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Abstract: This paper analyzes the impacts of importing intermediate digital inputs (IDIs) on income inequality between high-skilled and low-skilled workers, using a novel dataset that merges recent EU KLEMS and OECD data for 29 countries and 15 industries for 2008-2020. We find that IDI imports significantly widen income inequality, because such imports are associated with higher technology and capital intensities, which directly increase income inequality by complementing high-skilled labor while substituting for low-skilled labor, and indirectly exacerbate inequality through workforce skill upgrading. Heterogeneity analysis shows that these occur primarily in highly digitalized countries and industries, as well as technology-intensive sectors. We also construct two shift-share instrumental variables, namely the global imported IDI shocks and the global digital export shocks, to address endogeneity.

Key Words: Imported intermediate digital input; income inequality; workforce skill upgrading
JEL Classification: F16, J31, O33

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1.Introduction

A new wave of technological change, driven by the diffusion of intermediate digital inputs (IDIs), is accelerating digital transformation across industries, thereby redefining production methods and workforce skill requirements, reshaping the labor market. The diffusion of these inputs, in addition to improving industry performance, profoundly reshapes the composition and demand for different skills within the labor force (Li and Liao, 2022). Inevitably, as industries increasingly rely on IDIs, understanding the implications for income distribution and workforce composition becomes essential.

This paper provides empirical evidence on how the adoption of IDIs influences industrial performance and labor market outcomes in the digital era. Importantly, we distinguish between imported and domestic IDIs, as imported IDIs enable countries to access frontier digital technologies through international exchange and diffusion. A fundamental reason for the reliance on imports is that substantial R&D investment required to develop advanced IDIs has concentrated in a few leading economies, creating a persistent technology gap. Currently, the top 2000 R&D firms are concentrated in the United Stated, China, Japan and Germany.[1] And, these top firms are at the forefront of digital technology development, holding approximately 75 percent of global ICT-related patents, 55 percent of ICT-related designs, and 75 percent of IP5 patent families related to artificial intelligence.[2]

Specifically, we first construct a novel dataset by merging recent data from the EU

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[1] The United States alone accounts for 42.1% of global corporate R&D expenditure, substantially exceeding the shares of China (17.8%), Japan (9.3%) and Germany (8.3%). Switzerland (3%) and the United Kingdom (2.9%) together account for a smaller share than Germany.

[2] https://www.oecd.org/content/dam/oecd/en/publications/reports/2017/11/oecd-science-technology-and-industry-scoreboard-2017_g1g74dc7/9789264268821-en.pdf.

KLEMS and OECD databases, covering 29 countries and 15 industries from 2008 to 2020. In our main analysis, we estimate the effect of imported IDIs on income inequality between high- and low-skilled workers, and find it to be significantly positive. To test whether this effect is specific to the digital nature of intermediate inputs, we also estimate the impact of imported non-digital intermediates (non-IDI) on the same inequality measures, and find it to be insignificant. The contrast is likely because imported IDIs contain more advanced digital technology than non-digital intermediate inputs, effectively representing technology spillover from more advanced countries. Our baseline results remain robust after a series of checks, including alternative measures of income inequality, changing the specification to a multi-level regression model, winsorizing the data, and using alternative base years in shift-share IVs.

To explore the causal mechanisms, we examine both the direct and indirect effects of importing IDIs on income inequality. Directly, we show that imported IDIs are more technology- and capital-intensive than their either domestic or non-IDI alternatives, enabling them to complement high-skilled labor while substituting for low-skilled labor, in turn raising wages for the former and depressing them for the latter; Indirectly, we find that the domestic access to imported IDIs is skill-biased, increasing the premium on skilled labor: the estimates indicate that a 1% increase in imported IDIs is associated with a 0.332% increase in the domestic skill ratio, suggesting that imported IDIs drive a notable shift toward higher-skilled labor. Thus, importing IDIs is not only a response to inadequate domestic technology, but also a strategy to acquire cutting-edge digital capabilities and rapidly enhance competitiveness. In contrast, domestic IDIs in non-frontier economies tend to be more aligned with existing local skills and conditions, and therefore have a more neutral effect on wage structures.

Next, to address potential endogeneity, we employ two instrumental variables (IVs) for imported IDIs, both derived using the shift-share approach (Goldsmith-Pinkham et al., 2020). The first IV is constructed by interacting the base-year country-industry share of IDI imports (exposure) with global industry-level growth in IDI imports (shock). The second IV is constructed by interacting global digital export growth with country-industry digital exposure.

Finally, we undertake heterogeneous analysis by exploring country and industry characteristics, in terms of country-level digitalization (low and high), industry factor intensity (technology-intensive and non-technology-intensive), industry economic activities (services and manufacturing), industry digitalization levels (low and high), and the tangible versus intangible nature of imported IDIs. Evidence from this study suggests that the positive effects of importing IDIs on income inequality is primarily occurring in highly digitalized countries and industries, technology-intensive sectors, and being more pronounced in manufacturing than in services, as well as stronger for intangible than tangible IDI imports.

A growing body of literature highlights the critical role of IDIs in driving technological competitiveness and industrial upgrading in the digital era (Calvino et al., 2018; Reljic et al., 2021; Li et al., 2023). While both domestic and imported IDIs support industrial growth, the latter is particularly important in enabling access to frontier technologies and international knowledge spillovers, allowing countries to enhance productivity and innovation without incurring high R&D costs (Liu and Qiu, 2016; Chiappini and Gaglio, 2024).

Recent studies have also turned attention to the labor market impacts of IDIs, especially their role in skill-biased technological change (SBTC). Empirical evidence suggests that IDIs increase demand for high-skilled labor and raises the skill premium (Acemoglu and Restrepo, 2022; Taniguchi and Yamada, 2022; Jiang et al., 2024). Additionally, the impact of IDIs on income inequality is heterogeneous and context-dependent, varying by industry, sector, and the characteristics of the digital inputs (Reljic et al., 2021; Kim, 2023; Gravina and Foster-McGregor, 2024).

Nevertheless, there is a lack of study on the role of importing foreign IDIs and thereby benefiting from frontier foreign technology. The present paper thus addresses the gap by providing new theoretical and empirical evidence on how imported IDIs, enabled by international trade, influence wage structures and income inequality between high- and low-skilled workers.

Specifically, this paper makes the following contributions. First, to the best of our knowledge, this study provides the first causal evidence on the impact of imported IDIs on income inequality between high-skilled and low-skilled labor. On the one hand, we extend the existing research on IDIs, which has thus far focused on outcomes such as export-product quality upgrading (He et al., 2023; Chiappini and Gaglio, 2024) or environmental performance (Li and Liao, 2022; Li et al., 2023), leaving the distributional consequences unexamined. On the other hand, we introduce imported IDIs as a novel mechanism in the unsettled debate for income inequality, offering a new perspective beyond the factors previously emphasized in the literature. While recent studies highlight automation, SBTC, and task displacement as key drivers of rising inequality (Acemoglu & Restrepo, 2022; Taniguchi & Yamada, 2022), other research points to globalization, trade, education, market power, and unionization (Borrs & Knauth, 2021; Kerr & Wittenberg, 2021; Murakami, 2021; Lewandowski et al., 2024).[3]

Second, we distinguish between imported and domestic IDIs, providing new evidence that imported IDIs have a unique impact on income inequality. Additionally, we use an Input-Output framework to accurately measure industry-level dependence on imported and domestic IDIs, allowing for a precise assessment of international technology spillovers (Calvino et al., 2018). Unlike previous studies, we identify two distinct channels through which imported IDIs widen inequality: a direct channel, where its high technological intensity leads to skill complementarity that raises the skill premium, and an indirect channel, where its adoption accelerates skill upgrading by shifting the composition of labor demand.

