Artificial Intelligence and International Trade in Services: Evidence from the United States*

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Abstract

We examine whether and how the adoption of artificial intelligence (AI) across sectors in the United States impacted international trade in services over the period 2011-2024. The empirical analysis uses ordinary least squares and instrumental-variable regressions exploiting variation in exposure to AI across sectors and over time. Both the OLS and IV results reveal that U.S. services sectors experiencing stronger AI adoption tended to observe a larger increase in exports. These effects are observed in exports to both developed and developing economies, consistent with a stronger comparative advantage of the US in these sectors. There is no robust evidence that AI adoption reduces services imports, suggesting that it is not systematically replacing services sourced from other countries.

Keywords: Artificial intelligence, international trade in services, occupations.
JEL Classification: F1, J23, J24, O33

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1 Introduction

Recent empirical evidence reveals that Artificial Intelligence (AI) has already begun to significantly impact labor markets of high-income countries. Bonfiglioli, Crino, Gancia, and Papadakis (2025) estimate the causal impact of AI adoption on employment across commuting zones in the US over 2000–2020, and find robust negative effects on employment of some groups of workers, especially in services. This evidence raises the possibility that AI may have also impacted labor markets in other countries, even if they have not yet adopted this technology at scale. If tasks embodied in services that were commonly sourced from other countries can now be executed by AI at home, demand for those foreign workers might also be reduced.

In this paper, we empirically investigate whether and how the growing adoption of AI in the US impacted international trade in services over the period 2011-2024. Using bilateral data on US trade in services by sector, our identification strategy exploits variation over time in a measure of AI adoption by sector. The focus on the US is especially interesting for two reasons. First, AI was invented in the US and adoption picked up already at a meaningful scale across a range of sectors (Bonfiglioli, Crino, Gancia, and Papadakis, 2025; Bloom, Hassan, Kalyani, Lerner, and Tahoun, 2021; Bastos, Stapleton, Taglioni, and Wei, 2024). Second, the US economy is highly specialized in services, is a major services exporter, and is also a major importer of services from both developed and developing countries.

To guide the empirical analysis, we draw on the theoretical framework of Artuc, Bastos, and Rijkers (2023), who examine the effects of automation on international trade in the context of a Ricardian trade model with two-stage production.[1] In the model, AI can take over some tasks previously performed by humans in the production of both intermediate and final services. The range of tasks that may be performed by AI varies across sectors. The industry-specific automation frontier, relative factor prices and productivity determine the extent of AI use within sectors. Production of each final variety further requires a composite intermediate services from the same industry. In equilibrium, varieties of intermediate and final services are sourced from the country that supplies at the lowest price. Therefore, there are two layers of competition: (1) between AI and workers in factor markets; and (2) between countries in sector-specific product markets for inputs and outputs. Relative production costs (driven by factor prices and technology) determine country-specific patterns of AI adoption and and trade. An increase in the AI adoption (driven either by lower cost of adopting AI or lower AI input requirements) initially induces adoption in the US, where the cost of labor is relatively higher to begin with.

[1] Although the model was developed to examine the effects of robotization on trade in goods, it can be reinterpreted and applied to examine effects of AI on international trade in services.

This impacts relative production costs between countries, and therefore trade patterns. AI replaces domestic workers within sectors, leading to lower costs of production in the US, and hence to an increase in exports to the other countries. The effect of AI adoption in the US on imports sourced from lower income countries in the same sector is theoretically ambiguous. On the one hand, AI adoption makes US producers more competitive, which implies that some services that were previously sourced from lower-income countries are now sourced domestically. On the other hand, AI adoption leads to an expansion in the scale of production, which raises the demand for tasks embodied in services that continue to be sourced from other countries.

Results from OLS regressions (including country-year and sector fixed effects) reveal that US services sectors experiencing an increase in AI adoption tended to observe a faster increase in exports. These effects are observed in exports to both developed and developing economies, consistent with a stronger comparative advantage of the US in these sectors, resulting from enhanced productivity associated with AI adoption. The results reveal no evidence of a negative effect of AI adoption on services imports, suggesting that AI adoption in the US is not systematically replacing services sourced from other countries. In fact, the OLS estimates point to a positive effect of AI adoption on services imports.

However, there are reasons to worry that these relationships reflect various forms of endogeneity. Adoption of AI may in part be a response to changing trade patterns, for instance due to competition or scale effects. To account for this possibility, as well as biases associated with omitted variables and measurement error, we implement an instrumental variable strategy exploiting variation in the exposure to AI across sectors and over time. In particular, we use the interaction between the (time invariant) occupational exposure to AI in each sector and the US nationwide AI adoption as instrument for sectoral AI adoption. This instrument is intended to capture the interplay between (i) reductions in the cost of adopting AI; and (ii) the feasibility of AI use in each sector. For exports, the IV results confirm the message from the OLS estimates. We observe a positive and strongly significant causal effect of AI adoption on services exports. The effects on imports are statistically insignificant. Our results also hold in alternative specifications exploiting variation over 5- or 7-year intervals, and are robust to excluding the years of the COVID pandemic. The absence of significant IV estimates on imports is consistent with the theoretical model of Artuc, Bastos, and Rijkers (2023). All else being equal, the increase in production associated with AI adoption contributes to an increase in imports of intermediate services, which tends to offset potential substitution effects of AI adoption on tasks embodied in services sourced from other countries.

In addition to the papers cited above, this paper relates to several strands of existing re-

search. A small body of recent research examined whether AI impacts offshoring of services jobs. Stapleton and O'Kane (2021) use data on online job postings and services trade for UK firms to explore how the deployment of Machine Learning in the UK has affected services offshoring to lower-income countries. The study constructs detailed measures of the demand for Machine Learning (ML) skills in UK firms using a dataset of the near universe of job adverts posted online in the UK between 2012 and 2017. By exploiting technical advances in the task-specific capabilities of ML over time, which have affected some occupations relatively more than others, they show that ML deployment has led to an increase in services offshoring, particularly to lower-income countries, rather than high-income countries. This increase has mainly been in ICT-related and Business and Professional Services and India has been the main beneficiary country. In related ongoing work, Betai and Chen (2024) examine whether and how the introduction of generative AI impacted international services outsourcing in online labor marketplaces. They collect detailed micro-task transaction data by following 7,000 workers before and after the introduction of generative AI, and construct a skill-specific measure of generative AI exposure in order to examine ChatGPT's effects on outsourcing across skills. They find that the introduction of ChatGPT reduced volume and value of international service outsourcing in online labor market places, lowered the number of workers in exposed tasks, and increased work concentration among top-performing workers. At the disaggregated worker level, they find that the introduction of generative AI led to increased worker specialization in complex and time-intensive tasks, as well as entry into new, related skill areas. Using more comprehensive data on US trade in services, which is not restricted to online labor markets, our paper complements this literature by examining how AI adoption impacted overall levels of international trade in services with various countries.

