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Industrial Automation and Jobs in an Emerging Economy: Evidence from Viet Nam

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Abstract

We examine the labor market effects of industrial robot adoption in Viet Nam. Using differences between districts in their initial industrial structure and exposure to global robotization trends, we find that robot adoption between 2014 and 2020 increased employment, wages, and the inflow of skilled workers. More exposed districts also experienced faster growth in value added, labor productivity, and trade flows. Employment and wage gains were concentrated among middle and high-skilled workers, while low-skilled workers were driven into informal employment or out-migration. We also find positive spillovers to neighboring districts, consistent with production linkages and higher demand for non-tradable goods.

JEL classification

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Keywords

industrial robots, local labor markets, wages, informality, migration, export-led growth, Viet Nam

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I Introduction

For decades, the standard development model for emerging economies has relied on leveraging abundant low-cost labor to spur industrialization and structural transformation. For instance, labor-intensive, export-driven manufacturing underpinned the success of East Asian economies (Page et al., 1993; Stiglitz, 1996; Reed, 2024). The diffusion of industrial robots and other forms of automation technologies has not only raised questions about the future of work (Autor et al., 2003; Acemoglu and Autor, 2011; Brynjolfsson and McAfee, 2014; Frey and Osborne, 2017), but also about the viability of labor-intensive manufacturing as an engine of growth and economic transformation for developing countries (Rodrik, 2016, 2018).

Most empirical evidence on industrial automation comes from advanced economies and documents adverse effects on workers performing routine manual tasks, including employment losses and wage declines (Graetz and Michaels, 2018; Acemoglu and Restrepo, 2020). Yet the evidence is far from uniform. In Germany, employment losses in manufacturing were more than offset by gains in local service sectors (Dauth et al., 2021), while recent evidence for France shows that investments in modern manufacturing capital can increase employment, sales, and exports when productivity gains enable firms to expand production and capture market share abroad (Aghion et al., 2026). Evidence from developing economies remains scarce and mainly points to adverse impacts among vulnerable workers (Brambilla et al., 2023; Giuntella et al., 2025). Whether automation can instead support industrialization and structural transformation in developing countries remains an open empirical question.[1]

This paper contributes to the literature by studying the effects of industrial robot adoption in Viet Nam, a rapidly growing lower middle-income country that has undergone substantial industrial expansion and trade integration over the last two decades. Viet Nam presents a compelling case. Its industrial robot density—the stock of robots per thousand manufacturing workers—grew more than thirtyfold between 2010 and 2022, one of the fastest rates in the world. Such rapid pace of adoption provides a unique opportunity to assess the labor market consequences of automation technologies in the context of structural transformation in a developing economy.

Viet Nam's rapid industrialization has been supported by sustained economic reforms

[1] For evidence on the negative impact of automation-driven reshoring on developing countries, see Faber (2020), Kugler et al. (2020), Gravina and Pappalardo (2022), Stemmler (2023), and Díaz Pavez and Martínez-Zarzoso (2024). For evidence on the complementarity between offshoring, trade and automation decisions, see Stapleton and Webb (2023) and Artuc et al. (2023).

over the past three decades. The government stabilized the macroeconomy—e.g. bringing inflation down from double digits in the early 2010s to around 3–4 percent—while deepening trade integration through WTO accession in 2007 and subsequent free trade agreements, which helped reduce tariffs on manufactured goods from 16.6 percent to 1.1 percent and raise trade openness from 19 percent of GDP in 1988 to 184 percent in 2022. In parallel, service-sector reforms and investment incentives—including tax holidays and an expanding network of industrial parks and special economic zones—streamlined business entry, improved infrastructure, and attracted FDI (Zeng, 2016; Nguyen et al., 2017). These policies positioned Viet Nam to benefit from trade diversion away from China in the past decade, first through "China Plus One" strategies by multinationals from advanced Asian economies, and later through US–China trade tensions, helping transform Viet Nam into a major export platform (Sheldon and Kwon, 2023; Mayr-Dorn et al., 2026).

Together, domestic policy reforms and shifts in the external environment have driven the structural transformation of the Vietnamese economy, shifting export composition from primary commodities and low-value-added textiles toward higher-value-added industries, with electronics and machinery now accounting for nearly half of total export value (OECD, 2025; World Bank, 2025). These policy shifts and their economic consequences, however, pose threats to identifying the causal effects of robot adoption on labor market outcomes.

To address these potential identification threats, our empirical strategy relies on the Shift-Share Instrumental Variable (SSIV) approach following Acemoglu and Restrepo (2020). This method exploits exogenous variation in robot diffusion across industries—driven by global technological trends—to estimate the causal effects of robot adoption on district-level labor market outcomes. We instrument our measure of robot exposure by combining variation in districts' initial industry employment composition with global trends in robot adoption by industry. This allows us to isolate the impacts of robot adoption from confounding factors—such as concurrent policy reforms and external shocks—and to address concerns about reverse causality, omitted variable bias, and measurement error.

Identification relies on two key assumptions: (i) global industry robotization trends are uncorrelated with Viet Nam-specific industry shocks—including those arising from the policy reforms and external factors discussed above—and (ii) districts initially more specialized in industries that experience greater robot adoption are not differentially affected by other concurrent shocks or trends impacting the labor market, conditioning on district fixed effects and region-specific year effects. We implement this approach combining microdata from nationally representative labor force surveys collected by the General Statistics Office of

Viet Nam (GSO) with data on robot adoption from the International Federation of Robotics (IFR) across countries and industries.[2] We also utilize GSO's firm survey data to provide complementary evidence that supports our findings.

The conceptual framework underlying our empirical analysis is the task-based model of technological change (Autor et al., 2003; Acemoglu and Autor, 2011; Acemoglu and Restrepo, 2018). This framework emphasizes two primary opposing forces that mediate the impact of automation on employment and wages. On the one hand, displacement and substitution effects arise when robots take on tasks previously performed by workers, reducing labor demand and exerting downward pressure on wages. On the other hand, reinstatement effects emerge as productivity gains from automation lower unit costs and prices, stimulating product demand, expanding output, and ultimately raising labor demand.

There may also be broader general equilibrium effects from automation, arising from cross-sectoral spillovers through input-output linkages and intersectoral reallocation of labor and capital (Autor and Salomons, 2018). The net impact on employment and wages depends on the elasticity of substitution between labor and technology (robots), the price elasticity of product demand, and any inter-sectoral changes in output, all of which are mediated by international trade (Gregory et al., 2021; Baldwin et al., 2025). For instance, the price elasticity of demand is affected by access to and competition in external markets. If firms source most of their inputs from imports, robot adoption in one sector will generate smaller domestic spillovers to other sectors.

Following Acemoglu and Restrepo (2020), our empirical approach estimates the effects of robot adoption on local labor markets. The estimates capture the net equilibrium outcomes in the local labor market after any adjustments in labor supply and demand take place, including reallocation of workers across firms, occupations, and industries in response to changes in productivity, factor prices and wages. Because cross-district spillovers—through migration, trade, or wage equalization—are not modeled, our estimates reflect *relative* effects across districts—comparing high-exposure vs. low-exposure—and should be interpreted as local average treatment effects rather than economy-wide general equilibrium effects. We carry out additional analysis to assess cross-district spillovers, including through internal migration, and find that they are empirically important.

Our main empirical findings suggest that industrial automation had a significant impact on labor market outcomes, employment composition, and internal labor migration. First, we

[2] We also rely on industry employment data from the OECD to normalize robot adoption.

find that robot adoption increased both employment and average hourly wages. An additional robot adopted per thousand workers raises a district's total employment and average labor wages by approximately 6–9 percent and 2–4 percent, respectively. Employment and wage gains were also accompanied by an influx of skilled in-migrants. Nonetheless, employment *rates* remained unchanged, as both employment and population expanded in tandem.

We also document substantial heterogeneity in these effects. Employment gains in high-adoption districts were disproportionately captured by middle- and high-skilled individuals, whereas low-skilled workers engaged in routine, manual work experienced formal job losses and found employment in the informal sector and other low-adoption districts. Wage gains followed a similarly unequal pattern, favoring younger and more educated workers, and those at the upper percentiles of the wage distribution; thereby exacerbating labor market inequality.

We also uncover evidence of labor reallocation away from domestic private firms toward foreign-owned enterprises (FOEs). This pattern is consistent with larger, foreign-affiliated firms being better positioned to attract high-skilled workers who complement new automation technologies.

We provide evidence on two mechanisms behind our findings. First, Viet Nam's manufacturing sector is very export-oriented; the manufacturing industries that experienced robot adoption represent 32.5 percent of total exports in 2015 and 41.5 percent in 2022.[3] If automation leads to productivity-driven reductions in costs and prices and firms face an elastic demand for their products in global markets, robot adoption can translate into large, export-driven increases in the scale of production, offsetting any labor-displacing effects. We find that districts with increasing exposure to robot adoption experienced faster growth in firms' value-added, labor productivity, exports and imports, consistent with a productivity-enhancing scale effect enabled by Viet Nam's strong participation in Global Value Chains (GVCs).

Second, we examine whether automation generates positive local multiplier effects that raise employment in sectors not directly exposed to robotization. We find significant spillover effects on employment in other sectors not directly exposed to automation, such as services and construction. This is consistent with local multiplier effects operating through both production linkages and increased demand for local non-tradable sectors (Moretti, 2010,

[3]This figure covers the four top robot-adopting industries in Viet Nam: Computers/electronics, Electrical equipment, Plastics, and Automotive.

2011).

Our paper contributes to the nascent literature on the labor market impacts of automation in developing economies. First, our findings are consistent with studies documenting positive aggregate productivity effects of industrial robots, including increases in value added and total factor productivity, as well as reductions in output prices and improvements in product quality (Graetz and Michaels, 2018; Acemoglu and Restrepo, 2020; DeStefano and Timmis, 2024; Aghion et al., 2026). This pattern—whereby robot adopters tend to be large, export-oriented, high-productivity manufacturers—has been documented across many countries.[4] Moreover, robotization and exporting can be complementary drivers of productivity growth (Koch et al., 2021; Alguacil et al., 2022), with multinational enterprises (MNEs) playing a central role in technology diffusion and trade integration (Arnold and Javorcik, 2009; Guadalupe et al., 2012; Alfaro and Chen, 2018; Conconi et al., 2024).

Second, our findings that automation benefits higher-skilled workers while displacing those in routine, low-skilled jobs are consistent with the literature on Skill-Biased Technological Change (SBTC) and job polarization (Autor et al., 2003; Goldin and Katz, 2008). The findings contribute to the literature documenting labor-displacing effects for routine, manual labor (Graetz and Michaels, 2018; Acemoglu and Restrepo, 2020; Webb, 2020; Albinowski and Lewandowski, 2024), and increasing returns to high-skilled labor and managerial capabilities in adopting firms (Humlum, 2021; Dauth et al., 2021; Tang et al., 2021; Acemoglu and Restrepo, 2022b; César et al., 2022; Koru, 2023).