The remainder of this paper is structured as follows. Section 2 outlines the conceptual framework and hypothesis. Section 3 details the methodology and empirical specification. Section 4 presents the empirical results, including baseline results, endogeneity tests, robustness checks, and heterogeneity analysis. Section 5 examines the mechanisms through which imported IDIs contribute to reducing income inequality. Section 6 concludes and discusses policy implications.

[3] Besides, some evidence suggests that trade and technological change can increase the skill premium and wage polarization, while other research finds that certain policies and economic conditions may help reduce inequality (Acemoglu & Restrepo, 2024; Jiang et al., 2024).

2. Conceptual Framework and Hypothesis

We begin by providing detailed definitions and key characteristics respectively for intermediate input (II), intermediate digital input (IDI), domestic IDI and imported IDI, as in Table 1.

Table 1. Hierarchical comparison of intermediate inputs

Term	Definition	Key characteristic	Economic impact
Intermediate Input (II)	General goods and services used in the production process. Can be sourced domestically or imported. Broadest Category, including non-digital and digital intermediates.	Positive marginal cost. Acts as an input in the production process (Amiti & Konings, 2007).	Higher quality inputs lead to higher quality final products (Bas & Strauss-Kahn, 2015). Access to more and cheaper inputs improves production efficiency (Song et al., 2021).
Intermediate Digital Input (IDI)	**(1)** Refers to intermediate goods and services that are embedded with, or function through, digital technology and data (Ren at al., 2024). **(2)** Refers to investment in intermediate inputs from digital-intensive industries to other industry (Calvino et al., 2018). **(3)** A subset of II, containing both Imported and Domestic IDI.	Carrier of digital technology and digital resources (Li & Liao, 2022). Digital nature means near-zero marginal cost (Zhang et al., 2025). Dual role: Acts as a production input and a tool to optimize the entire production process (Li & Liao, 2022). Technology-intensive: Requires a skilled labor force to use effectively (Acemoglu & Restrepo, 2022)	Digital nature creates more extensive technology spillovers than non-digital inputs, fostering corporate R&D and digital innovation (Zhang et al., 2025). Raises demand for skilled labor (Acemoglu & Restrepo, 2022; Zhang et al., 2025).
Imported IDI	Refers to investment in II from foreign digital-intensive industries to other industry (Calvino et al., 2018).	Frontier IDI, embodying advanced technologies and designs (Ren et., 2024).	Critical channel for digital technology spillover and frontier IDI adoption. Enables data-driven quality control throughout the production process (Yu et al., 2022). Creates demand for a labor force that can work with cutting-edge international technology (Reljic et al., 2021).
Domestic IDI	Refers to investment in II from domestic digital-intensive industries to other industry (Calvino et al., 2018).	Embodies the highest level of technology available within the country.	National SBTC & Innovation: Facilitates skill-biased change based on local technology (Ren et al., 2024).

2.1. Direct mechanism: digital-skill complementarity

The digital-skill complementarity effect represents a direct mechanism through which imported IDIs impact income inequality. Particularly, importing IDIs serves as a critical channel for accessing frontier foreign digital technologies, given the uneven distribution of technological capabilities across countries. By facilitating the international exchange of digital technologies, IDI imports help bridge technological gaps and enable countries to benefit from global innovation. Importantly, the digital attributes embedded in imported IDIs are not merely additional factors in the production function; rather, they play a transformative role by facilitating the assimilation of advanced foreign technologies into domestic production processes (Ren et al., 2024). Owing to their high technological content, superior quality, and scalable nature, imported IDIs substantially enhance the marginal productivity of both capital and labor. These productivity gains enable industries to undertake organizational restructuring, stimulate endogenous digital innovation, alter the composition of labor demand, and ultimately strengthen competitive advantage in the digital economy.

However, since imported IDIs embody frontier digital technologies, their effective adoption necessitates a workforce with matching digital skills (Reljic et al., 2021). This requirement depresses the demand for low-skilled labor while increasing the demand for workers possessing complementary digital competencies and technological expertise. Consequently, the main factor behind this gap is SBTC, as the increased use of imported IDIs disproportionately benefits high-skilled labor due to stronger complementarity between advanced technologies and high-skilled labor relative to low-skilled labor (Jiang et al., 2024). Therefore, importing IDIs plays a pivotal role in shaping labor market dynamics and income distribution in the digital era. By virtue of their advanced technological content, imported IDIs exacerbate income inequality by increasing the relative demand for high-skilled labor through digital-skill complementarity, while simultaneously substituting for low-skilled workers and exerting downward pressure on their wages. Hence we propose the following hypothesis:

H1: *Imported IDIs, due to their higher technology intensity, complement high-skilled labor and substitute for low-skilled labor, thereby increasing the relative demand and wages for high-skilled workers and leading to greater income inequality.*

2.2. Indirect mechanism: skill-upgrading

Imported IDIs indirectly contribute to increasing income inequality by driving skill upgrading. Ren at al. (2024) argue that the effective implementation of IDIs requires a workforce with appropriately matched skills. This digital-skill complementarity effect leads to a restructuring of the workforce, where the overall quality of labor rises as more high-skilled workers is needed, but opportunities for low-skilled workers decline (Aum and Shin, 2025). Although this transition lowers the relative demand for low-skilled labor, the shift toward skilled workers results in an overall increase in the economy's aggregate human capital. As a result, the importation of IDIs upgrades the workforce by increasing the share of skilled labor, in turn raising labor efficiency, promoting digital technology spillovers, and enhancing overall productivity. However, the wage differentials between skill groups are also widened, thereby exacerbating income inequality, leading to the following mechanism hypothesis:

H2: *Importing IDIs widen income inequality by restructuring the workforce composition, shifting labor demand towards high-skilled workers and accelerating skill upgrading.*

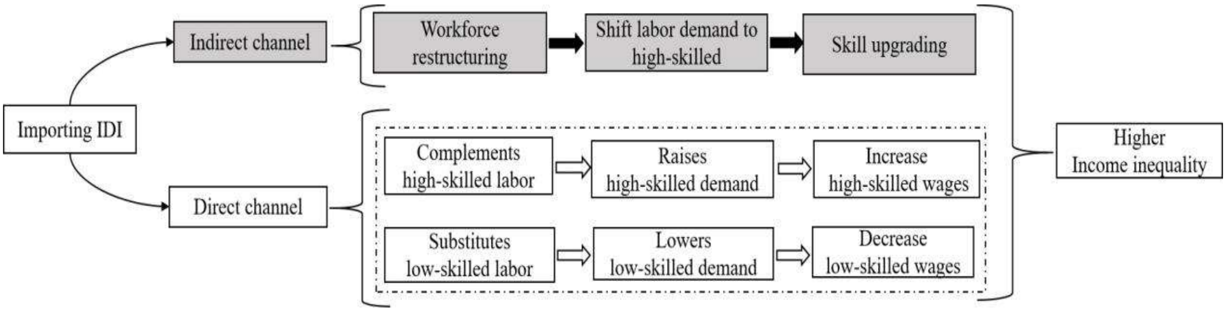

Figure 1: Mechanism--Imported IDIs increase income inequality

3. Data, Variables, and Empirical Framework

3.1. Sample data

We employ data from two different sources. First is the 2025 release of the EU KLEMS database, covering 29 countries and 20 industries (classified under NACE rev. 2) from 1995 to 2021. This database provides comprehensive, internationally comparable data on capital and labor prices and quantities across OECD countries. We extract two sets of variables: (1) labor variables from the labor account, including wages and employment share for high and low-skilled workers; and (2) control variables from the national and capital accounts, such as capital to value added ratio (lnk/va), industry size (lnsize), R&D expenditure (lnrd), and industry scale (lnscale).