Our approach for measuring AI adoption across sectors over time builds on the proxy proposed by Bonfiglioli, Crino, Gancia, and Papadakis (2025), which relies on the share of employment in occupations that are related to AI adoption within each sector (relative to total employment in the sector). They use this measure to estimate the effect of AI on employment across US commuting zones over the period 2000–2020. Using a shift-share instrument that combines industry-level AI adoption with local industry employment, they estimate robust negative effects of AI exposure on employment across CZs and time. They find that AI's works through services more than manufacturing. Moreover, the employment effect is especially negative for low-skill and production workers, while it turns positive for workers at the top of the wage distribution and for those in STEM occupations. Our empirical analysis adopts this measure of adoption, along with the sector's exposure to AI, drawing on the measure proposed by Felten,

Raj, and Seamans (2021). This methodology isolates the exposure to specific functions of AI at the occupation level by looking at the abilities used within an occupation. As in Felten, Raj, and Seamans (2021), we construct the sector-level measure of AI exposure by aggregating the AIOE across occupations within an industry, notably by taking the weighted average of the AIOE using 2019 industry employment employment data by occupation-industry. The interaction between nationwide AI adoption and occupational exposure across services sectors enables us to predict sector-level AI adoption and examine its causal effects on services exports and imports.[2]

Finally, our paper is related to the literature on how other automation technologies impact international trade in goods. Artuc, Bastos, and Rijkers (2023) examine how increased robotization of manufacturing production in developed countries impacts trade patterns with less developed countries. The empirical analysis exploits variation in exposure to robots across countries and sectors, and reveals that greater robot intensity in Northern production leads to a rise in imports sourced from less developed countries in the same industry (especially of intermediate goods), and to an even stronger increase in exports to those countries. Other related studies have examined the relationship between robot adoption and reshoring in manufacturing. Using industry level data with global coverage, Krenz, Prettner, and Strulik (2018) document that robot adoption is associated with increased reshoring. Yet, Stapleton and Webb (2020) analyze detailed firm-level data from Spain and show that robot adoption by firms had a positive impact on their imports from, and number of affiliates in, lower-income countries. In a related study, Wang (2021) finds that robot adoption by US manufacturing firms led to an increase in sales, productivity and imports, especially of inputs. In all, this evidence does not support the hypothesis that automation of production in developed countries induced reshoring of production away from developing countries. Focusing on AI and US services trade, we also find no evidence that AI adoption led to systematic reshoring of services sourced from either developed or developing countries.

The remainder of the paper is organized as follows. Section 2 describes the sources of data used in the paper, as well as the measures of adoption and exposure to AI. Section 3 explains the econometric methodology for estimating the effects of changes in a sector's AI adoption and exposure on services trade. Section 4 presents descriptive statistics on AI adoption and exposure, as well as on services trade. Section 5 presents and discusses the econometric results.

[2]Our paper is also related to the work of Brynjolfsson, Hui, and Liu (2019), who provide evidence that the introduction of machine translation from English to Spanish by eBay has significantly boosted international trade between the United States and Latin America on this platform, increasing exports by 17.5 percent. These effects reflect a reduction in translation-related search costs and demonstrate that AI has already begun to boost trade in North and South America. The empirical results further suggests that consumers benefit more than sellers because they gain both from reduced language frictions and lower prices.

Section 6 concludes the paper.

2 Data

The empirical analysis in this paper exploits and combines several sources of data, notably data on international trade flows in services in the United States by country and sector over the period 2011-2024.

2.1 International trade flows in services in the United States

We use data on bilateral exports and imports of services by sector from the United States Bureau of Economic Analysis (BEA). These services statistics are estimates of services transactions between foreign countries and the 50 states, the District of Columbia, Puerto Rico, the U.S. Virgin Islands, and other U.S. territories and possessions. Services trade calculations are based on quarterly, annual, and benchmark surveys and information obtained from monthly government and industry reports. Services trade data are available for eight broad sectors: (1) Maintenance and repair services (not included elsewhere); (2) Transport and travel (for all purposes including education); (3) Insurance services; (4) Financial services; (5) Charges for the use of intellectual property; (6) Telecommunications, computer, and information services; (7) Other business services; and (8) Personal, cultural, and recreational services. These bilateral sectoral-level data are available for trade with 78 countries/regions, as described in Table A1 in the Appendix, over the period 2011-2024.

2.2 Measuring varying AI adoption within sectors

To measure AI adoption within sectors in the United States, we build on the proxy proposed by Bonfiglioli, Crino, Gancia, and Papadakis (2025), which relies on the share of employment in occupations that are related to AI adoption within each sector (relative to total employment in the sector).

The premise behind this approach is that adopting AI technologies demands a wide spectrum of specialized software, which is essential for a firm to: execute existing machine learning algorithms; combine and adapt these algorithms to solve complex problems specific to the needs of the firm; generate, update and assemble the input datasets in real time; and train the algorithms and govern their learning process. Operating this specialized software requires a specific set of skills that are primarily possessed by professionals engaged in a narrow range of occupations in

the domain of computer science, statistics and operations research. These occupations comprise 19 titles and are displayed in Table A3 in the Appendix.

To identify these 19 AI-related occupations, Bonfiglioli, Crino, Gancia, and Papadakis (2025) draw on a novel section of the O*NET database called "Hot Technologies", which reports the 157 software requirements that are most commonly included in all current employer job postings in the United States. With the help of computer scientists, Bonfiglioli, Crino, Gancia, and Papadakis (2025) narrowed down the list to 54 software that are normally used for data collection and generation; for execution and adaption of machine learning algorithms; and to feed algorithms with large datasets. Using O*NET, they then identified occupations for which each software is in demand, and imposed two additional restrictions: first, restricted to occupations for which at least two software are "in demand"; second, limited to occupations that require skills falling within the typical domains of AI. This was achieved by combining occupational definitions from the SOC with the official crosswalks between the SOC and the classification of Instructional Programs, as provided by the National Center for Education Statistics of the US Department of Education, which made it possible to identify occupations with non-administrative, supportive or educational roles, whose required skills are provided by academic programmers in computer and information sciences and support activities, mathematics and statistics, and operations research.

