega_{io,2013} \, \Delta_L DAIOE_o. \tag{4}$$

Firms are therefore differently exposed to the same occupation-specific advances in AI capabilities because their workforces differed before those advances occurred. Equation (2) compares the subsequent growth of services trade across firms with different exposure changes, conditional on baseline firm characteristics and industry and region fixed effects. The fixed effects absorb average differences in trade growth across industries and regions.

The central identifying assumption is that, conditional on these controls and fixed effects, firms with different initial occupational compositions would not otherwise have experienced systematically different changes in services trade. Fixing occupational weights at their 2013 values prevents subsequent workforce reorganisation from mechanically changing measured exposure. The long-difference transformation absorbs time-invariant determinants of firms' trade levels, although it does not by itself eliminate differential trends associated with their initial workforce composition. We therefore interpret $\beta_{f,s}$ as the conditional longer-run association between exposure to AI-capability advances and trade growth. We estimate the specification separately for imports and exports and for each service category.

4 AI Exposure and International Trade in Services

Our central empirical question is whether firms whose pre-existing task structures became more exposed to advances in AI subsequently changed their international sourcing and sales of digitally deliverable services. We first examine total DDS imports and exports and then disaggregate these flows across service categories. Import and export regressions are estimated separately on their respective outcome samples. The estimates describe conditional long-difference associations as described in Section 3.

4.1 Total DDS imports and exports

Table 1 reports four nested specifications for changes in total DDS trade. Column (1) conditions on initial DDS trade, firm size, and firm age. Column (2) adds foreign ownership and the corresponding import- or export-activity control. Column (3) additionally accounts for workforce education, measured by the share of employees with a bachelor's degree or higher. Column (4), our most comprehensive specification, further controls for occupational exposure to robots and software. The number of observations remains unchanged across specifications within each panel. Panel A shows a consistently positive relationship between changes in AI exposure and

Table 1: AI Exposure and Total Trade in Digitally Deliverable Services

	(1) Baseline	(2) Firm characteristics	(3) Workforce skills	(4) Technology controls
Panel A: Imports				
Change in AI exposure	0.189**	0.189**	0.160*	0.243**
	(0.083)	(0.084)	(0.089)	(0.107)
Log DDS-trade control	−0.281***	−0.300***	−0.309***	−0.307***
	(0.038)	(0.040)	(0.042)	(0.042)
Log employment	0.206***	0.202***	0.211***	0.203***
	(0.048)	(0.049)	(0.050)	(0.050)
Firm age	−0.001	−0.001	−0.001	−0.001
	(0.003)	(0.003)	(0.003)	(0.003)
Foreign ownership		0.006	0.021	0.027
		(0.137)	(0.137)	(0.137)
Import-activity control		0.026	0.027	0.026
		(0.017)	(0.017)	(0.017)
Bachelor's-or-higher share			0.366	0.394
			(0.371)	(0.372)
Webb robot index				0.173
				(0.120)
Webb software index				−0.158*
				(0.095)
Observations	421	421	421	421
R^2	0.188	0.193	0.195	0.201
Panel B: Exports				
Change in AI exposure	0.111	0.109	0.066	0.058
	(0.098)	(0.098)	(0.104)	(0.126)
Log DDS-trade control	−0.337***	−0.351***	−0.370***	−0.373***
	(0.050)	(0.051)	(0.053)	(0.053)
Log employment	0.109*	0.102*	0.116*	0.124**
	(0.058)	(0.059)	(0.060)	(0.060)
Firm age	−0.005	−0.006	−0.006	−0.006
	(0.004)	(0.004)	(0.004)	(0.004)
Foreign ownership		−0.101	−0.101	−0.099
		(0.168)	(0.168)	(0.168)
Export-activity control		0.025	0.025	0.027
		(0.019)	(0.019)	(0.019)
Bachelor's-or-higher share			0.588	0.592
			(0.460)	(0.464)
Webb robot index				−0.014
				(0.198)
Webb software index				−0.094
				(0.149)
Observations	322	322	322	322
R^2	0.231	0.236	0.240	0.244