Second, this study draws on the 2023 release of the OECD Inter-Country Input-Output (IOT) tables, covering 67 countries and 45 industries (classified under ISIC Rev.4) over the period 1995-2020. These IOT tables provide the necessary data to calculate both imported (lnFdigital) and domestically IDI (lnDdigital), as well as key control variables such as intermediate input (lnII), non-digital IDI (lnNonDigital) and import (lnImp).

Finally, since the OECD IOT database uses the ISIC Rev.4 industry classification, which is compatible with the NACE Rev. 2 classification used in the EU KLEMS database, we thus match the data for 29 countries and 15 industries. Moreover, the analysis focuses on the period 2008-2020, as labor characteristic data are unavailable before 2008 and the OECD database only extends to 2020.

Table 2. Variable definition

Symbol	**Variable**	**Description**	**Source**
lnInequ	Income inequality	Logarithm value of high-skilled wage/ low-skilled wage ratio. ln(Income inequality+1)	EU KLEMS
lnTdigital	Total intermediate digital input	Logarithm value of total intermediate digital inputs multiplied by gross output, divided by total intermediate inputs. ln(Tdigital+1)	OECD
lnFdigital	Foreign intermediate digital input	Logarithm value of foreign intermediate digital inputs multiplied by gross output, divided by total intermediate inputs. ln(Fdigital+1)	OECD
lnDdigital	Domestic intermediate digital input	Logarithm value of domestic intermediate digital inputs multiplied by gross output, divided by total intermediate inputs. ln(Ddigital+1)	OECD
lnNonDigital	Non-digital intermediate input	Logarithm value of non-digital intermediate multiplied by gross output, divided by total intermediate inputs. ln(Nondigital+1)	OECD
lnNonFdigital	Foreign non-digital intermediate input	Logarithm value of foreign non-digital intermediate multiplied by gross output, divided by total intermediate inputs. ln(NonFdigital+1)	OECD
lnNonDdig	Domestic non-digital	Logarithm value of domestic non-	OECD

ital	intermediate input	digital intermediate multiplied by gross output, divided by total intermediate inputs. ln(NonDdigital+1)	
lnk/va	Capital to value added ratio	ln(capital to value added ratio+1)	EUKLEMS
lnImp	Industry total import	ln(import+1)	OECD
lnsize	Industry size	ln(people employed+1)	EU KLEMS
lnscale	Industry scale	ln(gross output+1)	EU KLEMS
lnrd	Industry research and development expenditure	ln(r&d expenditure to gross output ratio+1)	EU KLEMS
Gini	Income inequality	Measured by the Gini coefficient	EU KLEMS
Theil_Index	Income inequality	Measured by the Theil_Index	EU KLEMS
Lnemp_H	High-skilled labor	ln(high-skilled labor share +1)	EU KLEMS
Lnemp_L	Low-skilled labor	ln(low-skilled labor share +1)	EU KLEMS
lnWage_H	High-skilled wage	ln(high-skilled labor wage +1)	EU KLEMS
lnWage_L	Low-skilled wage	ln(low-skilled labor wage +1)	EU KLEMS
lnH-hour	High-skilled labor working hour	ln(high-skilled labor working hour +1)	EU KLEMS
lnL-hour	Low-skilled labor working hour	ln(low-skilled labor working hour +1)	EU KLEMS
lnSkill_Ratio	High-skilled to low-skilled labor ratio	ln(Skill_Ratio+1)	EU KLEMS

3.2. Variables

3.2.1. Dependent variable: Income inequality

Following existing research (Feenstra & Hanson, 1996; Deb et al., 2024), this study adopts the wage ratio between high-skilled and low-skilled workers as a measure of income inequality.

$$\mathrm{Inequ}_{\mathrm{cit}} = \frac{\mathrm{HighSkilledW}age_{\mathrm{cit}}}{\mathrm{LowSkilledWage}_{\mathrm{cit}}} \tag{1}$$

3.2.2. Independent variable: Imported intermediate digital input (IDI)

Imported IDIs refer to the use of intermediate inputs from foreign digital-intensive industries. Based on Timmer et al. (2015) and Reljic et al. (2021), and using the Input-Output table provided by OECD, the imported IDI variable is constructed as follows: 1) We first select 4 digital industries based on the OECD and UNCTAD classification criteria (see Table 3);[4] 2) Following Timmer et al. (2015), we compute the direct consumption coefficient (DCC) and the complete consumption coefficient (CCC), where DCC refers to the total intermediate inputs consumed per unit of output and CCC measures one industry's use of intermediate inputs from other digital-intensive industries, both foreign and domestic (eq. (2)), then we compute the total IDI value by aggregating CCC (eq. (3)), where Tdigit represents one industry’s use of intermediate inputs from other digital-intensive industries, which includes the use of intermediate inputs from foreign digital-intensive industries (Fdigit), and local digital-intensive industries (Ddigit); 4) Using the method in Wei et al. (2024), we derive the final imported IDI variable as in eq. (5), where TOT is the amount of output and II represents the total of intermediate inputs.[5]

$$\mathrm{CCC_{cit}} = \mathrm{DDC_{cit}}\,(\mathrm{I} - \mathrm{DDC_{cit}})^{-1} \quad (2)$$

$$\mathrm{Tdigit_{cit}} = \sum \mathrm{CCC_{cit}} \quad (3)$$

$$\mathrm{Fdigit_{cit}} = \mathrm{Tdigit_{cit}} - \mathrm{Ddigit_{cit}} \quad (4)$$

$$\mathrm{Fdigital_{cit}} = \frac{\mathrm{Fdigit_{cit}} \times \mathrm{TOT_{cit}}}{\mathrm{II_{cit}}} \quad (5)$$

[4] As specified by the OECD, digital industries refer to industries that are mainly aimed to carry out or enable the function of information processing and communication by electronic means, including transmission and display (OECD, 2020). In addition, according to the ISIC rev.4 industry classification, industries that produce or distribute ICT products as a main activity constitutes a first-order approximation of the ICT sector.

[5] Where I is the identity matrix, and $(\mathrm{I} - \mathrm{DDC_{cit}})^{-1}$ is the Leontif inverse.

Table 3. Digital industry

Industry code	Industry
C26	Manufacture of computers, electronics, and optical products
J61	Telecommunications
J62-J63	Information technology and other information services
J58T60	Audition and broadcasting activities

3.2.3. Control variables

We control for industry-level characteristics that may affect income inequality, including non-digital intermediate input (lnNonDigital), capital to value added ratio (lnk/va), industry size (lnsize), R&D expenditure (lnrd), industry scale (lnscale), and imports (lnImp). We also control for the fixed effect of country*industry, and country*year to reduce the risk of omitting explanatory variables. Table 2 provides the detailed definition of the variables.