Finally, we contribute to understanding the factors that mediate the impact of the adoption of automation technologies on labor markets in developing countries. Firms cite a variety of motives for automating, including rising labor costs (Lordan and Neumark, 2018; Jung and Lim, 2020; Fan et al., 2021), aging of the workforce (Acemoglu and Restrepo, 2022a) and participation in global value chains (Fontagné et al., 2024) that demand quality upgrading and process improvements (Acemoglu and Restrepo, 2022a). Unlike in high-income countries, where automation is primarily driven by high labor costs or an aging workforce, robot adoption in Viet Nam is intimately linked to participation in GVCs as foreign-owned enterprises (FOEs) and exporters are at the vanguard of robot adoption. The scale effects enabled by trade integration, together with employment spillovers to non-automating sectors, offset the labor-displacing effects of automation. For other developing economies, Viet

[4] In France (Acemoglu and Restrepo, 2020; Bonfiglioli et al., 2021), Spain (Koch et al., 2021), Denmark (Humlum, 2021), the United States (Acemoglu and Restrepo, 2022a; Dinlersoz and Wolf, 2024), and Indonesia (Ing and Zhang, 2022).

Nam's experience illustrates how integration into global markets can simultaneously accelerate automation—through foreign firm entry and new investment—and mitigate its adverse labor market impacts, though the benefits are not equally distributed.

The paper is organized as follows. Section 2 provides a detailed presentation of the data sources and highlights key trends that underpin our empirical analysis. Section 3 describes the identification strategy and empirical models we adopt to obtain robust and credible results. Section 4 presents and discusses the empirical findings. Finally, Section 5 concludes. The Appendix contains additional tables and figures with supplementary results from our analysis.

II Data and trends

Our analysis combines several datasets. First, we use the Labor Force Survey (LFS) conducted annually by the General Statistics Office (GSO) of Viet Nam. The survey is representative at the national and provincial level and collects detailed information on individuals' labor market outcomes, including employment status and sector, labor earnings, work hours, social security coverage (formality), as well as demographic and other individual characteristics. While the survey is not designed to be representative at the district level, the cumulative sample across years is large enough to support reliable estimation of the labor market indicators of interest. The definitions of the variables included in the analysis are discussed in Section III.

The second data source is the Viet Nam Enterprise Survey (VES), which is an economic census also conducted by the GSO. The VES collects data on all officially registered enterprises in Viet Nam, including state-owned enterprises (SOEs), foreign-owned enterprises (FOEs), and domestic private firms across all economic sectors. The VES excludes unregistered (informal) firms, including family businesses and self-employment. The survey collects detailed information on firm characteristics such as revenue, value added, capital, employment and wage bills, among others.

We use data from the LFS and VES for the period 2010-2020 for the descriptive analysis, and focus on the 2014–2020 period—which captured the surge in robot adoption—for our econometric estimations. While we have data for 2021 and 2022, we do not include these years since, as in most countries, the data collection, economic activity and labor market were significantly affected by the COVID-19 pandemic. These impacts were felt during the second quarter of 2020 (a two-to-three-week nationwide lockdown) and much more severely in 2021 due to prolonged (3-4 months) and stricter lockdowns, which impacted especially the capital and the southern industrial provinces. The GSO used computer-assisted telephone interviewing during periods of strict lockdowns but there were still delays in data collection, especially in 2021. The pandemic also impacted negatively the Vietnamese labor market and firm performance, especially in 2021, when declines in economic activity were more severe especially in the services sector (overall employment dropped sharply by 4.6 million from pre-pandemic levels). There was a robust recovery in 2022.

Finally, the robot data come from the International Federation of Robotics (IFR), the standard source used in the literature starting with Acemoglu and Restrepo (2020).[5] The IFR collects regular standardized data on the number of industrial robots installed per year across countries and by industry as well as on the stock of robots calculated as the sum of installations over the last 12 years at any given year. The IFR data covers approximately 90 percent of the global industrial robots market, with information sourced directly from robot suppliers.

Following the literature, we standardize the stock of robots in each country by the level of employment of each industry in 1995 to ensure that variation in robot adoption by country-industry is solely driven by temporal changes in the stock of robots:[6]

$$Robot\ Adoption_{cjt} = \frac{Stock\ of\ Robots_{cjt}}{L_{cj,1995}/1000} \tag{1}$$

where c, j and t index countries, industries and time, respectively. Employment by country-industry comes from the OECD Statistics (Trade in Employment dataset, 2023 edition). The stock of robots varies at the country-industry-year level, with industry disaggregation closely aligned with the 2-digits of ISIC Rev.4 (within manufacturing).

The top panel of Figure 1 shows the evolution of the stock of industrial robots per thousand workers over the last two decades in Viet Nam and other parts of the world. The figure presents the trends for other developing East Asian countries as well as averages for Europe,

[5]The IFR defines an industrial robot, following the International Organization for Standardization (ISO 8373:2012), as an *automatically controlled, multipurpose manipulator that is programmable in three or more axes and can be either fixed or mobile for use in industrial automation applications.* These machines are primarily used in manufacturing tasks such as material handling, welding and soldering, painting and dispensing, assembly, mechanical cutting, and semiconductor clean rooms.

[6]Changing the baseline year (used for normalization by industry employment) does not alter our findings.

high-income countries (HIC), middle-income countries (MIC), and the world.[7] The series are normalized to 1 in 2010 to illustrate relative growth. Robot adoption has accelerated in all countries since 2010, with Viet Nam experiencing the most pronounced growth especially after 2015. Appendix Figure B1 shows the actual levels of robot adoption in levels and since 1998. The adoption surge has positioned Viet Nam close to Malaysia and Thailand in terms of industrial automation intensity (i.e., around 8 robots per thousand workers in manufacturing in 2022).

The bottom panel of Figure 1 presents the evolution of industry composition of Viet Nam's total stock of robots between 2010 and 2022. Robot adoption has concentrated primarily in high-tech industries such as electrical equipment, computers and electronics and, to a lesser extent, the automotive sector. Robot adoption also expanded in the rubber and plastics industry, which accounted for the majority of robots before the mid-2010s expansion and usually supplies intermediate inputs to the most technologically advanced sectors. Appendix Figure B2 presents the evolution of the stock of robots in Viet Nam for each industry over the same period.

Figure 2 displays the correlation between changes in robot adoption across manufacturing industries in Viet Nam and the rest of the world during 2010–2020. The figure reveals a strong and statistically significant positive correlation ($\rho = 0.91, p < 0.01$), suggesting that global technological trends in robotization are mirrored in Viet Nam's industry-level patterns. Industries positioned above the 45-degree line experienced faster robot adoption in Viet Nam compared to the global average–most notably, electrical equipment, computers and electronics, and rubber and plastics. The automotive sector shows similar adoption rates, while other industries experienced lower adoption in Viet Nam relative to the world. This alignment also holds when comparing Viet Nam to specific country groups (e.g., high-income, Europe, or other East Asian and Pacific countries). This supports the view that domestic automation trajectories are shaped by global supply-side forces, including technological advances that reduce robot prices and broaden their applicability across industries.

Figure 3 shows the correlation between the change in (log) industry employment from 2010 to 2020 and the stock of industrial robots in 2020 across industries. Bubble size represents the average of each industry's value added between 2010 and 2020.[8] Industries with higher

[7]World average corresponds to 57 countries with complete and comparable information in the IFR and OECD datasets. These countries account for 69 percent of world's population and close to 85 percent of global GDP in 2020.

[8]Within manufacturing, the largest bubble corresponds to textiles, which is highly labor-intensive and employs 8.8 percent of Vietnamese workers in 2020. This industry exhibits very little adoption of robots

robot adoption tend to experience relatively stronger employment growth than less robot-intensive industries. Correlation coefficients between robot adoption and employment growth are approximately 0.6–0.7, both across all sectors and when restricted to manufacturing industries. The figure reveals that industries with low robot penetration–such as textiles, utilities, and services—also registered strong employment growth. This reflects the broader structural transformation of Viet Nam's economy during the period: a substantial decline in employment in the primary sector (-6.8 million jobs between 2010 and 2020), which was more than offset by net job creation in manufacturing (+4.3 million) and services (+6.4 million).

Appendix Figure B3 presents evidence that industries with higher robot adoption have experienced expansions in output and trade integration. Panel (a) illustrates the correlation between robot adoption and the change in (log) industry value added during the 2010-2020 period, documenting that industries with higher robot density experienced relatively stronger output growth than lower adoption industries. Panel (b) shows that industries with greater adoption are significantly more trade integrated using two complementary measures. The bottom-left plot corresponds to the 2010-2020 change in the share of re-exported intermediate imports over total intermediate imports. This metric captures the importance of imported inputs used to produce goods and services for export and can be interpreted as a measure of global trade integration (OECD, 2022). The bottom-right figure shows that robot-adopting industries also have a greater fraction of exporting firms.[9]

Taken together, these trends indicate that Viet Nam's rapid adoption of industrial automation technologies—particularly since 2016—has enabled the country to converge toward regional peers in terms of robot intensity. Robot adoption has been heavily concentrated in export-oriented sectors such as electrical equipment, computers and electronics, and automotive, as well as upstream industries such as rubber, plastics, and fabricated metal products. These sectors exhibit robust employment and output growth and deeper trade integration, potentially reflecting scale effects from global demand. These descriptive trends guide our empirical examination of the causal impacts of robot adoption, which we present in the next two sections.

worldwide. The fraction of workers employed in the industries with the highest robot adoption in 2020 are: computers and electronics (1.77 %), rubber and plastic products (0.55 %), electrical equipment (0.33 %), and automotive (0.28 %).

[9] All of these correlations remain qualitatively similar when using the 2010–2020 change in the stock of robots per thousand workers rather than the log level in 2020.

III Empirical strategy

We estimate district-level shift-share IV regressions, exploiting variation in robot diffusion across industries driven by global technological trends, to identify the causal impact on labor market outcomes across districts and over time. Our empirical strategy closely follows prior work, particularly Acemoglu and Restrepo (2020) and Dauth et al. (2021), who employ similar approaches to assess the labor market effects of automation in the United States and Germany, respectively. The baseline regression equation is:

$$Y_{lt} = \beta_0 + \beta_1 ER_{lt} + X'_{l0}\beta_2 + \delta_{rt} + \alpha_l + \varepsilon_{lt} \tag{2}$$

where l and t index districts and time, respectively. The dependent variables, represented by Y, include a set of employment and wage outcomes such as total employment, salaried employment (both formal and informal), unemployment, and average hourly wages, all measured in logs.[10] Due to data limitations, the wage analysis is restricted to salaried workers.[11] We also report results from analysis of impacts on employment, unemployment, and informality rates in the Appendix (e.g., Table B5, Figure B4). Additionally, we assess impacts on population and workforce dynamics, specifically total and working-age (15–65) population, labor force participation, and internal migration flows (all in logs).[12] All of these variables are constructed from Labor Force Survey (LFS) microdata.

The explanatory variable ER measures exposure to robots per thousand workers at the district level. Formally, exposure to robots in district l at time t is defined as:

$$ER_{lt} = \sum_j \left(\frac{L_{jl,2011}}{L_{l,2011}} \right) \times Robot\ Adoption_{jt} \tag{3}$$

where j indexes industries. $Robot\ adoption_{jt}$ represents the stock of robots per thousand workers in Viet Nam in industry j at time t (as defined in equation (1)). $L_{jl,2011}$ is the number of workers in industry j in district l in 2011, and $L_{l,2011}$ is the total number of workers in district l in 2011. Since these weights reflect the *initial* industry composition of employment (pre-adoption surge) and remain constant over time, variation in robot exposure

[10] We define formal workers as those that contribute to Viet Nam's pension system.