Notes: Each column reports a separate firm-level long-difference regression. The dependent variable is the change in log imports in Panel A and the change in log exports in Panel B. Standard errors are reported in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

changes in total DDS imports. The coefficient is 0.189 in the baseline specification and remains unchanged when foreign ownership and import activity are added. Controlling additionally for workforce education reduces the coefficient modestly to 0.160, while adding exposure to robots and software increases it to 0.243. The estimates are statistically significant at the 5 percent level in Columns (1), (2), and (4), and at the 10 percent level in Column (3). The stability of the sign and the limited sensitivity of the estimate to the progressively richer control set make the import association the clearest empirical result in the paper.

Panel B reports the corresponding estimates for total DDS exports. The coefficients are positive in all four specifications but decline from 0.111 in Column (1) to 0.058 in Column (4) as additional controls are introduced. None of the export estimates is statistically distinguishable from zero, and their standard errors are larger relative to the point estimates than in the import

regressions. The data therefore provide substantially clearer evidence of a positive association with foreign service sourcing than with foreign service sales.

Total DDS trade may conceal offsetting responses across economically distinct services. We therefore next examine whether the aggregate patterns are concentrated in particular DDS categories.

4.2 Variation across service categories

Table 2: AI Exposure and Changes in Trade across Service Categories

	Product-related	Enterprise-related	Intellectual property	ICT	Financial and insurance	Personal
Panel A: Imports						
Change in AI exposure	0.886^{**}	0.344^{*}	0.187	0.079	−0.360	−0.243
	(0.346)	(0.184)	(0.614)	(0.221)	(0.408)	(0.377)
Log trade in category (baseline)	-0.268^{***}	-0.331^{***}	-0.630^{***}	-0.396^{***}	-0.478^{***}	-0.438^{***}
	(0.091)	(0.055)	(0.093)	(0.059)	(0.093)	(0.088)
Firm characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Import-activity control	Yes	Yes	Yes	Yes	Yes	Yes
Workforce education	Yes	Yes	Yes	Yes	Yes	Yes
Other technology exposure	Yes	Yes	Yes	Yes	Yes	Yes
Observations	168	286	110	277	119	110
R^2	0.232	0.251	0.441	0.282	0.397	0.370
Panel B: Exports						
Change in AI exposure	1.135^{**}	−0.118	1.818^{*}	0.103	−1.179	−1.071
	(0.532)	(0.248)	(1.022)	(0.296)	(1.657)	(1.225)
Log trade in category (baseline)	-0.341^{**}	-0.568^{***}	-0.690^{***}	-0.401^{***}	−0.028	-0.588^{*}
	(0.130)	(0.084)	(0.141)	(0.069)	(0.403)	(0.313)
Firm characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Export-activity control	Yes	Yes	Yes	Yes	Yes	Yes
Workforce education	Yes	Yes	Yes	Yes	Yes	Yes
Other technology exposure	Yes	Yes	Yes	Yes	Yes	Yes
Observations	95	150	54	136	35	35
R^2	0.284	0.391	0.658	0.357	0.374	0.428

Notes: Each column reports a separate firm-level long-difference regression for the indicated service category. The dependent variable is the change in log imports in Panel A and the change in log exports in Panel B. Firm characteristics include log employment, firm age, and foreign ownership. The regressions additionally control for the firm's corresponding import or export activity, the share of workers with a bachelor's degree or higher, and the Webb robot and software exposure indices. Standard errors are reported in parentheses. Estimation samples are outcome specific. $^{*}p < 0.10$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

Table 2 examines whether the relationship between AI exposure and total DDS trade extends across individual service categories. Each column reports the most comprehensive specification from Table 1, estimated separately for the indicated category. Panel A reports imports and Panel B reports exports. Because participation differs across categories, the regressions are estimated on category-specific samples. Product-related services provide the clearest common result. Greater AI exposure is positively associated with both imports and exports in this category. The import coefficient is 0.886, with a standard error of 0.346, while the export coefficient is 1.135, with a standard error of 0.532; both are statistically significant at the 5 percent level. Product-related services are therefore the only category for which we find a statistically detectable positive association for both directions of trade.