2.3 Measuring sectors' exposure to AI

To quantify a sector's exposure to AI in the US, we draw on the measure of an occupation's exposure to AI (AIOE) proposed by Felten, Raj, and Seamans (2021). This methodology isolates the exposure to specific functions of AI at the occupation level by looking at the abilities used within an occupation. Felten, Raj, and Seamans (2021) first linked common AI applications to occupational abilities using a crowd-sourced data set, notably the Electronic Frontier Foundation (EFF) AI Progress Measurement project. The measure focuses on selected AI applications: abstract strategy games, real-time video games, image recognition, reading comprehension, language modeling, translation, speech recognition, and instrumental track recognition. They then aggregate at the ability-level in order to construct a measure that identifies the potential exposure of occupations to AI, drawing on data on occupational abilities from the Occupational Information Network (O*NET) database developed by the US Department of Labor. The resulting AIOE measure thus links specific applications of AI to occupational abilities, thus capturing the degree of occupational exposure to AI, but is agnostic as to whether AI substitutes for or complements workplace abilities and occupations.

As in Felten, Raj, and Seamans (2021), we construct the sector-level measure of AI exposure by aggregating the AIOE across occupations within an industry, notably by taking the weighted average of the AIOE using 2019 industry employment data by occupation-industry. The sector classification is based on the NAICS sector classification, which is made compatible with the sectoral classification used in the BEA services trade statistics (see Table A4 in the Appendix). This measure allows us to identify which sectors have the most exposure to AI. We also construct a nation-wide measure of adoption using a similar approach.

3 Empirical methodology

In this section, we describe the econometric strategy for examining whether and how the adoption of AI in the US impacted services trade flows with other partners across sectors. We adopt the following baseline econometric specification:

$$Trade_{scp} = \beta Adoption_{sp} + \gamma_{cp} + \lambda_s + \epsilon \tag{1}$$

where $Trade_{scp}$ denotes the log of (1+ exports) from the US to country c in sector s in period p, or alternatively the log of (1+imports) sourced by the US from country c in sector s in period p; $Adoption_{sp}$ denotes the measure of AI adoption in the US in sector s in period p; γ_{cp} is an importing country by period fixed effect; λ_s is a sector fixed effect; and ϵ is the error term. We therefore account for importer-period specific effects that might impact trade and/or AI adoption (such as distance, having a common language, population, income and exchange rates), as well as industry fixed effects to account for factors that are specific to each sector in each period. Standard errors are clustered by importing country.

An important concern is that AI adoption is potentially endogenous. It may be a response to, rather than a cause of, changing patterns of trade in services. For example, increased import competition may influence the decisions of US producers to use AI (Bloom, Draca, and Van Reenen, 2016; Autor, Dorn, Hanson, Pisano, and Shu, 2020). The consequences of increased exports for technology adoption are also ambiguous. Although a body of evidence suggests that exporting has positive effects on technology adoption (Lileeva and Trefler, 2010; Bustos, 2011; Atkin, Khandelwal, and Osman, 2017), a related strand of work suggests that such effects may depend on the income level of export destinations. In particular, exporting to less developed countries might lead to an expansion of less technology-intensive lines of production within firms (Verhoogen, 2008; Bastos and Silva, 2010; Bastos, Silva, and Verhoogen, 2018).

To account for this possibility of reverse causality in the relationship between AI adoption

and trade in services, as well as biases caused by omitted variables or measurement error, we adopt an instrumental variables approach exploiting variation in exposure to AI across sectors. In particular, we use the interaction between the (time invariant) occupational exposure to AI in each sector and the US nationwide AI adoption as instrument for sectoral AI adoption. This instrument is intended to capture the interplay between (i) reductions in AI prices (or in the AI unit requirements in production); and (ii) the feasibility of AI use in each sector. The measure of nationwide AI adoption in the US varies over time and proxies for AI prices (or capacity/quality). The occupational exposure measure ($Exposure_s$) is an employment-weighted measure of occupations exposure to AI in sector s. It varies across sectors and captures the feasibility of using AI in each sector to perform tasks previously performed by workers in each sector.

4 Descriptive statistics

In this section, we present descriptive statistics on the level and evolution of the main variables of interest over the period of analysis. Figure 1 displays the variation of the employment-weighted measure of AI exposure across sectors in the United States. As discussed above, this sector-level measure of AI exposure results from the aggregation of the AIOE across occupations within an industry, notably by taking the weighted average of the AIOE using 2019 industry employment employment data by occupation-industry. This measure allows us to identify which sectors have the most exposure to AI, but is agnostic as to whether AI substitutes for or complements workplace abilities and occupations. Figure 1 reveals that the sectors with higher exposure to AI are "Insurance services", followed closely by "Financial services". Exposure levels are also relatively high in "Telecommunication, computer and information services", and in "Personal, cultural and recreational services". By contrast, exposure to AI is the lowest in "Maintenance and repair Services", "Transport and travel" and "Construction services".

Figure 2 depicts the evolution of the measure of AI adoption in the US over the years 2011, 2017 and 2024. As discussed above, this measure follows that proposed by Bonfiglioli, Crino, Gancia, and Papadakis (2025), which relies on the share of employment in occupations that are related to AI adoption (relative to total employment). We observe a progressive increase in AI adoption over the period of analysis, moving from a share of employment of about 0.024 in 2011 to 0.041 in 2017, and 0.06 in 2024. Figure 3 shows the level and the growth in AI adoption has been concentrated in a few sectors. Adoption is highest in "Telecommunication, computer and information services" (with an employment share of AI-related occupations above 0.1), followed

by "Other business services", "Insurance services" and "Financial services". From a dynamic perspective, growth in AI adoption was most pronounced in "Telecommunication, computer and information services", but was also observed in all other sectors that already had a relatively high adoption in 2011, notably: "Other business services"; "Insurance services"; and "Financial Services". By contrast, AI adoption increased relatively little in sectors that had relatively low adoption of AI in the base period: "Transport and Travel"; "Construction"; "Maintenance and repair"; and "Personal, cultural and recreational services."

Turning to international trade in services in the United States, Figure 4 displays the evolution of (the log of) total services exports and imports over the period 2011-2024. We observe that exports were always above imports in all years, and increased relatively steadily over the period 2011-2024, with exception of the fall observed in 2020 caused by the COVID pandemic. As is standard in the literature on automation and trade, we will examine the robustness of our results to excluding the years of the pandemic, and we will also consider variation over longer time horizons in order to focus on longer-term structural trends and avoid contamination from business cycle fluctuations.

Figures 5 and 6 show the level and evolution of services exports and imports across sectors over 2011, 2017 and 2024. Figure 5 reveals that services exports are relatively higher in "Transport and Travel", "Financial services" and "Telecommunication, computer and information services". From a dynamic perspective, exports growth was most clearly observed in "Financial Services"; "Insurance services"; "Telecommunication, computer and information services" and "Other business services". With regard to imports, they were greatest in "Transport and Travel" and "Other business services", but also relatively high in "Financial services" and "Telecommunication, computer and information services". From a dynamic perspective, growth in services imports was most clearly observed in "Other business services" and "Personal, Cultural and Recreational Services."