[11] The LFS did not collect data on labor earnings of the self-employed in the study period.

[12] Migrants are individuals that report having resided in the district for less than one year. District-level out-migration is calculated using the formula $Outmigrants_{lt} = Population_{lt-1} + inmigrants_{lt} - population_{lt}$.

is driven solely by changes in the industry-level robot stock, rather than by evolving local employment patterns. As discussed below, identification relies on within-district variation in robot exposure and labor market outcomes over time.

Other explanatory variables included in X_{l0} capture district-level covariates measured in the baseline year (2011) that are interacted with year fixed effects to flexibly control for differential pre-existing trends across districts in demographics, industry structure, and labor market conditions. δ_{rt} are subregion $\times$ year fixed effects that control for time-varying regional shocks, such as macroeconomic and climate-related events; α_l are district fixed effects to control for time-invariant unobserved heterogeneity, including geographical, institutional, and socio-economic factors; and ε_{lt} is a mean-zero error term.[13]

Besides the main evaluation of the average labor market impacts of automation, we conduct several complementary analyses. We assess heterogeneous effects of robot adoption across workers by education, sex, age, and wage quartiles, allowing us to identify displacement effects, labor reallocation dynamics, and the unequal distribution of automation gains. We further examine spatial spillovers and internal migration responses to assess how local labor markets adjust to automation shocks and whether our estimates understate broader general equilibrium effects.

Finally, we explore possible mechanisms behind our documented labor market effects by examining the impact of robot adoption on firm's employment and value added using the microdata from the VES enterprise surveys. We estimate these effects separately by broad economic sectors (manufacturing, construction, and services). Given the role of trade as a potential factor mediating the effects of automation, we also examine the effects of robot adoption on firms' import and export behavior.[14]

III.1 Descriptive statistics

Appendix Table B1 presents district-level descriptive statistics for selective years, namely 2011, 2014, 2017 and 2020. The stars indicate whether the mean for year t differs significantly from the mean for $t-3$. From 2011 to 2020, robot adoption increased significantly, from

[13] Viet Nam is divided into eight subregions: Red River Delta, Northeast, Northwest, North Central Coast, South Central Coast, Central Highlands, Southeast, and Mekong River Delta.

[14] Detailed information related to firms' import and export values is available only in 2 years of the VES dataset (2011 and 2019), so we estimate the adoption effects using changes between the two years 2011 and 2019.

the nationwide average of 0.04 to 0.78 robots per thousand workers, surpassing the world's average robot adoption. The sustained robot penetration is reflected in the statistically significant difference in the means across all 3-year periods.

Within this decade, Viet Nam also experienced a steady employment rate–the share of working-age population who are employed hovered at around 80 percent, and remained above 75 percent even during the COVID-19 year in 2020. The unemployment rate fluctuated around 2 percent. At the same time, key labor market indicators improved: the informality rate fell sharply (by 14.5 p.p.), the share of salaried jobs rose substantially (by 14.4 p.p.), and both monthly labor incomes and hourly wages increased markedly (by 28.8 and 31.6 percent, respectively).

This period also coincided with sustained improvements in educational attainment and structural transformation. The share of adults who completed secondary and tertiary education increased by 1.1 and 4.6 percentage points, respectively. Alongside, there were marked changes in the employment structure: the share of employment in the primary sector decreased by 14.1 p.p., while manufacturing and services increased by 6.6 and 7.4 p.p., respectively. Similarly, the employment shares in private domestic firms and FOEs increased by 3.6 and 8.3 p.p., respectively.

The descriptive statistics from the VES dataset, which covers all registered enterprises in Viet Nam, corroborate these patterns (Table B2). During the same period, firm's value added, employment, average wages, and average value added per worker all increased markedly. In line with the evidence presented in Table B1, these trends suggest that the overall quality of employment in Viet Nam improved substantially over the period.

III.2 Identification

Our econometric analysis focuses on the period 2014–2020 which registered the sharp increase in robot adoption beginning in 2016. The period 2011–2014 is used to assess pre-existing trends and perform a set of robustness checks. We use 2011 as the baseline year to construct district-level employment composition across IFR-available industries and to measure initial district characteristics, including demographics, industrial structure, and labor market conditions. Crucially, because Viet Nam's robot adoption in 2011 was virtually zero, it is unlikely that baseline employment patterns were shaped by subsequent automation trends.

Figure 4 displays the geographic distribution of changes in robot exposure across districts, measured as the average annual change in ER_{lt} (calculated using equation (3)) between 2014 and 2020. The figure reveals substantial spatial variation, which is crucial for our identification strategy. Among districts in the top quartile of adoption, average annual increases in robot exposure range from 0.04 to 2.01 per thousand workers (up to 0.81 in the 99th percentile); whereas approximately half of all districts exhibit very low exposure (between 0 and 0.04). Districts with the highest levels of adoption are geographically spread across Viet Nam's major industrial hubs: in the north (Red River Delta)–especially around Ha Noi and nearby other provinces such as Bac Ninh, Hai Duong, and Hung Yen; in the south–around Ho Chi Minh City and (formerly) Binh Duong and Dong Nai; and in the central region around Da Nang province.

As discussed before, robot adoption is potentially endogenous since firms' decisions to adopt automation technologies can be affected by other industry-specific supply or demand shocks, which could also impact their labor demand and overall labor market outcomes. Additionally, measurement error in district-level robot exposure (due to error in either the industry-level robot counts or the local employment shares) could introduce attenuation bias. To address these concerns, following Acemoglu and Restrepo (2020) and Dauth et al. (2021), we instrument ER_{lt} with a measure of global robotization trends across industries—that is, the average industry-level robot adoption across 56 countries with comprehensive and comparable data from the IFR and OECD, excluding Viet Nam. The instrument is constructed as follows:

$$ER_{lt}^{World} = \sum_j \left(\frac{L_{jl,2011}}{L_{l,2011}} \right) \times \frac{1}{56} \sum_{c \in World} Robot\ Adoption_{cjt}, \tag{4}$$

where j and c denote industries and countries, respectively, and $Robot\ Adoption_{cjt}$ refers to the number of robots per thousand workers in each industry-country pair. The weights correspond to the baseline (2011) industry employment shares at the district level, ensuring that the temporal variation in the instrument stems exclusively from worldwide robot adoption rather than local employment dynamics. We interpret ER_{lt}^{World} as a proxy for improvements in the availability of industrial robots technology for firms in Viet Nam during the period of study.

Figure 5 plots the unconditional first-stage relationship between average annual district-level changes in ER_l on ER_l^{world} during 2014–2020. The relationship is strong and statistically significant ($p < 0.01$), with a coefficient of 3.88 (std. error 0.24, R-squared of 0.81). This confirms that the global trends in robot adoption are a strong predictor of the observed adoption patterns in Viet Nam during this period, consistent with the descriptive evidence at the industry level reported earlier (see Figure 2). To account for potential outlier influence, we also report results from a specification that excludes the top 1 percent of districts with the highest robot exposure.[15]

The shift-share instrumental variable approach leverages the cross-industry and intertemporal variation in robot diffusion combined with the initial industry employment composition across districts. Our identification strategy leverages the variation in global robot adoption as capturing exogenous technological shifts that affect the availability and affordability of robots in Viet Nam. Specifically, our identifying assumptions are: (i) global industry-level robotization trends are orthogonal to Viet Nam-specific industry shocks, and (ii) districts with greater initial employment shares in industries undergoing faster robot adoption are not differentially affected by other concurrent labor market shocks or trends.

A potential threat to the validity of the instrument would arise if Vietnamese industries most exposed to global robotization were also affected by other shocks–such as surges in foreign investment, trade policy changes, or sector-specific input supply or demand shifts. If these shocks were correlated with industry robot adoption, our estimates could be biased. However, three features of our empirical design help mitigate this concern. First, our instrument relies exclusively on robot adoption trends in other countries and is weighted using pre-determined (before the robot adoption surge) industry employment shares. Second, we control for a rich set of district-level initial conditions, including demographics, industry composition, and baseline labor market characteristics. Third, we control for region-specific year effects to capture shocks to local labor markets and explicitly control for exposure to the trade diversion from China, specifically Chinese imports and export demand, to account for its direct effects on labor market outcomes in Viet Nam. Finally, our results remain broadly unaffected when we conduct several other robustness checks, including control for the economic activity of FOEs and the establishment of Special Economic Zones. In the next section, we partially evaluate the second identifying assumption using a pre-trend analysis.

[15] These are districts with ER values between 0.81 and 2.01.

IV Results

IV.1 Validation tests

Before discussing our estimates, we first assess the validity of the empirical strategy. First, we check whether districts with higher exposure to robot adoption differ systematically from less exposed districts in terms of initial labor market conditions and other relevant characteristics. Second, we conduct pre-trend tests to examine whether employment and wage trajectories were similar across districts with varying automation exposure, after accounting for baseline differences in district characteristics (Borusyak et al., 2025, 2022). These exercises provide important checks on the validity of our identification strategy.

Baseline balance tests. Appendix Table B3 presents estimates from regressions of the baseline characteristics of districts (measured in 2011) on the average annual change in robot exposure between 2014 and 2020. Columns 1-3 correspond to the direct measure of exposure, ΔER_l, while columns 4-6 report results for the instrumental variable, ΔER_l^{World}. Estimates for most indicators reveal that districts more exposed to robot adoption already exhibited stronger economic and labor market conditions at baseline. In particular, high-exposure districts had higher labor incomes and wages, and lower overall employment rates and informality. They also featured a larger, urban, young and more educated population, and had a larger share of employment in manufacturing and services, salaried jobs, foreign-owned enterprises (FOEs) and districts had on average lower exposure to China's import competition. These correlations become insignificant or are considerably weakened once we control for our full set of baseline demographic, labor market, and sectoral employment characteristics (columns 2 and 5). This underscores the importance of controlling for initial cross-district differences in socioeconomic characteristics and labor market conditions to mitigate potential confounders and reinforce the validity of our identification. We do so accordingly in all of our empirical specifications.

Pretrend tests. Appendix Table B4 reports estimates from regressions of the average annual change in robot exposure between 2014 and 2020 on average annual changes in district characteristics during the pre-treatment period (2011–2014). Building on the previous discussion and results presented in Table B3, the objective is to assess whether pre-existing trends in district-level characteristics are correlated with subsequent exposure to robots, and whether any potential bias in our estimates can be addressed by controlling for linear time trends of average district baseline characteristics. As before, columns 1-3 use the direct exposure measure, ΔER_l, and columns 4-6 report the results when adopting the instrumental variable, ΔER_l^{World}. Columns 1 and 4 present specifications without controlling for linear trends of initial characteristics, including demographics, labor market outcomes, and industry composition. The other columns include these controls.