The remaining estimates point to different patterns across the two flows. For imports, the coefficient for enterprise-related services is positive at 0.344 and statistically significant at the

10 percent level. For exports, the intellectual-property coefficient is positive at 1.818 and significant at the 10 percent level. Estimates for ICT, financial and insurance, and personal services are imprecise, and their signs differ across imports and exports. The category evidence therefore does not indicate a uniform expansion of DDS trade. Rather, the statistically detectable associations are concentrated in a limited number of service groups.

5 The Role of Task Structure and Workforce Education

The aggregate results leave open why firms with greater exposure to advances in AI expand their purchases of foreign services. To assess which economic interpretations are consistent with this relationship, we examine two dimensions of firms' initial workforce composition: the offshorability of their occupational tasks and the share of workers with a bachelor's degree or higher. These characteristics capture distinct margins of adjustment. Offshorability measures the extent to which work can be performed at a distance, while workforce education captures the human capital available to implement new technologies and combine them with specialised service inputs.

The interaction estimates provide mechanism-relevant heterogeneity rather than direct tests of mechanisms. In particular, they do not reveal whether firms adopt AI, relocate tasks, replace foreign suppliers with internal production, or experience productivity gains. They instead show whether the conditional association between AI exposure and services trade is systematically stronger for firms with particular initial task and workforce structures.

5.1 Task offshorability

We construct firm-level task offshorability from the occupational measure of Autor and Dorn (2013), which uses O*NET task characteristics to assess whether work can be performed remotely. Higher values indicate that a firm's initial workforce is concentrated in occupations whose tasks are more amenable to being supplied from a distance. Offshorability is conceptually distinct from routine-task intensity: tasks may be non-routine but nevertheless deliverable remotely.

Offshorability can amplify either side of the relationship between AI and foreign service sourcing. If advances in AI enable firms to perform tasks internally that they previously purchased abroad, the association between AI exposure and imports may weaken as task offshorability increases. Alternatively, AI may lower the cost of coordinating remote production or increase demand for complementary expertise, producing a stronger import association among firms whose activities are already amenable to cross-border delivery. The export prediction is similarly ambiguous. Offshorable activities may benefit from AI-enabled scalability, but they may also face stronger displacement or international competition.

Table 3, Panel A reveals meaningful variation across import categories. For product-related services the interaction between AI exposure and task offshorability is -0.406 and statistically significant at the 10 percent level. The marginal association between AI exposure and product-related imports therefore becomes weaker as firms' initial tasks become more offshorable. The corresponding interaction for intellectual-property services is also negative, at -0.854, and sta-