5 Econometric Results

In this section, we report the econometric results yielded by the estimation of equation (1). We first present results for the full sample. Then we examine heterogeneity across source countries (OECD versus non-OECD). Finally, we examine the extent to which the results are robust to an alternative choice of periods.

5.1 Main results

Table 1 reports the baselines estimates for the full sample over the years 2011-2024. In columns (1) and (2) we report the OLS estimates (including country-year and sector fixed effects) on the effects of AI adoption on exports and imports, respectively. Column (1) reveals that increased adoption of AI within services sectors in the US leads to a significant increase in exports in that sector. These results are consistent with a stronger comparative advantage of the US in these sectors. In particular, the use of AI to perform tasks previously performed by workers, or that complement tasks perform by workers, leads to increases in productivity and thus to an increase in specialization and exports in these sectors. The results in column (2) reveal no evidence of a negative effect of AI adoption on services imports, suggesting that AI adoption in the US is not systematically replacing services sourced from other countries. In fact, the OLS estimates point to a positive effect of AI adoption on services imports.

However, there are reasons to worry that these relationships reflect various forms of endogeneity. Adoption of AI may in part be a response to changing trade patterns. To account for this possibility, as well as biases associated with omitted variables and measurement error, in columns (3) and (4) we implement an instrumental variable strategy exploiting variation in the exposure to AI across sectors and over time. In particular, we use the interaction between the (time invariant) occupational exposure to AI in each sector and the US nationwide AI adoption as instrument for sectoral AI adoption. As would be expected, the first stage coefficient is positive and highly significant and the Kleibergen-Paap rk Wald F-statistic shows the instrument is quite strong.

For exports, the IV results reported in column (3) confirm the message from the OLS estimates. We observe a positive and strongly significant causal effect of AI adoption on services exports. For imports, however, the IV estimates reported in column (4) are also positive but statistically insignificant. The absence of significant IV estimates on imports is consistent with the theoretical model of Artuc, Bastos, and Rijkers (2023). All else being equal, the increase in production associated with AI adoption contributes to an increase in the imports of intermediate services that continue to be sourced from other countries. This scale effect tends to offset potential substitution effects of AI adoption on tasks embodied in services imports.

5.2 Heterogeneity across countries

The theoretical channels discussed above might be expected to differ across countries. While the effects of AI adoption on exports would be expected to be unambiguously positive, the effects

on imports are ambiguous and hence could differ across countries. For example, if AI replaces systematically tasks previously performed by high-skill workers in developed countries, then the effects on imports sourced from those countries might be negative. At the same time, if AI performs tasks previously sourced from workers in low-income countries, such as call centers in India or the Philippines, then the effects on imports might be negative for developing countries.

In Table 2 we re-estimate the baseline specification but restricting the sample of US trading partners to OECD countries. Interestingly, the econometric results for this sub-sample of US trading partners are qualitatively similar to the baseline estimates. The IV estimates in column (3) suggest there is a positive effect of AI adoption on exports of services to OECD countries. The estimates in column (4) point to a positive but insignificant effect of AI adoption on imports sourced from OECD countries. In all, the results for OECD countries argue against the hypothesis of strong substitution effects of AI adoption on imports of services sourced from developed countries.

In Table 3, we turn to the sample of non-OECD countries. For exports, the estimates for this sub-sample of US trading partners are again qualitatively similar to the baseline estimates. The IV estimates reported in column (3) indicate a positive effect of AI adoption on exports of services to non-OECD countries. The estimates in column (4) show no evidence of a systematic effect of AI adoption on imports sourced from developing countries, arguing against the hypothesis of strong substitution effects of AI adoption on imports of services sourced from these countries.

5.3 Robustness to alternative choice of periods

In line with Artuc, Bastos, and Rijkers (2023), we have adopted a baseline specification using yearly data (including country-year and industry effects). In this section, we consider if the results are robust to excluding the years of the COVID pandemic, or when considering variation over longer time horizons. This makes it possible to focus on longer term trends and reduce the importance of year-to-year fluctuations in trade flows and AI adoption that might be driven by (or at least correlated with) other factors.

In Table 4, we continue to consider yearly data for the period 2011-2024 but exclude from the sample the years of the COVID pandemic (2020-2022). We observe in this table that the baseline results remain qualitatively similar. In Tables 5 and 6, we examine further the extent to which the results are robust to considering variation over longer time horizons. In Table 5 we consider variation between five-year intervals (notably between 2011, 2015, 2020 and 2024). In turn, in Table 6, we consider variation over seven-year intervals (notably between the years 2011, 2017 and 2024). As can be seen, the main qualitative findings hold under these alternative

time periods.

6 Conclusion

In this paper, we empirically examine if and how the growing adoption of AI in the United States impacted international trade in services over the period 2011-2024. Using bilateral data on US trade in services by sector, our identification strategy exploits variation over time in a measure of AI adoption by sector. The focus on the US is especially interesting for two reasons. First, AI was invented in the US and adoption picked up already at a meaningful scale across a range of sectors. Second, the US economy is highly specialized in services, is a major services exporter, and is also a major importer of services from both developed and developing countries.

Results from OLS regressions (including country-year and sector fixed effects) reveal that U.S. services sectors experiencing an increase in AI adoption tended to observe a faster increase in exports. These effects are observed in exports to both developed and developing economies, consistent with a stronger comparative advantage of the US in these sectors, reflecting enhanced productivity associated with AI adoption. Interestingly, however, the results do not provide evidence of a systematic negative effect of AI adoption on services imports, suggesting that AI adoption in the US is not systematically replacing services sourced from other countries. In fact, the OLS estimates point to a positive effect of AI adoption on services imports.

There are, however, reasons to be concerned that the OLS estimates reflect various forms of endogeneity. Adoption of AI may in part be a response to changing trade patterns, for instance due to competition or scale effects. To account for this possibility, as well as biases associated with omitted variables and measurement error, we implement an instrumental variable strategy exploiting variation in the exposure to AI across sectors and over time. Specifically, we use the interaction between the (time invariant) occupational exposure to AI in each sector and the US nationwide AI adoption as instrument for sectoral AI adoption. This instrument is intended to capture the interplay between (i) reductions in the cost of adopting AI; and (ii) the feasibility of AI use in each sector. For exports, the IV results confirm the message from the OLS estimates. We observe a positive and strongly significant causal effect of AI adoption on services exports. In contrast, the effects on imports are statistically insignificant. Our results also hold in alternative specifications exploiting variation over 5- or 7-year intervals, and are robust to excluding the years of the COVID pandemic. The absence of significant IV estimates on imports is consistent with the theoretical model of Artuc, Bastos, and Rijkers (2023). All else equal, the increase in production associated with AI adoption contributes to an increase in services imports, which

tends to offset potential substitution effects of AI adoption on tasks embodied in services sourced from other countries.