We find that districts which later experienced greater exposure to robot adoption do not display systematically different pre-treatment trends in labor market outcomes relative to less exposed districts, once linear trends in baseline district controls are accounted for (Panel A). This finding lends support to the parallel trends assumption underlying our identification strategy.[16] Likewise, we observe predominantly insignificant coefficients when examining pre-trend differences in demographic, labor market, and sectoral employment characteristics in Panel B. That said, two differential trends can be discerned in districts that later became more exposed to robotization. More exposed districts already exhibited an increase in the manufacturing employment share and in the inflow of migrants between 2011 and 2014–before the robot adoption surge—, although the latter trend is less robustly estimated. In a robustness check to our main specifications, we also control for these two differential pre-trends.

IV.2 Effects of robots on labor market outcomes

Having established support to the validity of our empirical design in the last section, we next examine our estimates of the causal effects of industrial robot adoption on local labor market outcomes in Viet Nam, focusing on employment, wages, and population dynamics.

Table 1 presents two-stage least squares (2SLS) estimates of equation (2), instrumenting local robot exposure ER_{lt} with its counterpart ER_{lt}^{World}, derived from global adoption trends. Panel A reports the first-stage results and Panels B and C display our estimates of the impacts on employment and wage outcomes (in logs), respectively. In addition to the impact on overall employment (B.1), Panel B presents impacts on four other indicators: (i) formal salaried employment, (ii) informal salaried employment, (iii) non-salaried employment (e.g., self-employment and family work), and (iv) unemployment. The impacts on wages are reported for average hourly earnings and separately for formal and informal salaried workers.

In order to gauge the robustness of the results, we estimate several specifications to

[16]There is a statistically significant coefficient between the labor informality rate and robot exposure derived from Viet Nam adoption trends, but the estimates become small and insignificant for the measure of robot adoption derived from global trends used in our IV regressions.

account for potential confounding factors. All specifications include district and subregion-by-year fixed effects to capture regional trends. Identification therefore relies on within district-variation in outcome and robot exposure variables over time. We introduce progressively controls for district-level baseline demographic and economic characteristics (column 2), labor market conditions (column 3), and Chinese trade flows (column 4), as discussed in the previous section.[17] To examine the influence of outliers, Column 5 shows results from estimating the most comprehensive specification (column 4) excluding the top 1-percent of the most robot-exposed districts in the sample. This specification allows us to examine whether the effects are driven by districts with the highest levels of robot adoption, or whether they reflect a more widespread pattern. Our discussion relies on the results from columns 4 and 5 as our preferred specifications. All regressions are weighted using the 2011 district's population and the standard errors are clustered at the province level to account for within-province correlation in errors; for instance, the possibility of workers commuting across districts within the same province.[18]

First-stage results. The result in Panel A in Table 1 indicates a strong relationship between the instrument and actual robot adoption, with T and KP F-statistics well above conventional thresholds, mitigating weak instrument concerns. This aligns with the unconditional first-stage correlation shown in Figure 5 between average annual changes in ER_l and ER_l^{World}.

Employment effects. Panel B reports the main results on employment from our analysis. We find that districts more exposed to robot adoption experienced significant growth in overall employment. The estimated elasticities in Columns 4 and 5 imply that one additional robot per thousand workers led to a 6.5 to 9.7 percent increase in total employment. The estimated impacts on the number of unemployed are positive but insignificant. We also find null impacts on the rates of employment (employment over population) and unemployment, the former result suggests that population changes offset the increase in employment (see results in Appendix Table B5).

[17]Specifically, demographics and industry structure include: log population and the share of migrants, educational attainment (primary, secondary, tertiary), age groups, female share, and sectoral employment composition (primary, manufacturing, services, and female share in manufacturing). Labor market conditions include: employment, unemployment and informality rates, average wage, female LFP rate, employment share in FOEs, and exposure to routinization (computed by interacting each district's 2011 employment by 2-digit ISCO-08 occupation with Viet Nam's routine-task intensity (RTI) index from Lewandowski et al. (2022) and Schotte et al. (2023)). Finally, Chinese trade exposure is measured by interacting district industry composition in 2011 with changes (and levels) in log Chinese imports and exports between 2000 and 2011.

[18]Results are robust to clustering at the district level.

Notably, the magnitude of the effects on employment increases when we exclude districts with the largest robot exposure (column 5). This confirms that the results are not driven by outlier districts with extreme robot exposure, but also suggests that the positive impacts on employment are diminished in districts with very high robot exposure.

Panel B in Table 1 also presents the estimated impacts by job type. The effects of robot adoption on both formal and informal salaried employment are positive, although not statistically significant. The effect on non-salaried employment is positive and significant when we exclude the 1% highly-exposed districts from the estimation. The number of self-employed workers increased by 5 to 7 percent in districts that adopted one more robot per thousand workers. Additionally, Table B6 shows effects on employment composition by firm ownership type, as reported by workers in the LFS. We find a small and statistically significant increase in employment of Foreign-owned Enterprises (FOEs), a decline of similar magnitude in employment of domestic private firms (excluding family businesses), and no effect on public sector employment.

The results shed some light on patterns of labor reallocation and potential spillover effects. One could expect to see any labor displacement effect from automation on the level of formal salaried employment. The null effects suggest that robot adoption has been accompanied by expansions in the scale of production that spurred greater labor demand which in turn offset the direct labor savings arising from automation. This is consistent with the employment gains concentrated in FOEs, which are more prevalent in technologically advanced, export-oriented manufacturing industries integrated into global value chains.[19] Finally, the results suggest that the boost in economic activity and employment in the robot-adopting sectors may have generated positive spillover effects for other sectors in the exposed locations, such as the lower-skilled service sectors which often employ self-employed workers. In section IV.5, we present evidence from enterprise surveys that supports this interpretation.

Wage outcomes. Panel C shows our estimated impacts of automation on wages. The result indicates that robot adoption boosted average wages modestly and the wage gains accrued to formal salaried workers. The estimates imply that one additional robot per thousand workers increased average wages of formal workers by approximately 3 to 5 percent. Informal sector wages remain unaffected. These results again contrast with the negative impacts of robot adoption documented for advanced economies (Autor and Salomons, 2018; Acemoglu and

[19]Interestingly, the estimated coefficients for formal salaried employment and FOEs become much larger when we exclude districts with very high robot exposure, although the former remains insignificant, which again may reflect larger displacement effects when automation deepens.

Restrepo, 2020), but align with the literature on skill-biased technological change and capital-skill complementarity to the extent that formal salaried jobs are relatively more skilled in developing economies like Viet Nam.

Taken together, our results of positive effects of automation on labor market outcomes in Viet Nam support a productivity-based explanation: robot adoption has enabled an expansion in production capacity alongside greater labor demand that have offset the direct labor-savings arising from automation. In Section IV.5, we provide supporting evidence showing that firms in robot-adopting districts experienced significant gains in value added, trade and employment. These firm-level dynamics corroborate the view that automation led to net job creation through scale effects.

However, these average effects may mask substantial heterogeneity across workers. The previous results already suggest that gains are not evenly distributed. For instance, formal jobs are more skill-intensive and benefit more from automation-induced productivity growth, thus gains may accrue more to better educated individuals. We examine heterogeneity effects in detail in the next section.

IV.3 Heterogeneous effects

To examine the employment and wage impacts of robot adoption across workers, we estimate equation (2) across subgroups defined by skill level (proxied by educational attainment), gender, age, and at different quartiles of the wage distribution. Figures 6 through 10 illustrate the 2SLS estimates from our preferred specifications, which include the full set of controls for regional trends and baseline district characteristics (Table 1, columns 4 and 5). We display coefficient estimates with 95% confidence intervals. The light bars correspond to estimates using the complete sample of districts and the dark bars illustrate estimates obtained excluding the top 1 percent of districts with the highest robot exposure.

Employment effects by educational (skill) level. Figure 6 shows the estimated impacts of robot exposure on employment by educational level. Several findings stand out. The overall employment gains from robot adoption are driven by the significant positive impact on more skilled workers, especially those with a college education. There are no significant effects on low-skilled workers (those with only primary education). We find no significant effects on the number of unemployed or labor force participants across skill groups (Panels E–F).

Differentiating by job type reveals how employment gains and displacement are distributed across skills level. Robot adoption increased employment for high-skilled workers in both formal and informal jobs (5-15%) while reducing formal wage employment among low-skilled workers (-15%). Effects for middle-skilled (high-school educated) and low-skilled informal workers are positive but statistically insignificant. These findings—districts with greater robot exposure experience high-skilled employment gains alongside displacement of low-skilled formal workers—are consistent with the literature documenting the uneven labor-market impacts of automation (Autor and Dorn, 2013; Autor et al., 2015; Acemoglu and Restrepo, 2020).

Appendix Figure B5 (Panel A) presents further heterogeneity analysis using skill-based occupational classifications to unpack the negative employment effect of robot exposure on low-skilled workers.[20] Displacement concentrates among low-skilled formal wage workers in occupations intensive in routine manual tasks—specifically, elementary occupations, plant and machine operators, and craft and trade workers—which the literature identifies as most susceptible to automation (Acemoglu and Autor, 2011; Acemoglu and Restrepo, 2020).

The results shown in Appendix Figures B4 (Panel C) and B5 (Panel D) offer suggestive evidence that workers most exposed to displacement by automation find shelter in the informal sector. Districts with greater robot penetration exhibit a significant increase in the labor informality rate among low-skilled workers performing routine manual tasks. The reallocation of displaced low-skilled workers into informal employment may explain the absence of significant effects of robot adoption on aggregate or low-skilled unemployment.

It is noteworthy that both the magnitude and precision of the estimated effects is larger across all groups and outcomes when we exclude the districts most highly exposed to robots. This confirms that our estimates are not driven by a small number of highly exposed locations.

We use our estimates and robot adoption trends in Viet Nam to roughly quantify the number of high-skilled formal jobs spurred by robot adoption and the number of low-skilled jobs displaced. Given our empirical design, our estimates reflect net employment effects attributable to differential robot exposure across districts.[21] Robot adoption is estimated to have led to around 255,000 formal jobs for workers with tertiary education in 2018–22

[20] We use the International Labour Organization occupational classification by skill level (1-digit ISCO).

[21] These calculations combine the preferred 2014–2020 employment estimates with the observed evolution of robot exposure through 2022. They assume that the estimated marginal effects remain constant over the observed range of adoption and continue to hold beyond the estimation period. The figures should therefore be interpreted as illustrative and do not fully account for broader equilibrium adjustments or spatial spillovers.

(or 2.7 percent of formal employment with tertiary education in 2022), with a 90-percent confidence interval ranging between 39,000 and 471,000 workers. In contrast, we estimate that 66,800 low-skilled workers in the formal sector were displaced by robots in 2018–22 (or 2 percent of low-skilled formal employment in 2022), with a 90-percent confidence interval ranging between 15,000 and 119,000 workers. These figures represent estimated job creation or displacement in districts with above-average robot exposure, relative to a counterfactual of average exposure. They should be interpreted as approximate local-equilibrium effects. To the extent that robot adoption generates positive spillovers across districts through migration, trade, and production linkages, these calculations are likely to understate the broader economy-wide impacts——as discussed in the next section.