Table 3: AI Exposure and Services Trade: Heterogeneity by Task Offshorability

	Product-related	Enterprise-related	Intellectual property	ICT	Financial and insurance	Personal
Panel A: Imports						
Change in AI exposure	1.163^{***}	0.128	0.516	-0.355	-0.650	0.064
	(0.400)	(0.231)	(0.791)	(0.272)	(0.522)	(0.499)
Task offshorability	-0.616^{*}	0.275	-0.317	0.557^{**}	0.418	-0.407
	(0.317)	(0.178)	(0.649)	(0.220)	(0.464)	(0.432)
AI exposure × task offshorability	-0.406^{*}	0.048	-0.854^{**}	0.231^{*}	0.023	0.007
	(0.235)	(0.100)	(0.404)	(0.129)	(0.258)	(0.252)
Observations	168	286	110	277	119	110
R^2	0.260	0.258	0.472	0.307	0.402	0.377
Panel B: Exports						
Change in AI exposure	1.109^{*}	-0.116	1.590	-0.103	-5.373^{**}	-0.881
	(0.575)	(0.305)	(1.490)	(0.347)	(2.393)	(2.339)
Task offshorability	-0.145	0.000	0.610	0.252	5.173^{**}	-1.020
	(0.462)	(0.270)	(1.094)	(0.275)	(2.035)	(1.537)
AI exposure × task offshorability	-0.300	-0.004	-0.332	0.136	0.126	-0.970
	(0.325)	(0.173)	(0.475)	(0.193)	(1.122)	(0.891)
Observations	95	150	54	136	35	35
R^2	0.292	0.391	0.666	0.364	0.541	0.476
Full control set	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Each column reports a separate firm-level long-difference regression for the indicated service category. The dependent variable is the change in log imports in Panel A and the change in log exports in Panel B. The independent variables of interest are AI