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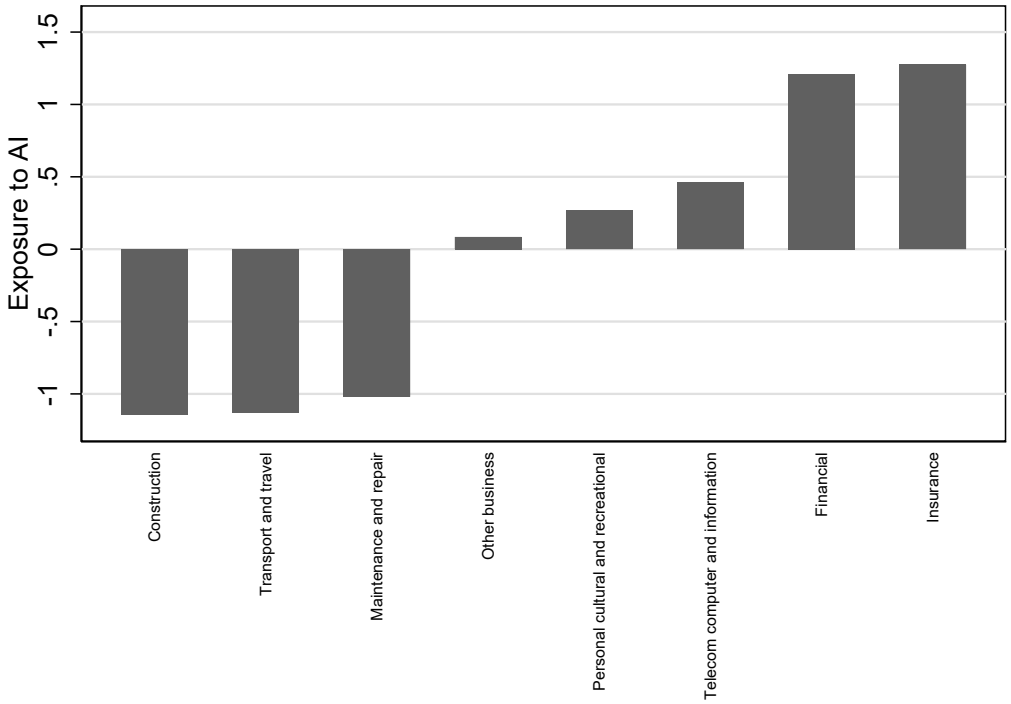
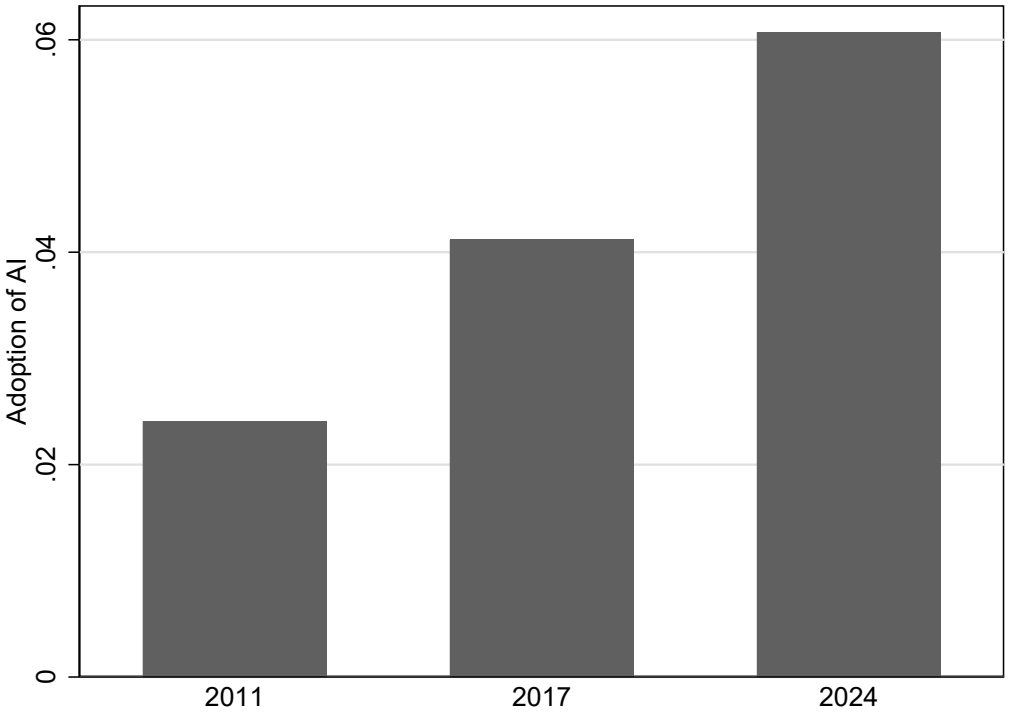
Figure 1: Exposure of occupations to Artificial Intelligence across sectors in the US



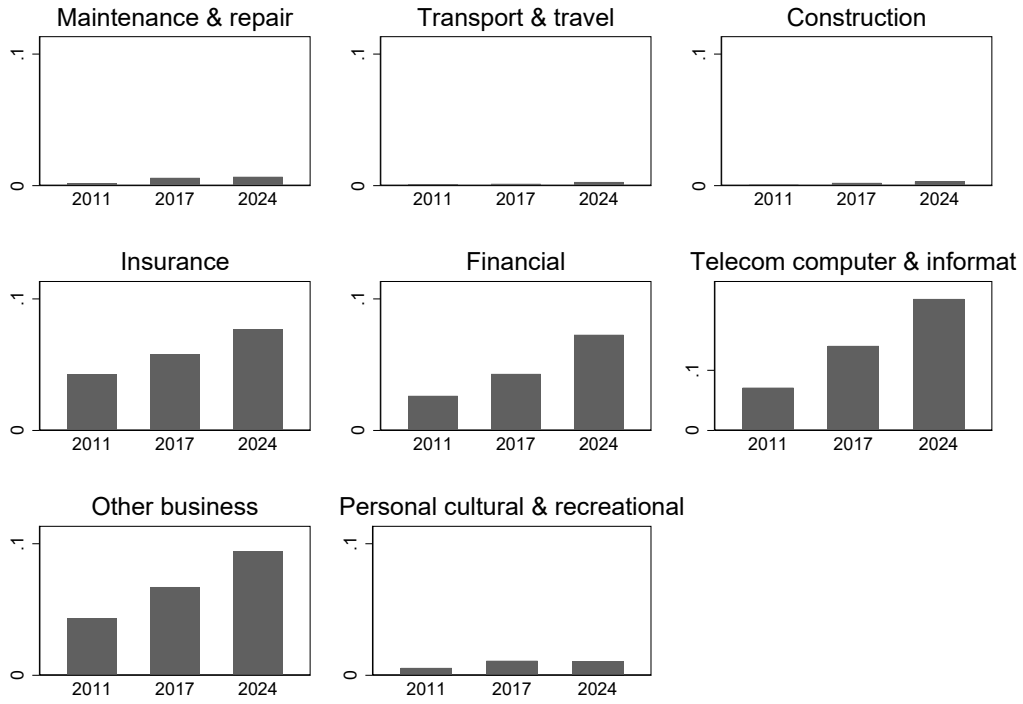
Notes: Figure depicts an employment-weighted measure of the exposure to AI across sectors in the United States, based on the methodology of Felten, Raj, and Seamans (2021).