Employment effects by sex and age. Figure 7 shows the employment estimates by sex and age groups. The results indicate that men and women in districts with greater robot adoption experience similar gains in overall employment. Overall, employment gains are positive across all age groups, though somewhat weaker and less precisely estimated among older workers.

Disaggregating by type of work, robot adoption boosted formal employment among men, while women shifted toward informal wage and self-employment. The results suggest that men were better positioned to capture the formal employment gains spurred by robot adoption, while women benefited more from spillover opportunities into informal, lower-skilled service sectors in higher-adopting districts.

By age group, the employment effects are uniformly positive but imprecisely estimated. Middle-aged and older workers in more exposed districts show larger point estimates for formal wage employment and unemployment, though these become imprecise when the most highly exposed districts are excluded. No discernible age differences emerge in the effects on informal wage and self-employment or labor force participation. Appendix Figure B6 reports results for employment, unemployment, and informality rates, which are broadly consistent with Figure 7.

Wage effects across worker groups. Figures 8 and 9 present heterogeneity results for wage outcomes. Consistent with the employment results, wage gains in districts with higher robot exposure are concentrated among high-skilled workers in formal and informal wage jobs (Figure 8, Panels A-C) and disproportionately benefit workers at the top quartiles of the wage distribution (Figure 9). Workers at the bottom wage quartile did not experience wage gains.

Panels D-F of Figure 8 report the heterogeneous wage effects of robot adoption by gender and age group, distinguishing by job type. Across all groups, wage gains are concentrated in the formal sector—consistent with automation-driven productivity gains flowing primarily to formal sector workers—while effects on informal wages are statistically insignificant. Male and female formal workers both experience positive and significant wage gains, with point estimates for women somewhat larger but less precisely estimated. By age group, young and middle-aged formal workers see the most robust wage gains, while estimates for older workers are positive but imprecise. Across all subgroups except older workers, excluding the most highly exposed districts yields larger and more precisely estimated effects, suggesting that wage gains are a broad phenomenon across local labor markets rather than driven by outlier districts, and that displacement pressures in the most intensely exposed districts may partially offset wage gains. For older workers, the restricted sample only reveals discernible wage gains in informal jobs.

Taken together, the heterogeneity results suggest that the benefits from robot adoption are unevenly distributed and, at least in the short run, tend to exacerbate labor income inequalities in Viet Nam. High-skilled and younger workers benefit most, in terms of both employment and wage gains, while low-skilled formal workers in routine manual occupations face displacement and a push into informality. The pattern is mixed by gender: men are better positioned to capture formal employment and wage gains, while women benefit primarily through spillover opportunities into informal wage and self-employment—-consistent with recent evidence from Latin America and China (Brambilla et al., 2023; Linghu, 2025).

Older workers tend to benefit less from automation, with considerable heterogeneity in how they are affected. This aligns with findings in other developing East Asian countries. In China, robot adoption is associated with lower wages and greater employment loss among older workers, especially among low-skilled (Giuntella et al., 2025). This contrasts with evidence from developed countries such as the United States, where displacement affects more heavily middle-age workers (Acemoglu and Restrepo, 2020, 2022b). The difference likely reflect the lower educational attainment and task composition of jobs of older workers in developing countries–predominantly routine manual tasks–which make them more vulnerable to automation.

IV.4 Spatial spillovers and labor migration

As discussed, our empirical strategy does not directly capture spillover effects arising from commuting or inter-district linkages. For instance, if robot adoption depresses labor demand in high-exposure districts and triggers significant worker migration, the ensuing labor supply shift in low-exposure districts will compress cross-district employment and wage differentials and attenuate our estimates. This does not invalidate our identification strategy. The key requirement is that the instrument for district i—constructed from other countries' adoption patterns—does not directly affect outcomes in district j through channels other than j's own exposure. If neighboring district exposure is correlated with own-district exposure–which may be the case if geographically proximate districts have very similar industrial structures–then omitting neighbor robot exposure from our baseline regressions will bias our estimates. Depending on the sign and magnitude of the spillovers, ignoring them will either attenuate or bias our estimates, causing them to misstate the economy-wide effects of robot adoption. We conduct an empirical exercise to detect spatial spillovers from robot exposure in neighboring districts and to assess the nature and extent of cross-district labor migration.

Measuring spatial spillovers. We begin by constructing a district-level distance matrix, where each element captures the average distance between the centroids of each pair of districts i and j. Using this matrix, we compute alternative measures of exposure to robot adoption in nearby locations by defining distance-based thresholds, of 20, 30, and 40 kilometers. Figure 4 shows that changes in district-level robot exposure tend to be concentrated in relatively tight pockets so these distance thresholds allow us to gauge the spread of local spillovers. The correlations between own-district robot exposure and neighbor exposure are 0.64, 0.62, and 0.60 for the 20, 30, and 40 km thresholds, respectively. For each district, we calculate a population-weighted average of robot exposure in all other districts falling within the corresponding distance cutoff. We then estimate a two-stage least squares regressions for the main labor market outcomes using our preferred specifications that control for baseline district characteristics and regional trends (full sample and excluding outliers) and including two endogenous variables: (1) robot exposure in the own district and (2) exposure in nearby districts. Both are instrumented using shift-share IVs constructed as in our baseline specifications.

This approach allows us to isolate the direct effect of automation within a district from potential spillover effects arising from robot exposure in neighboring districts and associated migration flows. Significant spillover coefficients would imply that our baseline estimates are attenuated and subject to omitted variable bias. The direction of attenuation or bias depends on both the sign and strength of the spillover and of the correlation between own and neighbor robot exposure. If neighboring robot exposure has a direct negative effect on local employment (e.g., through demand competition) and is positively correlated with own exposure, the baseline coefficient on own exposure will be biased downward–reinforcing any attenuation arising from migration driven by a district's own robot exposure. Conversely, if spillovers are positive (through agglomeration or local demand effects), our baseline estimates may overstate the own-district direct effect. Comparing own-district coefficients between the baseline (Table 1) and augmented specifications clarifies whether the baseline estimates represent lower bounds—when positive spillovers are present—or upper bounds—when spillovers are negative.

The results of the analysis are presented in Appendix Tables B7 and B8. The analysis reveals positive spillovers from robot adoption in neighboring districts, particularly for wages and non-salaried employment. Neighbor robot exposure is not statistically significant in the employment regressions and the coefficients on own-district robot exposure remain largely unchanged relative to our baseline estimates that omit neighbor exposure. In contrast, neighbor robot exposure leads to statistically significant increases in average wages, concentrated in the formal sector and robust across distance bands. In addition, robot adoption generates positive spillovers to non-salaried employment in nearby districts, that are stronger at intermediate distances. Notably, the coefficients on own district robot exposure are somewhat lower than in our baseline regressions and even turn insignificant for non-salary employment, while the magnitude of the spillover effects is comparable to, and in some cases larger than, the corresponding own-district effects.

The absence of significant neighbor spillovers and the stability of our own-district exposure coefficients confirm that our positive employment effects are robust to either attenuation or omitted variable bias. For wages and self-employment, the results suggest that our baseline estimates overstate the direct own-district effects of robot exposure. The positive wage and self-employment spillovers further suggest that migration-induced labor supply shifts are not a dominant force compressing cross-district differentials and hint at the importance of local demand and agglomeration effects, at least for wage outcomes. Next, we examine directly how robot adoption impacted cross-district labor mobility.[22]

[22]Labor mobility in Viet Nam has been historically restricted by the Household Registration (Ho Khau) system. This limited migration both across and within provinces by linking citizens access to public education and healthcare services to their officially registered address. Two significant revisions to the Law on Residence eased the restrictions. The 2007 reform relaxed residency requirements for permanent registration from three years of continuous living to just one year in most cities. The 2014 reform, conversely, tightened requirements

Internal labor mobility. Table 2's Panel A shows that robot-exposed districts saw an expansion in total population, both of working-age and non-working age. The number of labor force participants increased by 6 to 10 percent in districts exposed to an additional robot per thousand workers. Panel B further shows that districts with greater robot exposure received more migrants. The estimated elasticity of in-migration is around 14 percent. The elasticity of out-migration is positive and about half the magnitude but is imprecisely estimated. These results suggest that net in-migration accounts for most of the population increase driven by robot adoption.

Figure 10 displays results to unpack the characteristics of working-age migrants. Migration inflows into robot-adopting districts are driven primarily by young-to-middle-aged, more skilled workers, and are similar across genders. In contrast, the estimated effect on out-migration is significant only among low-skilled workers.

Taken together, the spatial spillover and migration results sharpen the interpretation of our baseline estimates. The fact that robot-adopting districts are net recipients of skilled, working-age migrants indicates that positive employment effects reflect both job creation and labor force expansion through in-migration–which also explains why employment rates remain unchanged (Appendix Table B5). For wages, our baseline estimates capture the net wage premium after partial attenuation by the in-migration of skilled workers, implying that the true wage impact of automation-driven productivity gains is larger than our estimates suggest. For low-skilled displacement, significant out-migration implies that our baseline understates the true extent of displacement–some low-skilled workers exit robot-adopting districts rather than transitioning into local unemployment or informality. Finally, positive wage and self-employment spillovers to neighboring districts, robust across distance bands and comparable in magnitude to own-district effects, are inconsistent with migration-driven compression of cross-district differentials as the dominant force, and instead point to local demand and agglomeration effects as the primary transmission channel.

The findings underscore the importance of labor mobility in shaping adjustment to trade and technology shocks. In the United States, workers affected by automation or import competition show slow geographic reallocation and long-term wage scarring (Acemoglu and Restrepo, 2020; Autor et al., 2025). Similar rigidity has been documented in Brazil and India (Topalova, 2010; Dix-Carneiro and Kovak, 2017). In contrast, in Viet Nam we uncover significant internal migration flows, both of skilled workers moving into high-adoption districts

for "Tier 1" cities like Hanoi and Ho Chi Minh City, raising the continuous living requirement to two or three years, and creating incentives to move other provinces that hosted the growing industrial zones.

and of unskilled workers migrating away.

Collectively, the results suggest that our baseline estimates are robust to potential biases arising from spatial spillovers and attenuation from cross-district labor migration. In the next section, we assess directly the evidence that robot adoption created new economic opportunities through shifts in labor demand, with particular focus on the mediating role of trade.

IV.5 Effects of robots on firm outcomes

In this section we provide complementary evidence on the effects of robot adoption on indicators of economic opportunities using data from the Viet Nam Enterprise Survey (VES), which covers the universe of registered firms with 30 or more employees and a representative sample of firms with fewer than 30 employees.[23] We specifically examine a key mediating factor: the export-driven scale effects in production that automation enables. These scale effects may have mitigated the labor-displacing effects of robots by expanding output and employment, especially among skilled workers who complement automation.

Table 3 presents 2SLS estimates from regressions of district-level changes between 2011 and 2019 since the trade data reported by firms in the VES is available only in those years. We use the same specifications and IV as in Tables 1-3 and also control for baseline (2011) differences in imports and exports (logs) to account for baseline differences in trade orientation across districts. The results show that firms in districts with greater exposure to robot adoption experienced significant increases in value added, employment, and average value added per worker (a measure of labor productivity) as well as in both imports and exports. In our preferred specifications, an increase of one robot per thousand workers is associated with a 2.6 to 2.9 percent increase in district-level firm value added, a 0.9 to 1.0 percent increase in employment, a 1.0 to 1.5 percent increase in value added per worker, and an 8 percent increase in exports and a 14 percent increase in imports. These results are robust across all specifications.