3.3. Empirical model

To assess the impact of importing IDIs on income inequality, we develop an econometric model based on the conceptual framework and hypotheses established earlier:

$$\mathrm{lnInequ}_{\mathrm{cit}} = \rho_0 + \rho_1 \ln(Fdigital)_{\mathrm{cit}} + \vartheta_{\mathrm{i}} \sum \mathrm{X}_{\mathrm{cit}} + \psi_{\mathrm{ci}} + \tau_{\mathrm{ct}} + \varepsilon_{\mathrm{cit}} \quad (6)$$

where the subscripts c, i, and t denote country, industry, and year, respectively. The variable $\mathrm{lnInequ}_{\mathrm{cit}}$ represents the income inequality between high-skilled and low-skilled labor, while $\ln(\mathrm{Fdigital})_{\mathrm{cit}}$ represents the logarithm of the imported IDI variable, $\mathrm{X}_{\mathrm{cit}}$ is a set of control variables, and $\varepsilon_{\mathrm{cit}}$ is the error term. To control for time-varying country-level effects and mitigate the potential impact of omitted variables, we include country*industry fixed effect (ψ_{ci}) and country*year fixed effect

(τ_{ct}). Furthermore, we address potential heteroskedasticity and correlation by clustering standard errors at the country-industry level, yielding more accurate estimates of the statistical significance of our results.

Table 4. Descriptive statistics

Variable	N	Mean	SD	Min	Max
lnInequ	4519	3.37	1.05	-7.74	5.33
lnTdigital	4585	7.22	2.72	0.00	18.10
lnFdigital	4585	6.40	2.55	0.00	16.62
lnDdigital	4585	6.54	2.83	0.00	17.89
lnNonFdigital	4585	10.09	2.72	0.00	20.66
lnNonDdigital	4585	6.54	2.83	0.00	17.89
lnNonDigital	4585	10.13	2.73	0.00	20.71
lnk/va	4564	1.61	1.53	0.00	8.59
lnImp	5460	6.03	2.68	0.00	11.98
lnsize	5401	4.98	2.41	0.00	16.21
lnscale	4907	9.85	3.00	0.00	18.60
lnrd	5460	0.03	0.06	0.00	0.62
Gini	5062	0.10	0.09	-0.24	0.54
Theil_Index	5062	0.16	0.21	-0.37	1.52
lnWage_H	5092	3.63	0.78	0.25	4.74
lnWage_L	5086	2.11	0.96	-0.69	4.42
lnemp_L	5092	2.38	0.93	0.01	4.38
lnemp_H	5070	3.38	0.80	0.00	4.49
lnL-hour	5029	9.41	1.98	0.01	11.94
lnH-hour	5007	10.52	1.97	0.00	12.07
lnSkill_Ratio	5066	1.61	1.04	0.04	5.71

Notes: This table shows the summary statistics between the variables defined in Table 2.

4. Empirical Results and Analysis

4.1. Baseline results

Table 5 reports contrasting baseline estimates of the effects of imports of IDIs and non-IDIs on income inequality between high- and low-skilled workers.

Table 5. Baseline results of imported intermediate inputs

	Panel A: IDIs		Panel B: Non-IDIs	
	(1)	(2)	(3)	(4)
	lnInequ	lnInequ	lnInequ	lnInequ

lnFdigital	0.0940*	0.1274**		
	(0.0559)	(0.0647)		
lnDdigital	-0.0407	-0.0421		
	(0.0500)	(0.0562)		
lnNonDigital	0.0707	0.1705		
	(0.1062)	(0.1079)		
lnNonFdigital			0.0215	0.0393
			(0.0464)	(0.0577)
lnNonDdigital			-0.1183	-0.1255
			(0.1027)	(0.1119)
lnTdigital			0.1431	0.1574
			(0.1274)	(0.1427)
lnk/va		-0.2285**		-0.2598**
		(0.0990)		(0.1020)
lnsize		-0.2634		-0.2113
		(0.2346)		(0.2323)
lnrd		0.5043		0.5248
		(1.1781)		(1.1884)
lnImp		-0.0073		-0.0056
		(0.0518)		(0.0521)
lnscale		-0.0177		-0.0220
		(0.0222)		(0.0398)
Constant	2.9812***	4.6880***	2.8913***	4.4556***
	(0.1800)	(1.3770)	(0.2360)	(1.3889)
CountrySectorFE	Yes	Yes	Yes	Yes
CountryYearFE	Yes	Yes	Yes	Yes
N	4080	3510	4080	3510
r2_a	0.9076	0.9105	0.9076	0.9105

Note: Robust standard errors clustered at County*Industry level. ** $p< 0.05$. *** $p< 0.01$.

Columns (1)-(2) present results for imported IDI, with column (1) including only country-sector and country-year fixed effects and column (2) additionally including the full set of controls. In both models, the coefficient on imported IDIs (lnFdigital) is positive and statistically significant, indicating that greater reliance on imported IDIs is associated with higher income inequality between high-skilled and low-skilled labor. By contrast, domestic IDIs (lnDdigital) are consistently insignificant. The asymmetry between imported and domestic IDIs indicates that the inequality effect is driven by exposure to frontier foreign technologies, which is consistent with existing evidence that domestic IDIs reflect the technological capabilities available within a country, which may not always be at the global frontier (Calvino et al., 2018). Besides, domestic IDIs in non-frontier economics tend to be more aligned with existing local skills and conditions, and therefore have more neutral effect on wage structures.

To test whether this effect is specific to IDIs, columns (3)-(4) replace IDIs with non-IDIs. Column (3) includes only country-sector and country-year fixed effects, while column (4) adds the full set of controls. In both specifications, the impact of importing non-digital intermediates on income inequality is statistically insignificant, suggesting that the inequality effect is driven primarily by the digital and technological content of imported IDIs rather than broad intermediate inputs.

Overall, the main analysis shows that imported IDIs significantly increase high-skilled and low-skilled income inequality, while domestic IDIs and non-digital intermediates have no measurable impacts.

4.2. Endogeneity tests

To address potential endogeneity, we construct two Bartik (shift-share) instruments derived from global imported IDI shocks and global digital export shocks.

4.2.1. Shift-share instrument with global imported IDI shocks

Following Goldsmith-Pinkham et al. (2020), we construct a Bartik instrumental variable (IV) using the shift-share method. Firstly, we compute the Bartik IV weights by taking the ratio of a country's IDI imports in a given industry relative to its total imports of IDIs in the initial year. These weights control for country-specific initial industry exposure, ensuring that subsequent variation in the Bartik IV reflects only industry-level shocks, not changes in import composition within a country.

$$w_{c,i,2008} = \frac{\text{Fdigital}_{c,i,2008}}{\text{TotalFdigital}_{c,2008}} \tag{7}$$

Secondly, we compute the global growth rate of imported IDIs for each industry i, $g_{i,t}$, which is the ratio of current global industry IDI imports ($\text{IndustryImpIDI}_{i,t}$) to their initial year level ($\text{IndustryImpIDI}_{i,2008}$). This component specifically captures exogenous global supply and demand shocks to imported IDIs for industry i. By using global industry shocks, we assume these are unaffected by country-specific factors. Consequently, $g_{i,t}$ is defined as:

$$g_{i,t} = \frac{\text{IndustryImpIDI}_{i,t}}{\text{IndustryImpIDI}_{i,2008}} \tag{8}$$

Finally, the shift-share IV, $Z_{c,i,t}$ is constructed by isolating exogenous variation, combining fixed country-sector exposure shares ($w_{c,i,2008}$) with global imported IDI shocks ($g_{i,t}$):

$$Z_{c,i,t} = \sum_i w_{c,i,2008} \times g_{i,t} \tag{9}$$

Based on the above analysis, $Z_{c,i,t}$ affects income inequality only through importing IDIs, thereby satisfying the exclusion restriction criterion. Moreover, the instrument addresses two key identification concerns. First, using global industry shocks ensures our measure is uncorrelated with country-specific omitted variables, satisfying the exogeneity requirement. Second, fixing the exposure shares to the base year prevents endogeneity from changes in industry composition over time. The regression results are shown in columns (1) and (2) of Table 6.