exposure, task offshorability, and their interaction. All regressions control for log employment, firm age, foreign ownership, the firm's import or export activity, the share of workers with a bachelor's degree or higher, and the Webb robot and software exposure indices. Standard errors are reported in parentheses. Estimation samples are outcome specific. $^{*}p < 0.10$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

tistically significant at the 5 percent level. ICT services exhibit the opposite pattern: the interaction is positive at 0.231 and statistically significant at the 10 percent level. The interactions for enterprise-related, financial and insurance, and personal services are small relative to their standard errors.

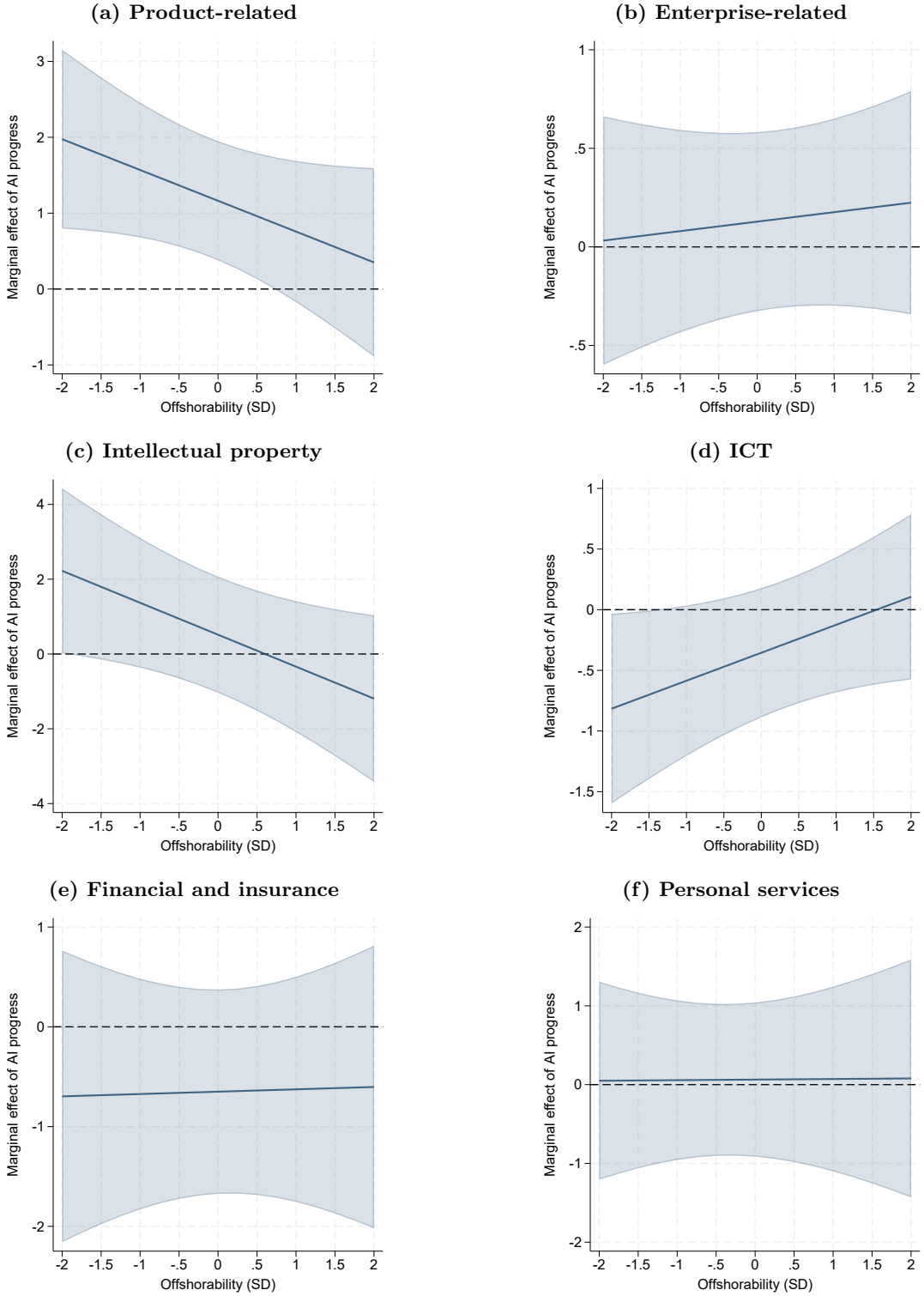
Figures 3 and 4 show the corresponding marginal associations over the observed range of task offshorability. For product-related imports, the estimated AI exposure gradient is positive at lower and intermediate levels of offshorability but declines as offshorability rises. For intellectual-property imports, the point estimate similarly falls from positive at low levels of offshorability to negative at the upper end of the plotted range. The ICT pattern runs in the opposite direction: the estimated association is negative among firms with less-offshorable task structures and moves towards zero as offshorability increases.