Figure 2: Adoption of Artificial Intelligence over time in the US, 2011-2024



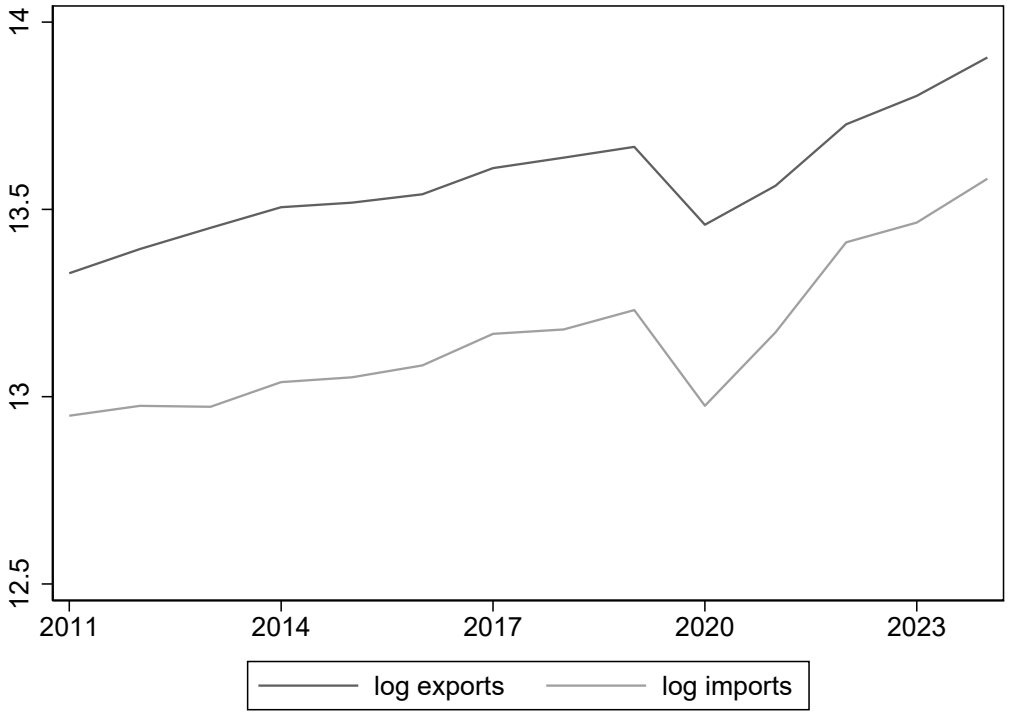
Notes: Figure depicts the evolution of the measure of adoption of Artificial Intelligence proposed by Bonfiglioli, Crino, Gancia, and Papadakis (2025) across services sectors in the United States over the period 2011-2024.

Figure 3: Adoption of Artificial Intelligence over time and across sectors in the US, 2011-2024



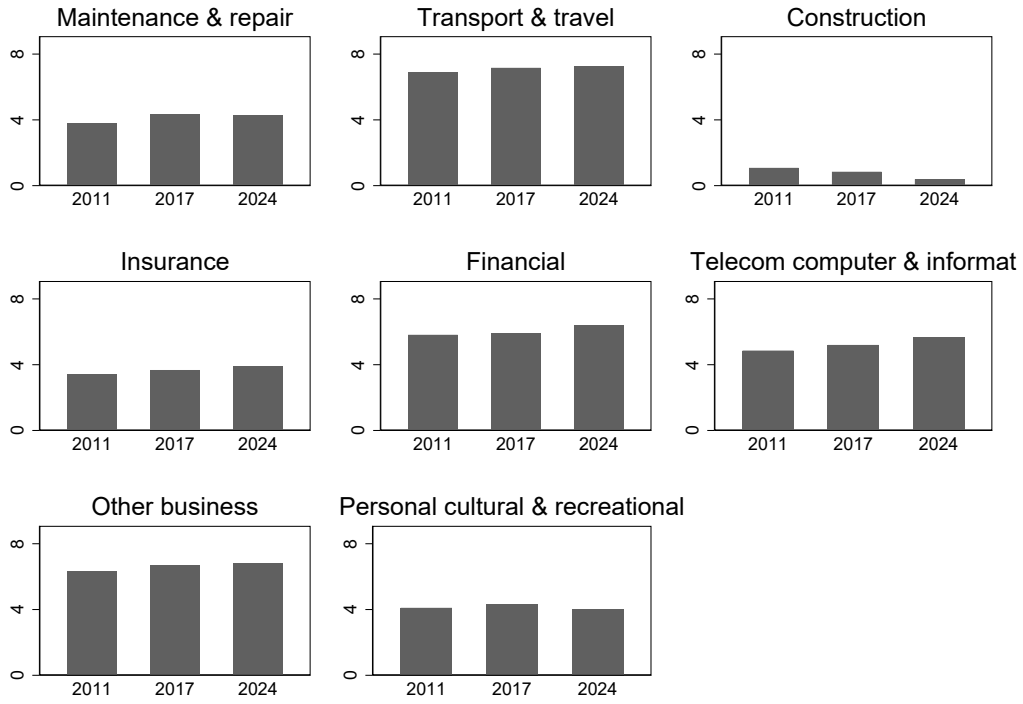
Notes: Figure depicts the evolution of the measure of adoption of Artificial Intelligence proposed by Bonfiglioli, Crino, Gancia, and Papadakis (2025) in each services sector in the United States over the period 2011-2024.