Figure 11 presents results of similar regressions of changes in outcomes to explore heterogeneity across major industries. The light bars report point estimates for the full sample with 90-percent confidence intervals, while dark bars exclude the top 1-percent most ex-

[23] We exclude the primary sector (e.g, agriculture) since registered firms in this sector make up only about 1% to 2% of the total formal enterprises in the VES dataset.

posed districts. We find that value added, employment and labor productivity gains were broadly distributed across sectors (except in trade, and employment in personal services), being specially pronounced in professional services. Notably, labor productivity gains are robust in manufacturing in both the full sample and the restricted sample that excludes the most-exposed districts. Wage gains are also positive and more pronounced in personal and professional services.

The estimated effects on firm-level labor outcomes differ somewhat from the LFS-based estimates, likely reflecting differences in data coverage. Wage effects are positive but statistically insignificant. Also, the magnitude of the estimated employment effects in the VES is smaller than those found with the LFS data (Table 1). These differences likely reflect the broader employment coverage of the LFS, which includes informal, agricultural, and self-employed workers, whereas the VES is limited to registered firms. Moreover, the LFS captures worker-level information on hourly earnings, while the VES aggregates total wage payments at the firm level, potentially obscuring labor supply and within-firm or skill-specific wage dynamics. The muted wage effects in manufacturing may reflect the offsetting influence of displacement and productivity gains.

Taken together, these firm-level results reinforce the labor market findings above. Robot adoption in Viet Nam led to productivity gains which, in turn, enabled scaled-up production alongside export growth, and created direct and indirect positive impacts on local labor markets. Effects that may have offset direct labor displacement.

These findings suggest that automation has supported Viet Nam's structural transformation by expanding production, employment, and labor productivity among registered firms. The evidence points to a combination of productivity spillovers and demand-side linkages: as robot adoption boosts output in high-tech, export-oriented manufacturing, it stimulates demand for business services such as logistics and professional support. Rising labor incomes in these sectors may, in turn, increase local demand, reinforcing the expansion of output and employment. These dynamics are consistent with the idea that robot adoption indirectly benefits service sectors by generating local multipliers, fostering production and trade, and reallocating displaced workers toward less-exposed but complementary industries.

IV.6 Robustness exercises

Finally, we discuss results from a battery of additional checks to assess the robustness of our findings. These include further accounting for potential confounding factors–including the expansion of Special Economic Zones and foreign-investment during the period–and alternative choices for the estimation sample, regressors, sources of identification, and inference methods. In all cases, we present results for our preferred specifications estimated in the full sample and excluding the 1% districts with the greatest robot exposure (except when we test alternatives for this threshold).

Accounting for differential pre-trends. Our earlier pre-trend analysis shows that controlling for districts' baseline socio-economic characteristics and industrial composition of employment captured reasonably well pre-existing trends in district labor and economic conditions that could bias our estimates (see Table B4). Two district variables still exhibited distinct trends during the 2011–2014 period: manufacturing employment and share of migrants. We re-estimated our main regression specification including these variables to more fully control for differential pre-trends in all of the observed demographic conditions, industry composition, and labor market conditions. Table B9 confirms that our estimates are robust when accounting for these pre-trends.

Accounting for SEZs and FOEs. One development occurring in parallel to robot adoption, which could simultaneously influence districts' economic performance, is the expansion of Special Economic Zones (SEZs) and FOEs, especially given the higher likelihood of adoption in foreign firms and in high-tech parks documented earlier. For instance, Tafese et al. (2025) document that the expansion of SEZs has led to structural shifts of employment from agriculture to manufacturing in foreign firms and improvements in overall employment and wages spreading toward workers in domestic firms.

While our empirical strategy relies on an IV approach that exploits global trends in robot-adoption, we conduct two additional robustness exercises to further alleviate the concern that the impacts of FOEs and SEZs maybe confounding factors that bias our estimates. First, we control for initial differences in the shares of district-level production, employment, and capital accounted by SEZs and FOEs, interacted with year dummies, utilizing available data from the VES survey.[24] In the second exercise, we include additional controls for

[24]The VES includes a question to identify firms operating in industrial zones during the years 2010 to 2016. This variable is correlated with the measure of SEZs created by Tafese et al. (2025) using satellite data. The correlation between the dummy of SEZs (sourced from that paper) and the share of employment in industrial zones across districts (from the VES data) is 0.60.

differential SEZ pre-trends using alternative measures of SEZ intensity from Tafese et al. (2025). Specifically, we control for initial differences in (i) SEZs presence (extensive margin) and for (ii) the number of SEZs established in each district (intensive margin). Tables B10 and B11 present the results corresponding to the two exercises, respectively. Our estimates remain robust in all of these specifications, reinforcing the conclusion that our findings are driven by the isolated robot-adoption treatment, and are unlikely biased by concurrent shocks related to the expansion of SEZs and FOEs in Viet Nam.

Covariates selection. Next, we conduct robustness checks on the stability of our empirical specifications. We used a two-step LASSO regression analysis on the choice and number of covariates (following Belloni et al. (2014)). First, we include all the baseline covariates: demographics, industry composition, labor market conditions, and trade exposure variables. Second, we included additional controls for initial differences in SEZ and FOE activities. And third, we incorporate additional controls for pre-trends in demographics, industry composition, and labor market conditions. Table B12 confirms that our findings remain robust to this alternative method of selecting relevant control variables.

Excluding most-exposed industries (Rotemberg weights) and most-exposed districts. We next examine the robustness of our results to industry composition and alternative exclusion of outlier districts. Figure 1 (panel B) shows that robot adoption in Viet Nam is concentrated in only a handful of manufacturing industries. To assess whether our estimates are driven by unobserved shocks specific to these few industries, we follow Goldsmith-Pinkham et al. (2020) and conduct a decomposition of the shift-share instrument using Rotemberg weights. Table B18 provides a summary of these weights. The results confirms descriptive evidence from Figure 1-Panel B, showing that computers and electronics explain 49 percent of the identifying variation, followed by electrical equipment (36 percent), automotive (8 percent), and rubber and plastics (6 percent). Next, we conduct a regression analysis excluding each of these industries (one at a time) from the computation of robot exposure variable. Table B13 shows that our main estimation results are not sensitive to any particular industry and if anything become stronger, except for the positive effects of non-wage employment which become less precise in some specifications. This reassures us that our results are not driven by trends in particular manufacturing industries that are unrelated to robot adoption.

We then conduct another robustness exercise by estimating our models in samples that exclude the top 5, 10, 15, 20, 25, and 30 districts with the highest exposure to robots. Table B14 presents these results which suggest that our estimates are not driven solely by districts with greater robot exposure defined more expansively. Notably, many of the estimates become stronger as we lower the threshold to exclude high-adoption districts. Specifically, we identify positive, sizable and precisely measured impacts on overall unemployment and informal wages, while the magnitude of the in-migration effects become much larger. At the same time, the main effects on overall employment remain and even become stronger. As noted before (see footnote 21), the 2014 reform of the Law on Local Residence made it more difficult to migrate to "Tier 1" cities, which already feature more urban and vibrant agglomerations, and thus migration to other provinces that hosted the growing industrial zones. Thus, the results on Table B14 are consistent with internal mobility playing an important role in attenuating the labor displacement effect of automation in districts with very high robot exposure and helping fuel agglomeration and local demand spillover effects. They also add a nuance to our positive effects since many in-migrants seem to find themselves queuing for jobs in their new district destinations where local labor demand effects are not strong enough to absorb the inflows of labor.[25]

Alternative definitions of the IV. The instrumental variable used throughout the paper is based on global industry robotization trends, calculated as the simple average of industry robot adoption across 56 countries (equation 4). We assess the robustness of our results to alternative ways to measure this variable using different samples of countries. First, we compute an exposure-IV consisting of the highest robot-adopting countries, defined as the top 15 countries with the largest number of robots adopted per thousand workers in 2020.[26] In the second and third checks, we compute the IV using adoption in strictly high-income countries and strictly middle-income economies. Finally, we compute a weighted measure of ER_l^{World}, with country-specific weights given by the ratio of population above 56 years old to middle-age population (21-55): i.e. the weights are higher for aging countries.[27] This last exercise is based on recent findings of Acemoglu and Restrepo (2022c), who document that aging leads to greater industrial automation because it creates a shortage of middle-aged workers specialized in manual production tasks. Table B15 shows that our estimates are strongly robust to these alternative definitions of our instrument.

Regressions in changes. An alternative empirical approach utilized in existing studies (including Acemoglu and Restrepo (2020)) is to estimate regressions in period-changes in

[25] In the last case, 30 represents the 4.4 percent of all districts and account for 6.5 percent of Viet Nam's population in 2011.

[26] These countries are South Korea, Singapore, Taiwan; China, Japan, Germany, Slovenia, Czech Republic, Austria, Slovak Republic, Sweden, Italy, Switzerland, Denmark, and the United States.

[27] The countries with the highest *normalized* weights, in a 1-100 scale, are Japan (4.65), South Korea (3.5), Finland (3.24), Thailand (3.1) Lithuania (2.95), Singapore (2.91) and Germany (2.88). The countries with the lowest weights are Saudi Arabia (0), Egypt (0.01), Argentina (0.48), South Africa (0.51), India (0.64) and Philippines (0.65). The corresponding weight for Viet Nam would be 0.68.

both the treatment (robot exposure) and outcome variables. These differences models rely on within-district period changes and allow to check that our main findings are not an artifact of a particular base year or end year. However, they carry a loss of statistical precision since they rely on a more limited source of variation, effectively smaller sample sizes, and may amplify measurement error in both the treatment and outcome variables. Table B16 presents the estimated results following these alternative specifications, using four different periods to calculate the changes: 2014 vs 2020, 2014 vs 2019, 2015 vs 2020, and 2015 vs 2019. Although with the anticipated loss of statistical precision, the estimated coefficients remain largely consistent with our baseline estimates and provide a complementary robustness check that our findings are not driven by idiosyncratic shocks concentrated in a specific sub-period unrelated to the timing of robot adoption.

Alternative inference method. Finally, in shift-share regression designs, errors could share a common component in districts with similar industrial composition. Borusyak et al. (2022) developed an econometric framework (SSIV) that allows exposure shares to be endogenous under the assumption that industry shocks are quasi-randomly assigned. In our context, this implies that global shocks leading to increased robot adoption are orthogonal to unobserved district-level trends in Viet Nam. The SSIV method is based on equivalent industry-level regressions that produce the same point-estimates and new adjusted standard errors. The results in Table B17 from this analysis reinforces the robustness of our main results.[28]

V Conclusion

This paper examines the local labor market effects of industrial robot adoption in Viet Nam, a rapidly developing economy that experienced one of the fastest increases in robotization worldwide during the past decade. Drawing on detailed microdata from labor force and enterprise surveys, we document that—contrary to widespread fears of automation-induced unemployment—robot adoption led to employment and wage gains in districts with greater robot exposure. Our findings from firm-level production analysis point to simultaneous increases in value added, employment, labor productivity, and trade volumes in robot-exposed districts.