The category definitions sharpen the economic interpretation of these patterns. The negative gradients for product-related and intellectual-property imports are consistent with the relationship between AI exposure and purchases of foreign product-development, technical, and intangible inputs being strongest among firms whose existing tasks are less readily performed at a distance. One possible interpretation is that AI raises demand for complementary foreign expertise in these firms, while the scope for substitution or organisational reconfiguration becomes greater as tasks become more offshorable. The positive ICT interaction shows, however, that this interpretation does not apply uniformly across services.

We find substantially less evidence of an offshorability gradient for exports (Table 3, Panel B). None of the six export interactions is statistically significant, and the marginal estimates are

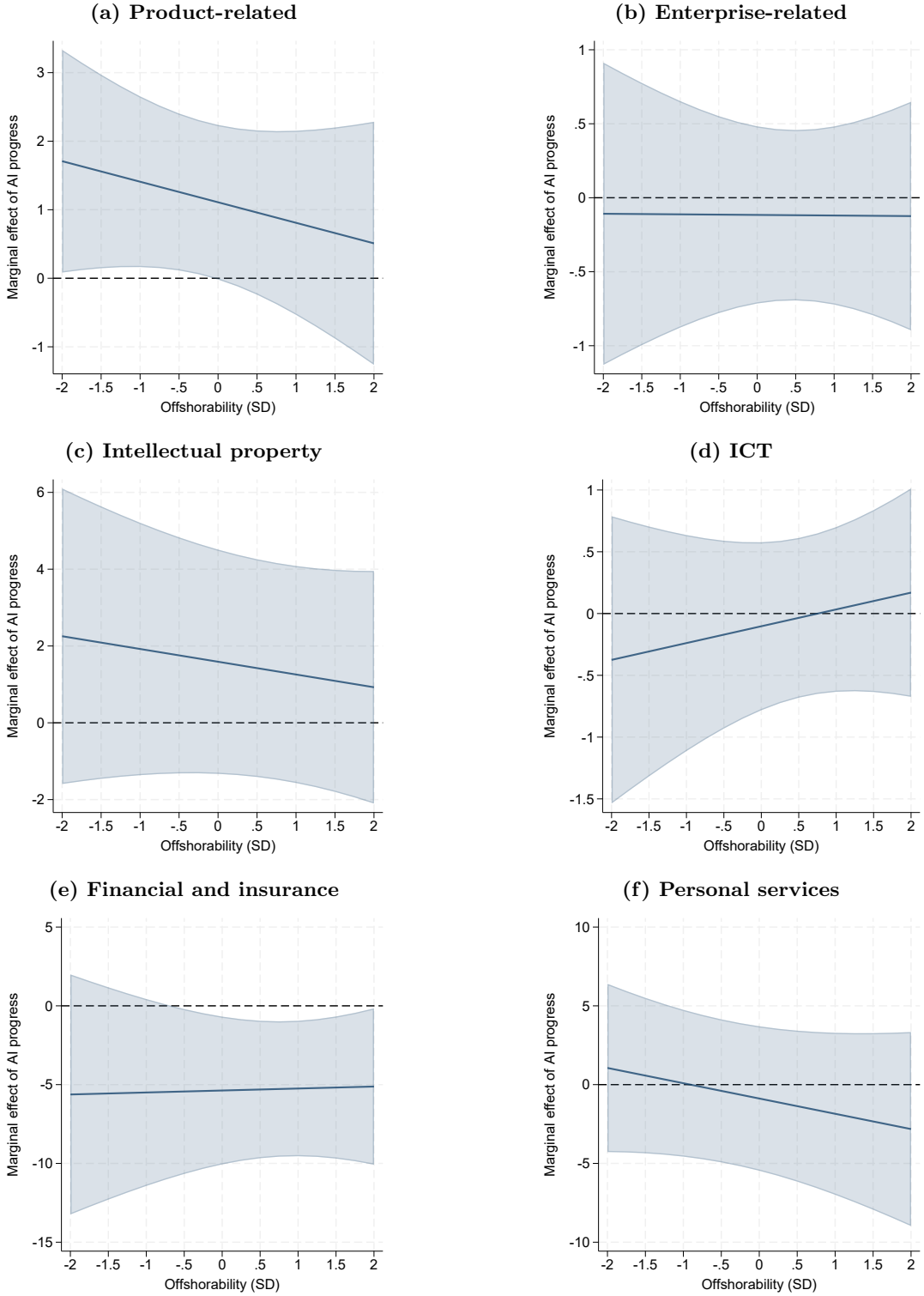
generally imprecise. The results therefore suggest that task offshorability structures the import association in selected service categories but does not organise a comparable pattern for foreign sales.

Figure 3: The AI-Exposure Gradient in DDS Imports across Task Offshorability



Notes: Each panel plots the estimated marginal association between the change in occupational AI exposure and the change in firm-level trade value (in logs) in the indicated service category, evaluated over task offshorability measured in standard-deviation units. Shaded regions represent 95% confidence bands. Table 3 reports the corresponding regression results.

Figure 4: The AI-Exposure Gradient in DDS Exports across Task Offshorability



Notes: Each panel plots the estimated marginal association between the change in occupational AI exposure and the change in firm-level trade value (in logs) in the indicated service category, evaluated over task offshorability measured in standard-deviation units. Shaded regions represent 95% confidence bands. Table 3 reports the corresponding regression results.

5.2 Workforce education

Workforce education captures a different potential margin of adjustment. A larger initial share of workers with a bachelor's degree or higher may increase a firm's capacity to adopt AI, reorganise production, and combine new technologies with specialised service inputs. This absorptive-capacity interpretation predicts a positive interaction between AI exposure and workforce education. Conversely, if advances in AI substitute more strongly for high-skill cognitive tasks, the association with foreign service sourcing or sales could weaken as the graduate share rises. Because both AI exposure and workforce education are derived from firms' workforce composition, these interactions remain descriptive and may partly capture broader differences in firms' occupational structures.