Figure 4: International Trade in Services in the US, 2011-2024



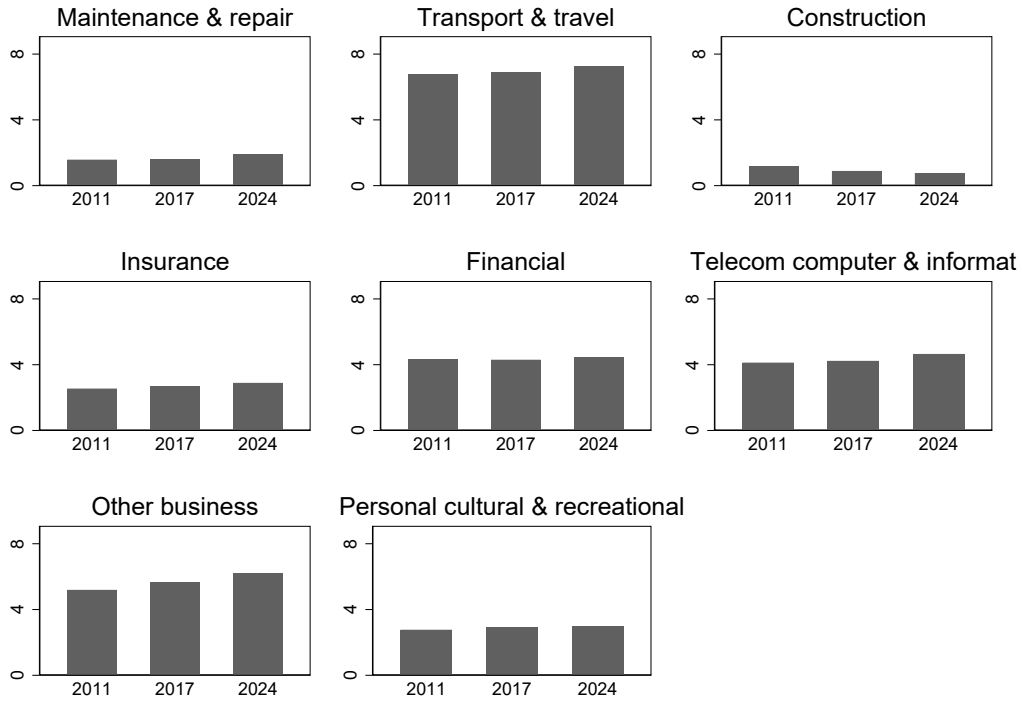
Notes: Figure depicts the evolution of services exports and imports in the United States over the period 2011-2024.

Figure 5: Services exports across sectors in the US, 2011-2024



Notes: Figure depicts the evolution of services exports across sectors in the United States over the period 2011-2024.

Figure 6: Services imports across sectors in the US, 2011-2024



Notes: Figure depicts the evolution of services imports across sectors in the United States over the period 2011-2024.

Table 1: The impact of AI on US trade in services, 2011-2024

	OLS		IV	
	log(1+exp)	log(1+imp)	log(1+exp)	log(1+imp)
	(1)	(2)	(3)	(4)
Adoption	3.8691***	2.1327**	7.6065***	1.0597
	(0.7497)	(1.0684)	(1.2581)	(2.1284)
First Stage:				
National adoption * exposure			0.0270***	0.0270***
			(0.0000)	(0.0000)
Observations	8,736	8,736	8,736	8,736
R^2	0.8440	0.7638		
Kleibergen-Paap rk Wald F-stat			78.0	78.0
Importer-year effects	Y	Y	Y	Y
Sector effects	Y	Y	Y	Y

Notes: Table reports OLS and IV results of equation (1) in text, using the baseline estimation sample. Columns (1)-(2) report the OLS results, while columns (3)-(4) report the IV and corresponding first stage estimates. Robust standard errors clustered by importing country are presented in parentheses. ***1% level, **5% level, *10% level.

Table 2: The impact of AI on US trade in services, OECD partners, 2011-2024

	OLS		IV	
	log(1+exp)	log(1+imp)	log(1+exp)	log(1+imp)
	(1)	(2)	(3)	(4)
Adoption	5.0474***	3.8887***	4.7603***	2.7170
	(0.8241)	(1.2323)	(1.6696)	(3.1668)
First Stage:				
National adoption * exposure			0.0270***	0.0270***
			(0.0000)	(0.0000)
Observations	3,920	3,920	3,920	3,920
R^2	0.8958	0.8349		
Kleibergen-Paap rk Wald F-stat			35.0	35.0
Importer-year effects	Y	Y	Y	Y
Sector effects	Y	Y	Y	Y

Notes: Table reports OLS and IV results of equation (1) in text, using the estimation sample for trade with OECD countries. Columns (1)-(2) report the OLS results, while columns (3)-(4) report the IV and corresponding first stage estimates. Robust standard errors clustered by importing country are presented in parentheses. ***1% level, **5% level, *10% level.

Table 3: The impact of AI on US trade in services, non-OECD partners, 2011-2024

	OLS		IV	
	log(1+exp)	log(1+imp)	log(1+exp)	log(1+imp)
	(1)	(2)	(3)	(4)
Adoption	2.9101**	0.7034	9.9230***	-0.2892
	(1.1476)	(1.6408)	(1.7755)	(2.8972)
First Stage:				
National adoption * exposure			0.0270***	0.0270***
			(0.0000)	(0.0000)
Observations	4,816	4,816	4,816	4,816
R^2	0.7975	0.6914		
Kleibergen-Paap rk Wald F-stat			43.0	43.0
Importer-year effects	Y	Y	Y	Y
Sector effects	Y	Y	Y	Y

Notes: Table reports OLS and IV results of equation (1) in text, using the estimation sample for trade with non-OECD countries. Columns (1)-(2) report the OLS results, while columns (3)-(4) report the IV and corresponding first stage estimates. Robust standard errors clustered by importing country are presented in parentheses. ***1% level, **5% level, *10% level.

Table 4: The impact of AI on US trade in services, excluding COVID, 2011-2024 (except 2020-2022)

	OLS		IV	
	log(1+exp)	log(1+imp)	log(1+exp)	log(1+imp)
	(1)	(2)	(3)	(4)
Adoption	5.7317***	2.8759**	9.3155***	2.6302
	(0.9692)	(1.3951)	(1.6520)	(2.3570)
First Stage:				
National adoption * exposure			0.0246***	0.0246***
			(0.0000)	(0.0000)
Observations	6,864	6,864	6,864	6,864
R^2	0.8418	0.7743		
Kleibergen-Paap rk Wald F-stat			78.0	78.0
Importer-year effects	Y	Y	Y	Y
Sector effects	Y	Y	Y	Y

Notes: Table reports OLS and IV results of equation (1) in text, using the baseline estimation sample, but excluding the years 2020-2022. Columns (1)-(2) report the OLS results, while columns (3)-(4) report the IV and corresponding first stage estimates. Robust standard errors clustered by importing country are presented in parentheses. ***1% level, **5% level, *10% level.