The findings show reasonably high values for the under-identification test statistics (KP rk LM statistics) and weak identification test (KP rk Wald F statistics), indicating that the rank condition is satisfied and the equations are identified. Furthermore, the second-stage regression results show that the impact of importing IDIs on income inequality remains positive and significant at the 1% significance level. Specifically, 1% increase in imported IDIs widens income inequality by 0.4831%, further supporting the validity and reliability of our instruments.

4.2.2. Shift-share instruments with global digital export shocks

Referring to Borusyak et al. (2024), the global digital export shocks based shift-share IV is derived by interacting the global digital export growth with the lagged share of imported IDIs in each country-industry.[6] Specifically, the global digital export shock is computed using ICT export data from the World Bank World Development Indicators (WDI). To construct an exogenous measure of global export demand shocks, we calculate the annual growth rate of global digital exports, subtracting each country's own exports to isolate the shock from country-specific factors, generating a global digital export shocks IV as:

$$\acute{Z}_{c,i,t} = \text{Global Digital Export Growth}_{c_*t} \times \text{Share of imported IDI}_{c,i,t-1} \quad (10)$$

Theoretically, this shift-share IV influences income inequality exclusively through its effect on IDI importation, as the global export shocks are exogenous to domestic labor markets. This single-channel mechanism satisfies the exclusion restriction by

[6] The use of lagged values ensures that the exposure measure is predetermined, mitigating concerns about endogeneity with respect to current shocks.

attributing any impact on income inequality across various skill groups to changes in the availability of imported IDIs. Columns (3) and (4) of Table 6 report the regression results.

Table 6. Endogeneity test

Instrument	With imported IDI shocks		With global digital shock	
	1st stage	2nd stage	1st stage	2nd stage
	lnFdigital	lnInequ	lnFdigital	lnInequ
	(1)	(2)	(3)	(4)
lnZ	2.9870***			
	(0.1270)			
lnFdigital		0.4831***		0.2240***
		(0.0728)		(0.0611)
ln$\acute{Z}$			0.2045***	
			(0.0073)	
lnDdigital	0.5102***	-0.3191***	0.4847***	-0.1657***
	(0.0118)	(0.0469)	(0.0123)	(0.0409)
lnNonDigital	-0.7744***	0.2099**	-0.6934***	0.0057
	(0.0331)	(0.0823)	(0.0348)	(0.0785)
lnk/va	0.1525***	-0.1375***	0.0114	-0.0955***
	(0 .0092)	(0.0173)	(0.0100)	(0.0175)
lnsize	-0.0428***	-0.2182***	-0.0956***	-0.2201***
	(0.0066)	(0.0120)	(0.0072)	(0.0123)
lnrd	-0.1161***	3.9471***	-0.1936	3.8766***
	(0.1261)	(0.2168)	(0.1336)	(0.2289)
lnImp	0.0898***	0.0193	0.0550***	0.0404***
	(0.0077)	(0.0142)	(0.0080)	(0.0146)
lnscale	0.3288***	-0.0613**	0.2890***	0.0001
	(0.0108)	(0.0280)	(0.0108)	(0.0256)
CountrySectorFE	Yes	Yes	Yes	Yes
CountryYearFE	Yes	Yes	Yes	Yes
KP rk Cragg	552.97	552.97	782.61	782.61
KP LM Statistic	478.89	478.89	619.93	619.93
N	3517	3517	2948	2948

Note: Robust standard errors clustered at County*Industry level. ** $p< 0.05$. *** $p< 0.01$.

The findings show high values for the under-identification test statistics (KP rk LM statistics) and weak identification test (KP rk Wald F statistics), indicating that the rank condition is satisfied and the equations are identified. In addition, the first-stage regression shows that the instrument has a positive and statistically significant effect on imported IDIs at the 1% level, suggesting that industries more reliant on imported IDIs are indeed more responsive to global digital shocks, thus satisfying the relevance criteria. Furthermore, the second-stage regression results show that the impact of importing IDIs on income inequality remain positive and significant at the 1% significance level. Specifically, a 1% increase in imported IDIs amplifies income inequality by 0.2240%, lending further support to the robustness of our findings.

4.3. Robustness tests

4.3.1. Substituting the explained variable

For robustness checks, we first employ two alternative income inequality measures: the Gini index (Messina & Silva, 2021; Lewandowski et al., 2024), and the Theil index (Erauskin, 2020). In Table 7, column (1) reports results using Gini index, while column (2) presents results based on the Theil index. Both specifications reveal a significant positive effect of importing IDIs on income inequality (at the 10% for the Gini index and 5 % for the Theil index), reinforcing our baseline results and verifying the robustness of our model.

4.3.2. Changing the model specification

While OLS regressions assume independence across industries, our data have a hierarchical structure, with industries nested within countries. This structure suggests that industries within the same country may be subject to common unobserved factors, such as national policies or labor market conditions, potentially biasing the results if unaccounted for. Referring to Jestl et al. (2022), we employ a multilevel regression model with random intercepts by country to explicitly model the dependence structure.[7] In column (3) of Table 7, the findings indicate that importing IDIs widens income inequality across skill groups, consistent with our baseline results. Therefore, this adjustment does not affect the validity of Hypothesis 1.

4.3.3. Winsorizing data

To address the potential influence of outliers, we winsorize the data at the 3rd and 97th percentiles, replacing extreme values with the corresponding threshold values. In column (4) of Table 7, the coefficient of imported IDIs remains positive and statistically significant across all specifications, consistent with the main findings and further supporting our previous results.

4.3.4. Using alternative base years in the shift-share IV

A potential concern with our first shift-share instrument (using global imported IDI shocks) is that the results may be sensitive to the choice of base year (2008) for constructing the initial weights. To address this, we reconstruct the instrument with 2009 and 2010 as alternative base years, and corresponding regression results are reported in columns (5) and (6) of Table 7, which remain consistent with the baseline, indicating that our findings are not driven by the specific choice of base year and confirming the robustness of our model.

[7] Generally, a multilevel model is similar to a multi-stage regression model, where the model is first run at the individual level for each industry and the results are subsequently used to run the regression at the industry level. However, in a multilevel regression framework, the regressions of both stages are estimated simultaneously (Jestl et al., 2022).