Table 4: AI Exposure and Services Trade: Heterogeneity by Workforce Skills

	Product-related	Enterprise-related	Intellectual property	ICT	Financial and insurance	Personal
Panel A: Imports						
Change in AI exposure	1.533**	0.216	0.616	−0.662	−0.983	1.389*
	(0.740)	(0.356)	(1.333)	(0.426)	(0.647)	(0.803)
Workforce share with a bachelor's degree or higher	1.407	0.823	−1.648	3.034***	−0.013	1.210
	(1.339)	(0.642)	(2.325)	(0.724)	(1.343)	(1.805)
AI exposure × workforce skills	−0.541	−0.140	−0.145	0.690	0.916	−2.556**
	(1.007)	(0.503)	(1.874)	(0.609)	(1.056)	(1.243)
Observations	168	286	110	277	119	110
R^2	0.245	0.257	0.444	0.301	0.407	0.407
Panel B: Exports						
Change in AI exposure	2.521**	−0.267	0.011	0.043	−6.094**	8.317*
	(1.154)	(0.533)	(2.306)	(0.592)	(2.382)	(4.461)
Workforce share with a bachelor's degree or higher	0.085	0.855	6.505*	1.931*	11.166*	−12.783
	(2.153)	(0.854)	(3.757)	(1.021)	(6.224)	(8.803)
AI exposure × workforce skills	−2.088	0.241	1.733	−0.116	2.979	−15.508**
	(1.535)	(0.721)	(2.387)	(0.820)	(3.682)	(6.947)
Observations	95	150	54	136	35	35
R^2	0.302	0.392	0.666	0.362	0.557	0.581
Offshorability and full control set	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Each column reports a separate firm-level long-difference regression for the indicated service category. The dependent variable is the change in log imports in Panel A and the change in log exports in Panel B. The independent variables of interest are AI exposure, the workforce share with a bachelor's degree or higher, and their interaction. All regressions control for log employment, firm age, foreign ownership, the firm's import or export activity, the Webb robot and software exposure indices, as well as task offshorability. Standard errors are reported in parentheses. Estimation samples are outcome specific. $^{*}p < 0.10$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

Table 4 provides little evidence of a systematic education gradient. The estimated interactions differ in sign across service categories and are generally imprecise for both imports and exports. The principal exception is personal services, for which the interaction is negative and statistically significant at the 5 percent level in both panels. This result implies that the association between AI exposure and personal-services trade becomes less positive as the graduate share increases. It should nevertheless be interpreted cautiously: the import regression contains 110 observations, the export regression only 35, and no corresponding pattern appears across the other service categories.

Taken together, the interaction estimates reveal more structured variation along task offshorability than along workforce education, particularly for imports. This is consistent with the

organisation and spatial separability of tasks being more informative for the AI–trade relationship than the aggregate graduate share.

6 Implications and Conclusion

Artificial intelligence changes not only the cost of exchanging knowledge across borders, but also the technology for producing knowledge-intensive tasks themselves. Whether this development substitutes for internationally traded services or deepens cross-border specialisation is therefore theoretically ambiguous. Linking Danish service transactions to firms' pre-existing occupational structures, we document that firms more exposed to advances in AI capabilities experience larger subsequent increases in imports of digitally deliverable services. The association is positive across four long-difference specifications. Export estimates are also positive, but considerably less precise. Because our measure captures exposure to frontier capabilities rather than realised adoption, the results describe how firms differentially positioned to benefit from AI adjust their international service trade.

The adjustment is not uniform across services. Product-related services—including research and development, product testing, architecture, engineering, and technical services—provide the clearest positive association for both imports and exports. The interaction results further indicate that firms' task structures matter. For product-related and intellectual-property imports, the association with AI exposure weakens as task offshorability rises, whereas ICT imports display the opposite gradient. Workforce education produces no similarly systematic pattern. These findings suggest that the relationship between AI and foreign service inputs depends on the nature and spatial organisation of the tasks involved, rather than following a single complementarity-or-substitution mechanism.