Our findings differ from existing empirical studies showing that the adoption of industrial

[28]Our estimates are also robust to allowing for serial correlations at the industry level. These additional results are excluded for brevity but are available upon request.

robots has hurt aggregate manufacturing employment and wages (see, for example, Graetz and Michaels (2018); Acemoglu and Restrepo (2020)). This difference likely reflects the comparative advantage of East Asian emerging economies such as Viet Nam in export-oriented manufacturing. As a result, firms face high price elasticity of demand in global markets. This high elasticity means that productivity-driven reductions in costs and prices lead to significant export-driven increases in the scale of production, which offset the labor-saving effects of robots.

Moreover, the positive local effects of robot adoption were accompanied by significant spatial spillovers and internal migration, suggesting that automation generates direct productivity and employment gains within districts that radiate outward through demand and agglomeration channels to benefit neighboring labor markets—rather than merely displacing workers from one location to another. These effects mirror those observed within exposed districts and point to the expansion of ancillary economic activities—such as services, household businesses, and other forms of self-employment—that benefit from increased industrial activity and local demand generated by automation hubs. Estimates that focus solely on own-district exposure likely understate the full spatial reach of robot adoption's effects, especially for wage growth and non-salaried employment.

Our results withstand a wide range of robustness checks. These exercises confirm that our estimated effects are not spurious and do not merely reflect concurrent changes in the Vietnamese economy unrelated to robot diffusion. These patterns reinforce our interpretation that industrial robot adoption in Viet Nam has driven significant economic transformation, distinct from other economy-wide or industry-specific trends.

Altogether, the results are consistent with automation raising firm productivity, enabling firms to scale production, expand employment, and compete more effectively in international markets. They underscore the role of labor mobility in amplifying local labor demand effects and facilitating structural transformation. Labor mobility responses mitigated labor displacement, supported employment in complementary sectors like services, and facilitated the expansion of output and exports by channeling workers with complementary skills to where they were most needed.

Finally, our findings also reveal that the labor market gains from robot adoption in Viet Nam were unevenly distributed. Employment and wage benefits accrued mostly to middle- and high-skilled workers, while low-skilled individuals faced job displacement and increased reliance on informal work. The results highlight that the dual nature of automation—

documented in advanced economies by Autor and Dorn (2013) and Acemoglu and Restrepo (2020)—applies in developing economies as well: automation can serve as a powerful engine of growth and structural transformation, but also exacerbates inequality.

Understanding these dynamics is critical for designing inclusive industrial and labor market policies that harness the productivity gains of automation while mitigating its disruptive effects in developing economies. Future research should explore how complementary investments—in education and skills, social protection systems, and regional integration—can ensure that the gains from automation are more widely shared.

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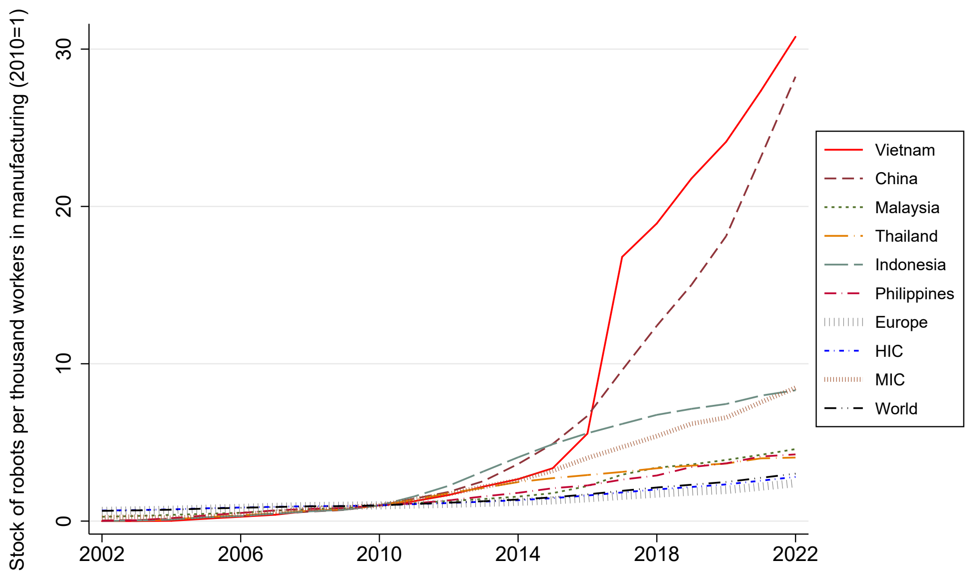
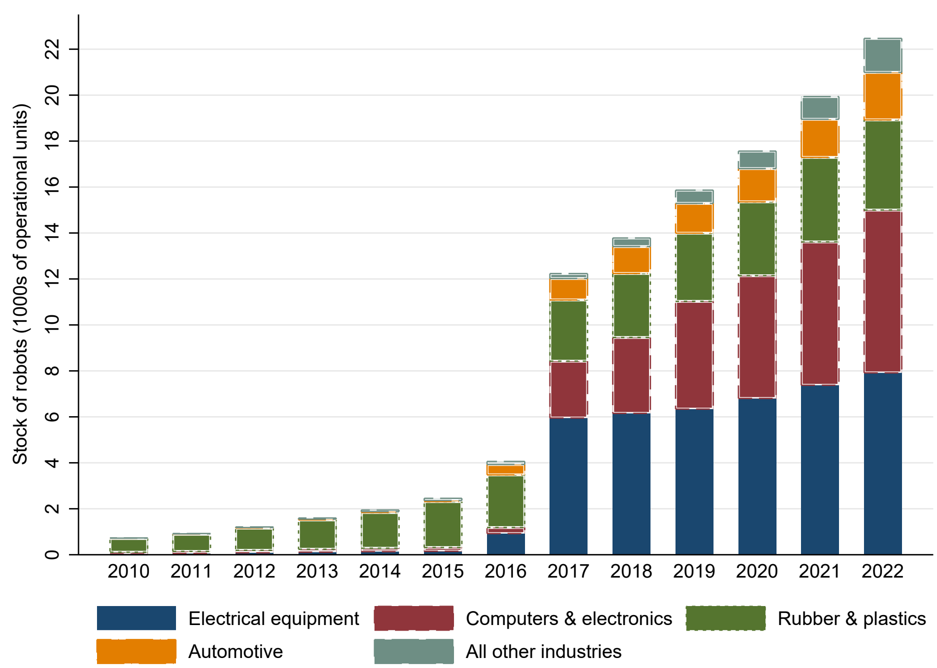
VI Main tables and figures

Fig. 1: Evolution of industrial robot adoption

(a) Country trends

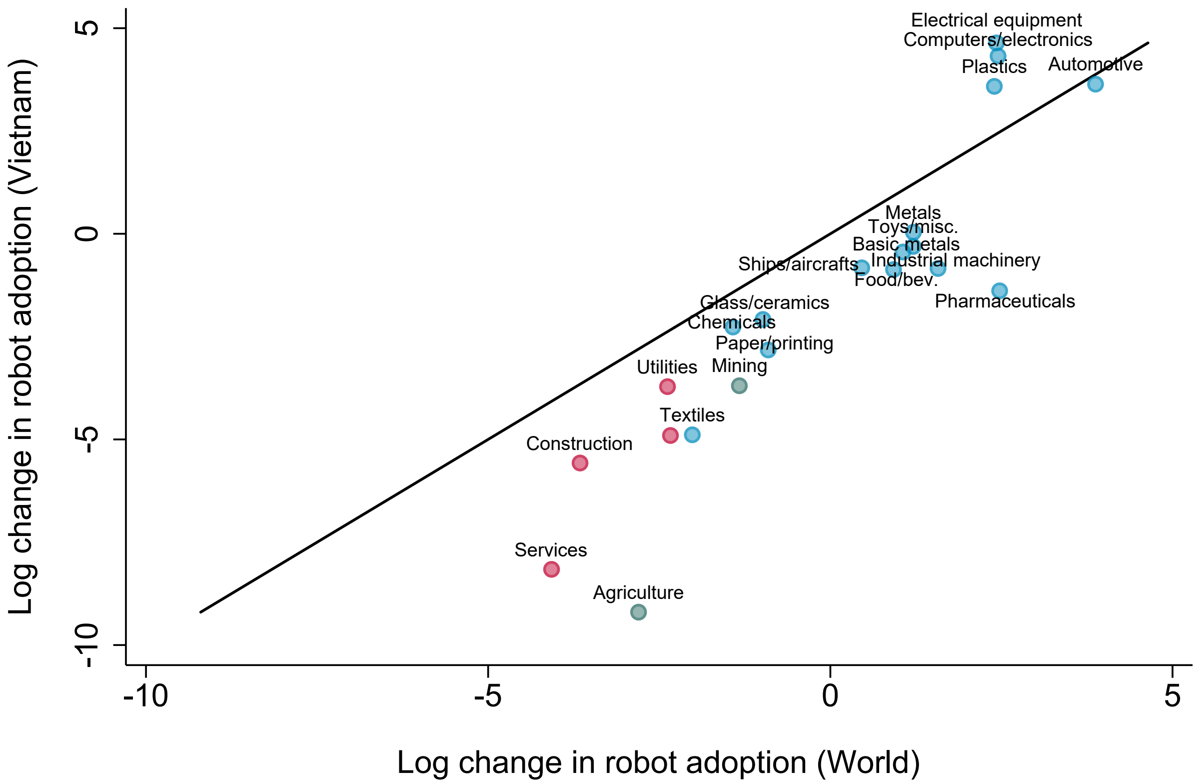


(b) Industry composition of Viet Nam's stock of robots



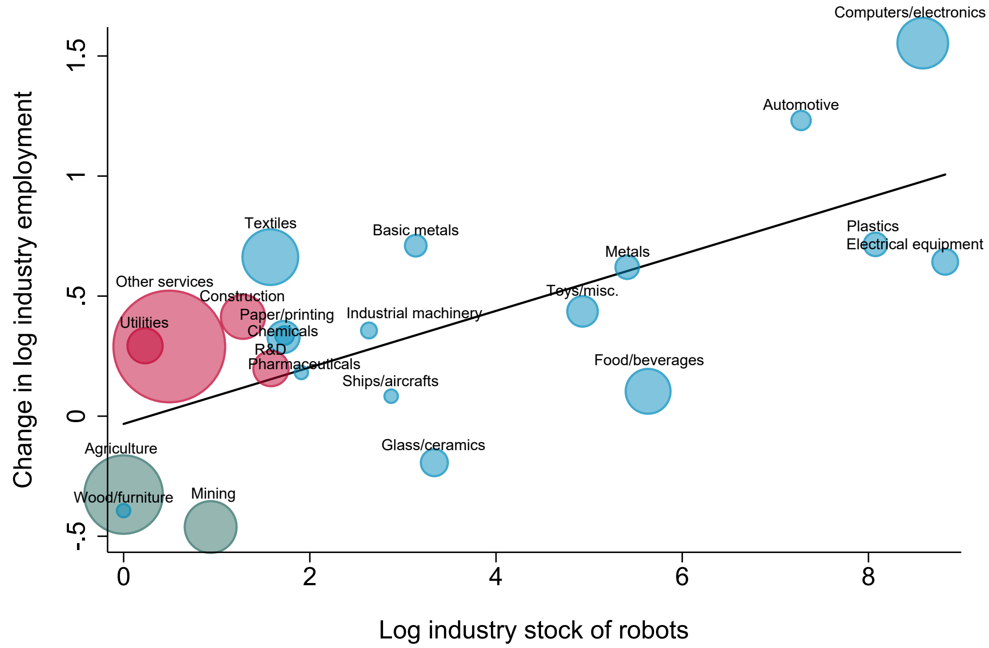
Notes. Top panel shows the evolution of the stock of robots per thousand workers (in manufacturing industries) in Viet Nam and different countries/groups between 2002 and 2022 (normalized to 1 in 2010). Bottom panel shows the evolution of industry composition of Viet Nam's total stock of industrial robots between 2010 and 2022. Sources: IFR and OECD.