Table 7. Robustness check

	Replacing explained variable		Multi-level regression model	Winsorizing data	IV with different Base years	
	(1)	(2)	(3)	(4)	(5)	(6)
	Gini	Theil_Index	lnInequ	lnInequ	lnInequ	lnInequ
lnFdigital	0.0137*	0.0353**	0.2680***	0.1249*	0.5965***	0.4392***
	(0.0078)	(0.0155)	(0.0410)	(0.0645)	(0.0734)	(0.0712)
lnDdigital	-0.0067	-0.0149	-0.2967***	-0.0401	-0.3855***	-0.2934***
	(0.0071)	(0.0142)	(0.0387)	(0.0560)	(0.0474)	(0.0459)
lnNonDigital	0.0319**	0.0759**	-0.0871	0.1699	0.3029***	0.1739**
	(0.0152)	(0.0317)	(0.0886)	(0.1071)	(0.0836)	(0.0810)
lnk/va	-0.0216	-0.0488*	0.0667**	-0.2123**	-0.1496***	-0.1328***
	(0.0136)	(0.0289)	(0.0306)	(0.0955)	(0.0177)	(0.0171)
lnsize	-0.0099	-0.0338	-0.0046	-0.2946	-0.2129***	-0.2203***
	(0.0199)	(0.0470)	(0.0388)	(0.2272)	(0.0122)	(0.0118)
lnrd	0.0900	0.1863	2.7834***	0.3978	3.9806***	3.9341***
	(0.1126)	(0.2344)	(0.6746)	(1.1824)	(0.2222)	(0.2150)
lnImp	-0.0057	-0.0104	-0.0014	-0.0201	0.0113	0.0224
	(0.0048)	(0.0100)	(0.0286)	(0.0473)	(0.0146)	(0.0141)
lnscale	-0.0012	-0.0087	-0.0057	-0.0140	-0.0942***	-0.0486*
	(0.0032)	(0.0072)	(0.0174)	(0.0226)	(0.0284)	(0.0275)
Constant	0.1711	0.3828	3.4636***	4.8806***		
	(0.1226)	(0.2802)	(0.2121)	(1.3329)		
CountrySectorFE	Yes	Yes	Yes	Yes	Yes	Yes
CountryYearFE	Yes	Yes	Yes	Yes	Yes	Yes
Imported IDI shocks IV	No	No	No	No	Base Year 2009	Base Year 2010
KP rk Cragg					574.49	572.57
KP LM Statistic					494.91	493.49
N	3967	3967	3523	3510	3517	3517
r2_a	0.9030	0.8990		0.9301		

Note: Robust standard errors clustered at County*Industry level. ** p< 0.05. *** p< 0.01.

4.4. Heterogeneity analysis

4.4.1. Classifying countries based on digitalization level

This part investigates the heterogeneous effects of importing IDIs on income inequality across countries with varying levels of digitalization. Following Calvino et al. (2018) and Reljic et al. (2021), we use national consumption of IDIs to measure digitalization. Accordingly, countries are classified as low and high level of digitalization using the median split method (see Table C in the Appendix). In Table 8, the findings show that importing IDIs significantly increases income inequality at the 5% level in highly digitalized countries, while there is no significant effect in less digitalized countries. Intuitively, the comparative advantage in digital infrastructure drives highly digitalized economies to pursue technological competitiveness, resulting in greater labor reallocation, skill-biased technological change, and increased wage dispersion following imported IDI adoption.

4.4.2. Heterogeneity in industry digitalization level

Following Chiappini & Gaglio (2024),[8] we classify industries into high and low digitalization groups using the median split method. In columns (1) and (2) of Table 9, the regression analysis reveals a significant positive effect at the 10% level in industries with a high level of digitalization. In contrast, the effect is not statistically significant for industries with low digitalization. These align with findings such as in Calvino et al. (2018), suggesting that IDI imports affect income inequality conditional on industry digitalization. Specifically, low-digitalization industries lack the capacity to integrate these inputs, showing no significant effect. High-digitalization industries, conversely, leverage imported IDIs for capital-labor substitution, driving labor displacement and increasing inequality.

[8] Chiappini & Gaglio (2024) argue that industry-level IDI reflects the diffusion of ICT-based goods and services as inputs, which have the potential to enhance the performance of other industries by being incorporated into product innovations and contributing to higher-quality products and services.

4.4.3. Industry factor intensity heterogeneity

Regarding technology-intensive versus non-technology-intensive industries, columns (3) and (4) of Table 9 indicate that importing IDIs significantly increases income inequality at the 5% level in technology-intensive industries, while the effects in non-intensive industries are not significant. This positive effect can be attributed to the greater reliance of technology-intensive sectors on imported IDIs, which drives labor market shifts and income disparities, consistent with Wu et al. (2024).

4.4.4. Industry category

Here industries are categorized into services and manufacturing sectors. Columns (1) and (2) of Table 10 report that imported IDIs significantly increase income inequality in both services and manufacturing sectors, with a more pronounced effect in manufacturing. Consistent with existing literature, the intensified impact in manufacturing reflects the historical vulnerability of manufacturing to automation (Acemoglu and Restrepo, 2022).

4.4.5. Heterogeneity in imported IDIs

We first classify the digital-intensive industries in Table 3 based on the type of IDIs they produce (tangible or intangible).[9] We further identify the investment in intangible intermediate inputs from foreign digital-intensive industries (imported intangible IDIs) and the investment in tangible intermediate inputs from foreign digital-

[9] Digital industry producing tangible assets: manufacture of computers, electronics, and optical products (C26); Digital industry producing intangibles assets: telecommunications (J61), information technology and other information services (J62-J63), audition and broadcasting activities (J58T60).

intensive industries. Columns (3) and (4) of Table 10 show that importing IDIs significantly increases income inequality at the 10% level for both tangible and intangible types, with a greater effect observed for intangible IDI imports. Consistent with existing studies, the increase in income inequality from intangible IDI imports reflects their strong complementarity with high-skilled labor, which raises skilled wages while displacing or limiting gains for low-skilled workers (Grant & Üngör, 2024).

Table 8. Country heterogeneity

	Low digitalization level	High digitalization level
	(1)	(2)
	lnInequ	lnInequ
lnFdigital	0.0707	0.2401**
	(0.0811)	(0.1202)
lnDdigital	-0.0015	-0.1195
	(0.0735)	(0.0984)
lnNonDigital	0.1809	0.1404
	(0.2124)	(0.1455)
lnk/va	-0.3386*	-0.1658
	(0.1743)	(0.1255)
lnsize	-0.4283	-0.1195
	(0.4431)	(0.1545)
lnrd	0.0531	-0.0527
	(0.0852)	(0.0688)
lnImp	-0.1136	0.9821
	(2.6959)	(0.8886)
lnscale	-0.0261	0.0461
	(0.0203)	(0.1267)
Constant	5.4953*	3.2806**
	(2.8567)	(1.3372)
CountrySectorFE	Yes	Yes
CountryYearFE	Yes	Yes
N	1600	1910
r2_a	0.9103	0.9055

Note: Robust standard errors clustered at County*Industry level. ** p< 0.05. *** p< 0.01.

Table 9. Industry heterogeneity

	Low digitalization	High digitalization	Technology intensive	Non-technology intensive
	(1)	(2)	(3)	(4)
	lnInequ	lnInequ	lnInequ	lnInequ
lnFdigital	0.0200	0.2261*	0.0392**	0.0271
	(0.0881)	(0.1280)	(0.0180)	(0.0438)
lnDdigital	0.0310	-0.1283	-0.0216	0.0231
	(0.0743)	(0.1091)	(0.0172)	(0.0269)
lnNonDigital	0.1108	0.2427	0.0698*	0.1501**
	(0.1707)	(0.1830)	(0.0420)	(0.0727)
lnk/va	-0.2180*	-0.3755**	-0.0711*	-0.0363
	(0.1256)	(0.1734)	(0.0369)	(0.0526)
lnsize	-0.0511	-0.0093	-0.0050	-0.1416**
	(0.1509)	(0.0282)	(0.0062)	(0.0704)
lnrd	-2.1094*	4.0401**	-0.3483	0.8241***
	(1.1777)	(1.7983)	(0.3335)	(0.2936)
lnImp	-0.0598	0.0926	-0.0132	0.0251
	(0.0554)	(0.0995)	(0.0110)	(0.0218)
lnscale	-0.3343**	-0.1307	-0.0863	0.1052
	(0.1630)	(0.5345)	(0.0635)	(0.0653)
Constant	6.0875***	3.2354	0.7338**	0.4839
	(1.6374)	(2.8637)	(0.3633)	(0.5431)
CountrySectorFE	Yes	Yes	Yes	Yes
CountryYearFE	Yes	Yes	Yes	Yes
N	1911	1599	2888	1079
r2_a	0.9385	0.8641	0.8987	0.8991

Note: Robust standard errors clustered at County*Industry level. ** p< 0.05. *** p< 0.01.