The central implication is that exposure to a potentially task-replacing technology can coexist with deeper foreign sourcing. AI need not make firms self-sufficient in knowledge-intensive activities. It may instead increase their demand for specialised software, technical expertise, intellectual property, and other capabilities available through international markets. Domestic AI capabilities and access to foreign digital inputs may therefore be complements rather than substitutes. This connection brings trade policy directly into debates about AI: digital infrastructure, cross-border data flows, regulatory compatibility, and access to specialised foreign suppliers may shape firms' ability to realise the opportunities created by technological progress. At the same time, the less precise export estimates caution against assuming that technological exposure alone automatically translates into stronger international competitiveness.

Future work linking technological exposure to actual adoption and firms' internal allocation of tasks can distinguish whether greater service imports reflect demand for complementary expertise, expansion in firm scale, or a reorganisation of production across firms and countries. Our findings establish a more immediate point: advances in AI are not necessarily a force for service self-sufficiency or deglobalisation. For the firms most exposed to them, these advances are associated with deeper foreign sourcing. The next stage of services globalisation may therefore be defined by how AI redraws the boundary between the knowledge firms produce internally and the capabilities they obtain from abroad.

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A Data

Table A1: Digitally Deliverable Services in EBOPS 2010

Service category	EBOPS 2010 code
Insurance and pension services	6
Financial services	7
Charges for the use of intellectual property n.i.e.	8
Telecommunications, computer and information services	9
Research and development services	10.1
Professional and management consulting services	10.2
Architectural, engineering, scientific and other technical services	10.3.1
Trade-related services	10.3.4
Other business services n.i.e.	10.3.5
Audio-visual and related services	11.1
Health services	11.2.1
Education services	11.2.2
Heritage and recreational services	11.2.3

Notes: The table reports the standard classification of digitally deliverable services supplied cross-border (Mode 1) according to IMF, OECD, UNCTAD and WTO (2023). Our empirical definition excludes trade-related services (EBOPS 10.3.4) and insurance services directly related to goods trade. These services are closely tied to merchandise transactions and may therefore primarily reflect changes in firms' goods-trading activity rather than changes in the international sourcing of service inputs.

Source: IMF, OECD, UNCTAD, and WTO (2023), Table 4.1, p. 68.

Table A2: Broad Categories of Digitally Deliverable Services

Broad category	Included service types
Product-related	Research and development
	Product testing
	Production of audiovisual and other artistic products
	Technical services
	Architectural services
	Engineering services
Enterprise-related	Legal services
	Auditing, bookkeeping, and tax consultancy
	Commercial and business services
	Advertising and market research
	Other product- or enterprise-related services
Intellectual property	Use of software
	Use of audiovisual products and other artistic copyrights
	Use of research findings, inventions, and processes
	Use of brands, trademarks, and franchises
	Use of other intellectual property rights
	Reproduction and distribution rights for computer software
	Reproduction, distribution, and transmission rights for audiovisual and other artistic products
	Other distribution rights
ICT	Communication services
	IT services
	News and information services
	Information storage and related infrastructure
Finance and insurance	Financial services
	Life insurance
	Secondary life insurance
	Other non-transport insurance
	Reinsurance
	Pension services
	Auxiliary insurance services
Personal	Health services
	Education services
	Recreational and heritage services

Notes: The grouping is adapted from the Deutsche Bundesbank's BPM6 service classification and is applied to the set of digitally deliverable services defined in Appendix Table A1. Subitems of the Bundesbank categories that do not fall within our definition of digitally deliverable services are not reported. We combine financial services and insurance and pension services into a single category. Trade-related services and insurance directly related to goods trade are excluded from the analysis.

Source: Biewen and Meinusch (2023).