Table 5: The impact of AI on US trade in services, variation over 5-year periods, 2011-2024

	OLS		IV	
	log(1+exp)	log(1+imp)	log(1+exp)	log(1+imp)
	(1)	(2)	(3)	(4)
Adoption	4.5022***	2.7526	5.1242***	-0.0768
	(1.1513)	(1.6848)	(1.9019)	(2.3766)
First Stage:				
National adoption * exposure			0.0243***	0.0243***
			(0.0000)	(0.0000)
Observations	2,496	2,496	2,496	2,496
R^2	0.834	0.7578		
Kleibergen-Paap rk Wald F-stat			78.0	78.0
Importer-year effects	Y	Y	Y	Y
Sector effects	Y	Y	Y	Y

Notes: Table reports OLS and IV results of equation (1) in text, using the estimation sample for the years 2011, 2015, 2020 and 2024. Columns (1)-(2) report the OLS results, while columns (3)-(4) report the IV and corresponding first stage estimates. Robust standard errors clustered by importing country are presented in parentheses. ***1% level, **5% level, *10% level.

Table 6: The impact of AI on US trade in services, variation over 7-year periods, 2011-2024

	OLS		IV	
	log(1+exp)	log(1+imp)	log(1+exp)	log(1+imp)
	(1)	(2)	(3)	(4)
Adoption	5.9775***	3.1415*	9.0790***	3.6241
	(1.1738)	(1.7359)	(2.1599)	(2.6106)
First Stage:				
National adoption * exposure			0.0232***	0.0232***
			(0.0000)	(0.0000)
Observations	1,872	1,872	1,872	1,872
R^2	0.8351	0.7755		
Kleibergen-Paap rk Wald F-stat			78.0	78.0
Importer-year effects	Y	Y	Y	Y
Sector effects	Y	Y	Y	Y

Notes: Table reports OLS and IV results of equation (1) in text, using the estimation sample for the years 2011, 2017, and 2024. Columns (1)-(2) report the OLS results, while columns (3)-(4) report the IV and corresponding first stage estimates. Robust standard errors clustered by importing country are presented in parentheses. ***1% level, **5% level, *10% level.

A.1 Appendix Tables

Table A1: Countries and regions included the in the sample of US partners of trade in services

Country code	Country name	Region	OECD member
2	Canada	NA	Yes
4	Austria	ECA	Yes
5	Belgium	ECA	Yes
6	Bulgaria	ECA	No
7	Croatia	ECA	No
8	Cyprus	ECA	No
9	Czech Republic	ECA	Yes
10	Denmark	ECA	Yes
11	Estonia	ECA	Yes
12	Finland	ECA	Yes
13	France	ECA	Yes
14	Germany	ECA	Yes
15	Greece	ECA	Yes
16	Hungary	ECA	Yes
17	Ireland	ECA	Yes
18	Italy	ECA	Yes
19	Latvia	ECA	Yes
20	Lithuania	ECA	Yes
21	Luxembourg	ECA	Yes
22	Malta	ECA	No
23	Netherlands	ECA	Yes
24	Norway	ECA	Yes
25	Poland	ECA	Yes
26	Portugal	ECA	Yes
27	Romania	ECA	No
28	Russia	ECA	No
29	Slovakia	ECA	Yes
30	Slovenia	ECA	Yes
31	Spain	ECA	Yes
32	Sweden	ECA	No
33	Switzerland	ECA	Yes
34	Turkey	AME	Yes
35	United Kingdom	ECA	Yes
36	Other Europe	ECA	No
39	Argentina	LAC	No
40	Brazil	LAC	No

Notes: Table displays the countries and regions available in the BEA trade in services database. The regions seek to approximate the World Bank's definition, and include North America (NA), Europe and Central Asia (ECA), African and Middle East (AME), Latin America and the Caribbean (LAC) and Asia and Pacific (EPA).

Table A2: Countries and regions included the in the sample of US partners of trade in services (continued)

Country code	Country name	Region	OECD member
41	Chile	LAC	Yes
42	Colombia	LAC	Yes
43	Costa Rica	LAC	Yes
44	El Salvador	LAC	No
45	Guatemala	LAC	No
46	Honduras	LAC	No
47	Mexico	LAC	Yes
48	Nicaragua	LAC	No
49	Panama	LAC	No
50	Peru	LAC	No
51	Venezuela	LAC	No
52	Other South and Central America	LAC	No
54	Bermuda	LAC	No
55	Dominican Republic	LAC	No
56	United Kingdom Islands, Caribbean	LAC	No
57	Other Western Hemisphere	LAC	No
59	Morocco	AME	No
60	Nigeria	AME	No
61	South Africa	AME	No
62	Other Africa	AME	No
64	Bahrain	AME	No
65	Israel	AME	Yes
66	Jordan	AME	No
67	Oman	AME	No
68	Saudi Arabia	AME	No
69	Other Middle East	AME	No
71	Australia	AP	Yes
72	Brunei	AP	No
73	China	AP	No
74	Hong Kong	AP	No
75	India	AP	No
76	Indonesia	AP	No
77	Japan	AP	Yes
78	Malaysia	AP	No
79	New Zealand	AP	Yes
80	Philippines	AP	No
81	Singapore	AP	No
82	South Korea	AP	Yes
83	Taiwan	AP	No
84	Thailand	AP	No
85	Vietnam	AP	No
86	Other Asia and Pacific	AP	No

Notes: Table displays the countries and regions available in the BEA trade in services database. The regions seek to approximate the World Bank's definition, and include North America (NA), Europe and Central Asia (ECA), African and Middle East (AME), Latin America and the Caribbean (LAC) and Asia and Pacific (EPA).

Table A3: Occupations used to measure AI adoption by sector in the United States

Occupation
Computer and Information Research Scientists
Computer Network Architects
Computer Network Support Specialists
Computer Occupations, All Other
Computer Programmers
Computer Systems Analysts
Computer User Support Specialists
Data Scientists
Database Administrators
Database Architects
Mathematicians
Network and Computer Systems Administrators
Operations Research Analysts
Software Developers
Software Quality Assurance Analysts and Testers
Statistical Assistants
Statisticians
Web and Digital Interface Designers
Web Developers

Notes: Table displays occupations used by Bonfiglioli, Crino, Gancia, and Papadakis (2025) to measure AI adoption in the United States. Occupations are classified according to the 6-digit level of the 2018 Standard Occupational Classification.

Table A4: Sectors included the econometric analysis

NAICS code	Sectors in services trade
811	Maintenance and repair services
48, 49	Transport and travel
23	Construction
524, 525	Insurance services
522, 523	Financial services
51	Telecommunications, computer, and information services
54, 55, 56, 812, 813	Other business services (including charges for intelectual property)
61, 62, 71	Personal, cultural, and recreational services

Notes: Table displays the NAICS codes of the employment statistics and the corresponding sectors in the BEA services trade data.