Table 10. Industry heterogeneity

	Service	Manufacturing	Intangible IDI	Tangible IDI
	(1)	(2)	(3)	(4)
	lnInequ	lnInequ	lnInequ	lnInequ
lnFdigital	0.0334**	0.0469**	0.1272*	0.1239*
	(0.0159)	(0.0232)	(0.0681)	(0.0723)
lnDdigital	-0.0091	-0.0282	-0.0424	-0.0649
	(0.0152)	(0.0176)	(0.0554)	(0.0602)
lnNonDigital	0.0632*	0.1031**	0.1579	0.1284
	(0.0343)	(0.0517)	(0.1109)	(0.1073)
lnk/va	-0.0541	-0.0417	-0.2316**	-0.2385**
	(0.0384)	(0.0340)	(0.0983)	(0.0995)
lnsize	0.0307	-0.0178	-0.2615	-0.2559
	(0.0657)	(0.0368)	(0.2328)	(0.2354)
lnrd	0.2260	0.7518	0.4696	0.5021
	(0.2479)	(1.1474)	(1.1750)	(1.1879)
lnImp	-0.0085	0.0066	-0.0083	-0.0055
	(0.0140)	(0.0131)	(0.0516)	(0.0517)
lnscale	-0.0074	-0.0195	-0.0130	-0.0113
	(0.0058)	(0.0284)	(0.0223)	(0.0232)
Constant	-0.0067	0.2098	4.7284***	4.7681***
	(0.4002)	(0.2567)	(1.3704)	(1.3629)
CountrySectorFE	Yes	Yes	Yes	Yes
CountryYearFE	Yes	Yes	Yes	Yes
N	3121	846	3510	3510
r2_a	0.9067	0.8944	0.9105	0.9104

Note: Robust standard errors clustered at County*Industry level. ** $p< 0.05$. *** $p< 0.01$.

5. Mechanisms Linking Imported IDIs to Income Inequality

Building on our conceptual framework, this study posits that importing IDIs increases income inequality through both direct and indirect channels. Directly, imported IDIs, owing to their higher technological intensity, complement high-skilled labor while substituting for low-skilled labor, thereby increasing the relative demand and wages for high-skilled workers and exacerbating income inequality; Indirectly, the importation of IDIs restructures workforce composition, shifting labor demand toward high-skilled workers and accelerating skill upgrading, thus further widening the income equality.

5.1. Direct channel: digital-skill complementarity

The following analysis provides empirical evidence for the digital-skill complementarity channel.[10] We begin by examining the differential wage effects of imported IDIs across skill groups. We then empirically test the hypothesis that this effect stems from imported IDIs acting as a complement to high-skilled labor and a substitute for low-skilled labor.

5.1.1. Impacts of imported IDIs on high-skilled and low-skilled wages

Specifically, eq. (11) estimates the impact on high-skilled wages, while eq. (12) assesses the effect on low-skilled wages.

$$\mathrm{lnWage\_H_{cit}} = \rho_0 + \rho_1 \ln(\mathrm{Fdigital})_{cit} + \vartheta_i \sum X_{cit} + \psi_{ci} + \tau_{ct} + \varepsilon_{cit} \tag{11}$$

$$\mathrm{lnWage\_L_{cit}} = \rho_0 + \rho_1 \ln(\mathrm{Fdigital})_{cit} + \vartheta_i \sum X_{cit} + \psi_{ci} + \tau_{ct} + \varepsilon_{cit} \tag{12}$$

Columns (1) and (2) of Table 11 present the corresponding regression results for low-skilled and high-skilled wages, respectively, showing that IDI imports have a significant negative effect on low-skilled wages but a significant positive effect on high-skilled wages. The findings imply that imported IDIs disproportionately benefit high-skilled labor due to a stronger complementarity with digital embedded technology. This heightened demand for skilled workers, consistent with previous literature (Jiang et al., 2024), subsequently increases their relative wages, thereby widening the income gap.

5.1.2. Complementarity vs. substitutability of imported IDIs

This part examines whether imported IDIs are complementary or substitutive to high- and low-skilled labor. In eq. (13), we regress wages on imported IDIs, including

[10] Test for technology compatibility is reported in Table D in the Appendix.

interaction terms between imported IDIs and high-skilled labor input ($\mathrm{lnFdigital_{cit}} * \mathrm{H\_Hour_{cit}}$), as well as between imported IDIs and low-skilled labor input ($\mathrm{lnFdigital_{cit}} * \mathrm{L\_Hour_{cit}}$). The coefficients ($\delta_1$) and ($\delta_2$) on these interaction terms are the key parameters for identifying whether imported IDI acts as a complement or substitute to labor across different skill levels. For instance, a positive and statistically significant coefficient for δ_1 would denote complementarity, while a negative and significant coefficient would suggest a substitutive effect. Additionally, to reduce potential omitted variable bias, we also control for both low-skilled ($\mathrm{lnL\_Hour_{cit}}$) and high-skilled ($\mathrm{lnH\_Hour_{cit}}$) labor inputs.

Table 11. Digital-skill complementarity mechanism

	Low-skilled wage	High-skilled wage	Complementarity effect
	(1)	(2)	(3)
	lnWage_L	lnWage_H	lnWage
lnFdigital	-0.0044*	0.0064*	0.0433**
	(0.0024)	(0.0034)	(0.0169)
lnDdigital	0.0024	-0.0034	-0.0174
	(0.0023)	(0.0033)	(0.0167)
LnFdigital*lnL-hour			-0.0089*
			(0.0053)
LnFdigital*lnH-hour			0.0135***
			(0.0050)
LnL-hour			0.0177
			(0.0285)
LnH-hour			-0.0269
			(0.0289)
Constant	-0.0444	-0.7246***	8.6781***
	(0.0700)	(0.1147)	(0.7810)
Controls	Yes	Yes	Yes
CountrySectorFE	Yes	Yes	Yes
CountryYearFE	Yes	Yes	Yes
N	3933	3933	3948
r2_a	0.9884	0.9893	0.9993

Note: Robust standard errors clustered at County*Industry level. ** p< 0.05. *** p< 0.01.

$$\mathrm{lnWage}_{cit} = \rho_0 + \rho_1 \ln(\mathrm{Fdigital})_{cit} + \delta_1 \mathrm{lnFdigital}_{cit} * \mathrm{H\_Hour}_{cit} + \delta_2 \mathrm{lnFdigital}_{cit} * \mathrm{L\_Hour}_{cit} + \delta_3 \mathrm{lnH\_Hour}_{cit} + \delta_4 \mathrm{lnL\_Hour}_{cit} + \vartheta_i \sum X_{cit} + \psi_{ci} + \tau_{ct} + \varepsilon_{cit} \tag{13}$$

Column (3) of Table 11 indicates a positive and significant coefficient for δ_1, while a negative and significant coefficient for δ_2, suggesting importing IDIs complement high-skilled labor while substituting for low-skilled labor, verifying H1.

5.2. Indirect channel: skill-upgrading

To test the indirect channel, we construct the following model:

$$\ln(\mathrm{Skill\_Ratio})_{cit} = \rho_0 + \rho_1 \ln(\mathrm{Fdigital})_{cit} + \vartheta_i \sum X_{cit} + \psi_{ci} + \tau_{ct} + \varepsilon_{cit} \tag{14}$$

$$\mathrm{lnInequ}_{cit} = \rho_0 + \rho_1 \ln(\mathrm{Fdigital})_{cit} + \rho_2 \ln(\mathrm{Skill\_ratio})_{cit} + \xi \ln(\mathrm{Skill\_Ratio})_{cit} * \ln(\mathrm{Fdigital})_{cit} + \vartheta_i \sum X_{cit} + \psi_{ci} + \tau_{ct} + \varepsilon_{cit} \tag{15}$$

where c is country, i is industry, and t represents year, $\ln(\mathrm{Skill\_Ratio})_{cit}$ is the mechanism variable. Eq. (14) examines how importing IDIs affects the skill ratio, where the sign and statistical significance of the coefficient (ρ_1) on the imported IDI term indicates the direction and strength of the effect. Eq. (15) tests whether importing IDIs affects income inequality through the skill ratio. That is, we include both the skill ratio and an interaction term between the skill ratio and imported IDIs. We hypothesize that the coefficient (ξ) on the interaction term is positive, suggesting that importing IDIs widens income inequality through skill upgrading.

In Table 12 column (1), the positive and significant sign of (ρ_1) suggests that importing IDIs is associated with an increase in the proportion of high-skilled workers in the workforce, supporting the idea that imported IDIs is restructuring the workforce by increasing demand for high-skilled labor, which can contribute to widening income inequality. In column (2), the findings show a positive and significant coefficient for (ρ_1), suggesting that importing IDIs raises income inequality. Also, the positive and significant coefficient for the interaction term (ξ) indicates that importing IDI indirectly raises income inequality through skill upgrading, thereby supporting our hypothesis 2.

Table 12. Skill upgrading mechanism

	(1)	(2)
	lnSkill_Ratio	lnInequ
lnFdigital	0.3324**	0.0631*
	(0.1398)	(0.0353)
lnDdigital	-0.2034***	-0.0193
	(0.0499)	(0.0127)
lnNonDigital	-0.2492**	0.0212
	(0.1104)	(0.0319)
LnFdigital*lnSkill_Ratio		0.0100***
		(0.0037)
lnSkill_Ratio		-0.0156
		(0.0100)
Constant	0.4567	0.3839**
	(0.7811)	(0.1564)
Controls	Yes	Yes
CountrySectorFE	Yes	Yes
CountryYearFE	Yes	Yes
N	3971	3967
r2_a	0.9560	0.9088

Note: Robust standard errors clustered at County*Industry level. ** p< 0.05. *** p< 0.01.

6. Conclusions and Policy Implications

New waves of digital technology are transforming labor markets, creating new challenges and uncertainties for workers at all skill levels. In this context, recent research highlights the increasing reliance on imported IDIs, which fosters more efficient resource allocation and redefines workforce skill requirements. Using a novel dataset that merges recent EU KLEMS and OECD data for 29 countries and 15 industries from 2008 to 2020, this study has assessed the impact of importing IDIs on income inequality. Our findings show that 1) importing IDIs raises income inequality between high-skilled and low-skilled workers; 2) the effect is more significant in highly digitalized countries and industries, technology-intensive sectors, and is notably more pronounced in manufacturing compared to services, as well as for intangible versus tangible IDI imports; 3) two mechanisms are found: directly, by complementing high-skilled labor and substituting for low-skilled labor due to their higher technological intensity, thereby raising the relative demand and wages for high-skilled workers and exacerbating income inequality; and indirectly, by restructuring workforce composition, shifting labor demand toward high-skilled workers, and accelerating skill upgrading.

Drawing on these results, we propose the following policy recommendations. First, to align the labor supply with new skill-biased demand and reduce the income gap, incentives should target reskilling and upskilling programs focused on digital skills. Second, strengthen labor market institutions by adding active support measures for workers displaced by imported IDIs, including wage insurance to ease financial transitions and targeted job-matching services to reduce unemployment. Third, perhaps encourage union participation in collective bargaining and policy discussions, as unions can advocate for fairer wage distribution and support measures that help workers adapt to digitalization.

While our analysis is limited to OECD countries due to data constraints, future research could explore the impact of imported IDIs on skill-based income inequality within individual countries. Also, while our study focuses only on income effects, further research could investigate broader labor market outcomes, including employment patterns, job creation, and occupational mobility resulting from imported IDI adoption.

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Appendix

Table A: List of countries in empirical analysis

ISO Code	Country Name
AT	Austria
BE	Belgium
BG	Bulgaria
CY	Cyprus
CZ	Czechia
DE	Germany
DK	Denmark
EE	Estonia
EL	Greece
ES	Spain
FI	Finland
FR	France
HR	Croatia
HU	Hungary
IE	Ireland
IT	Italy
JP	Japan
LT	Lithuania
LU	Luxembourg
LV	Latvia
MT	Malta
NL	Netherlands
PL	Poland
PT	Portugal
RO	Romania
SE	Sweden
SI	Slovenia
SK	Slovakia
UK	United Kingdom

Table B: List of industries in empirical analysis

NACE Code	Industry Economic Area
D	Electricity, Gas, Steam and Air Conditioning Supply
E	Water Supply; Sewerage, Waste Management and Remediation Activities
F	Construction
G	Wholesale and Retail Trade; Repair of Motor Vehicles and Motorcycles
I	Accommodation and Food Service Activities
K	Telecommunication, Computer Programming, Consulting, Computing Infrastructure, and other Information Service Activities
L	Financial and Insurance Activities
M	Real Estate Activities
N	Professional, Scientific and Technical Activities
O	Administrative and Support Service Activities
P	Public Administration and Defence; Compulsory Social Security
Q	Education
R	Human Health and Social Work Activities
S	Arts, Sports and Recreation
T	Other Service Activities

Table C: Country digitalization level

Country Code	Digitalization level	Country Name
CY	High	Cyprus
CZ	High	Czechia
DE	High	Germany
DK	High	Denmark
EE	High	Estonia
FI	High	Finland
HU	High	Hungary
IE	High	Ireland
LU	High	Luxembourg
MT	High	Malta
NL	High	Netherlands
PL	High	Poland
PE	High	Portugal
SE	High	Sweden
UK	High	United Kingdom
AT	Low	Austria
BE	Low	Belgium
BG	Low	Bulgaria
EL	Low	Greece
ES	Low	Spain
FR	Low	France
HR	Low	Croatia

IT	Low	Italy
JP	Low	Japan
LT	Low	Lithuania
LV	Low	Latvia
RO	Low	Romania
SI	Low	Slovenia
SK	Low	Slovakia

Table D: Technology intensity vs. capital intensity between imported IDIs, domestic IDIs, and non-IDI intermediates

	(1) Technology Intensity Lnk_hour	(2) Capital Intensity Lnrd_va
lnFdigital	0.0497***	0.0037**
	(0.0095)	(0.0016)
lnDdigital	-0.0411***	-0.0036**
	(0.0079)	(0.0017)
lnNonDigital	0.0257	-0.0001
	(0.0322)	(0.0047)
Constant	0.1679	0.0338
	(0.2328)	(0.0283)
Controls	Yes	Yes
CountrySectorFE	Yes	Yes
CountryYearFE	Yes	Yes
N	4132	4118
r2_a	0.9993	0.9604

Note: Robust standard errors clustered at County*Industry level. ** p< 0.05. *** p< 0.01.