Fig. 2: Correlation between robot adoption in Viet Nam and the World



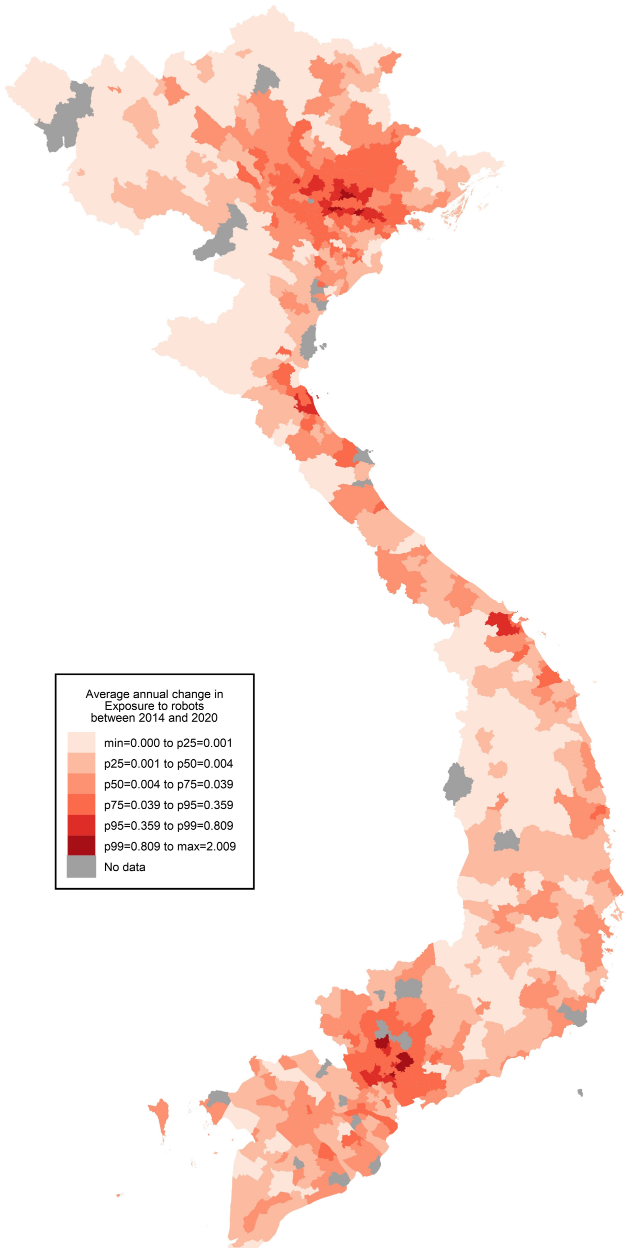
Notes. The figure presents the correlation between the 2010–2020 log changes in the stock of robots per thousand workers in 1995 by manufacturing industry in Viet Nam and the World average. The solid line is the 45° line. Sources: International Federation of Robotics (IFR) and OECD Employment Statistics.

Fig. 3: Industry employment and robot adoption in Viet Nam



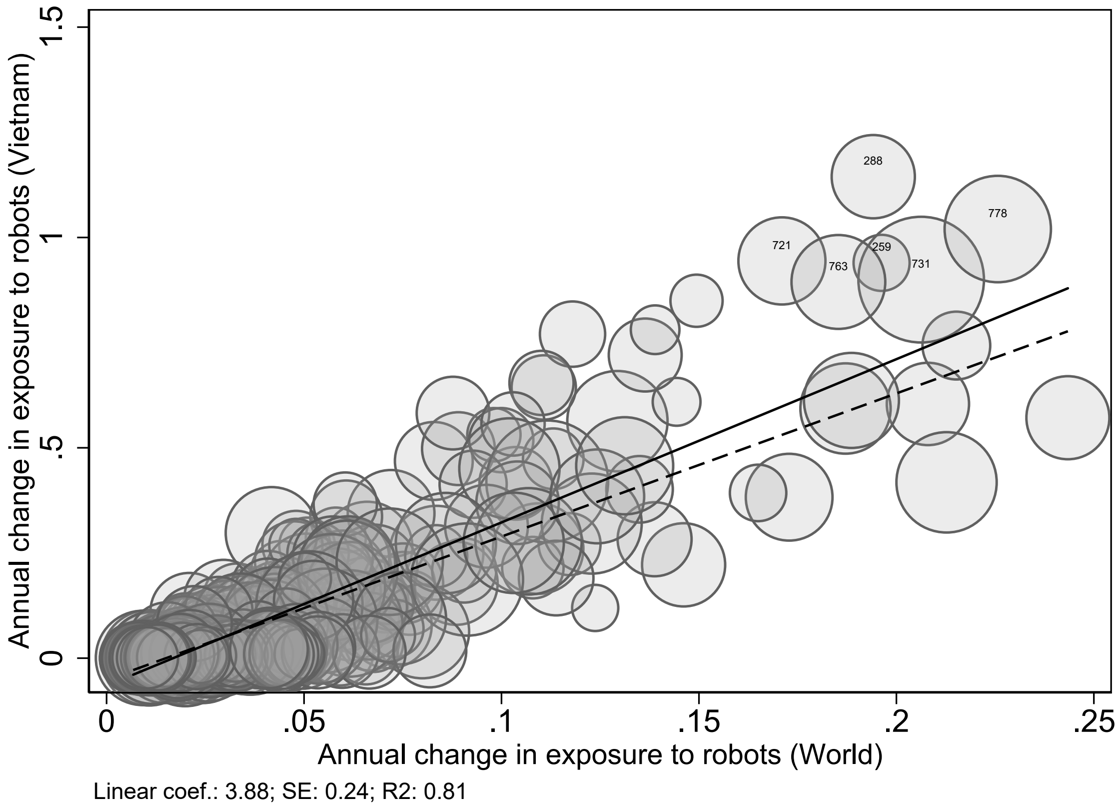
Notes. This figure shows the correlation between 2010-2020 changes in log industry employment and the log stock of robots in 2020 (in Viet Nam). Bubble size represents industry value added. Sources: IFR and OECD.

Fig. 4: Geographic variation in exposure to robots



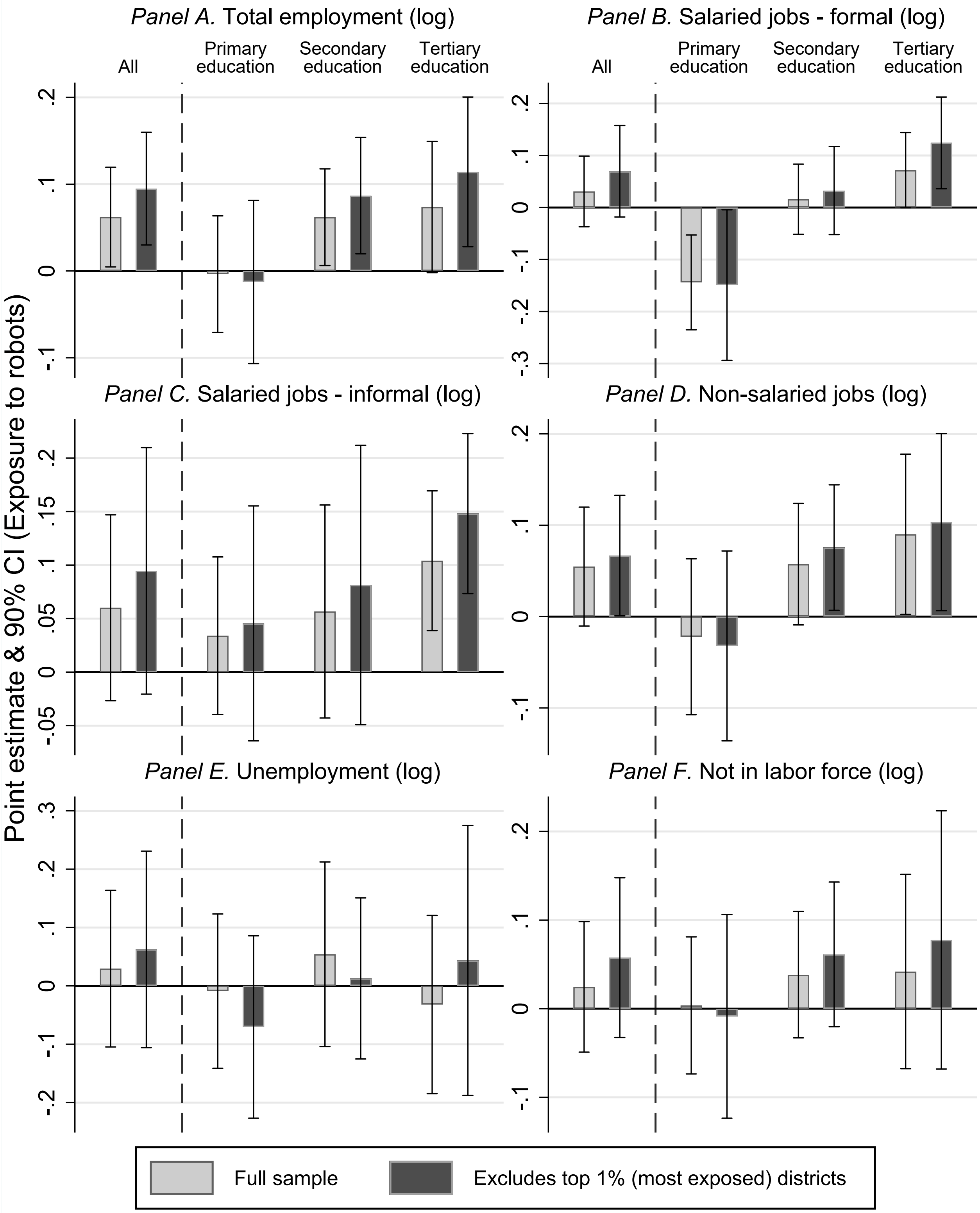
Notes. The figure illustrates the average annual change in exposure to robots between 2014 and 2020 across Vietnamese districts (N=680). Exposure to robots per thousand workers at the district level is measured as the interaction between district's industry employment shares in 2011 and robot adoption by industry-year. Sources: Labor Force Survey (2011), IFR and OECD.

Fig. 5: First-stage unconditional correlation



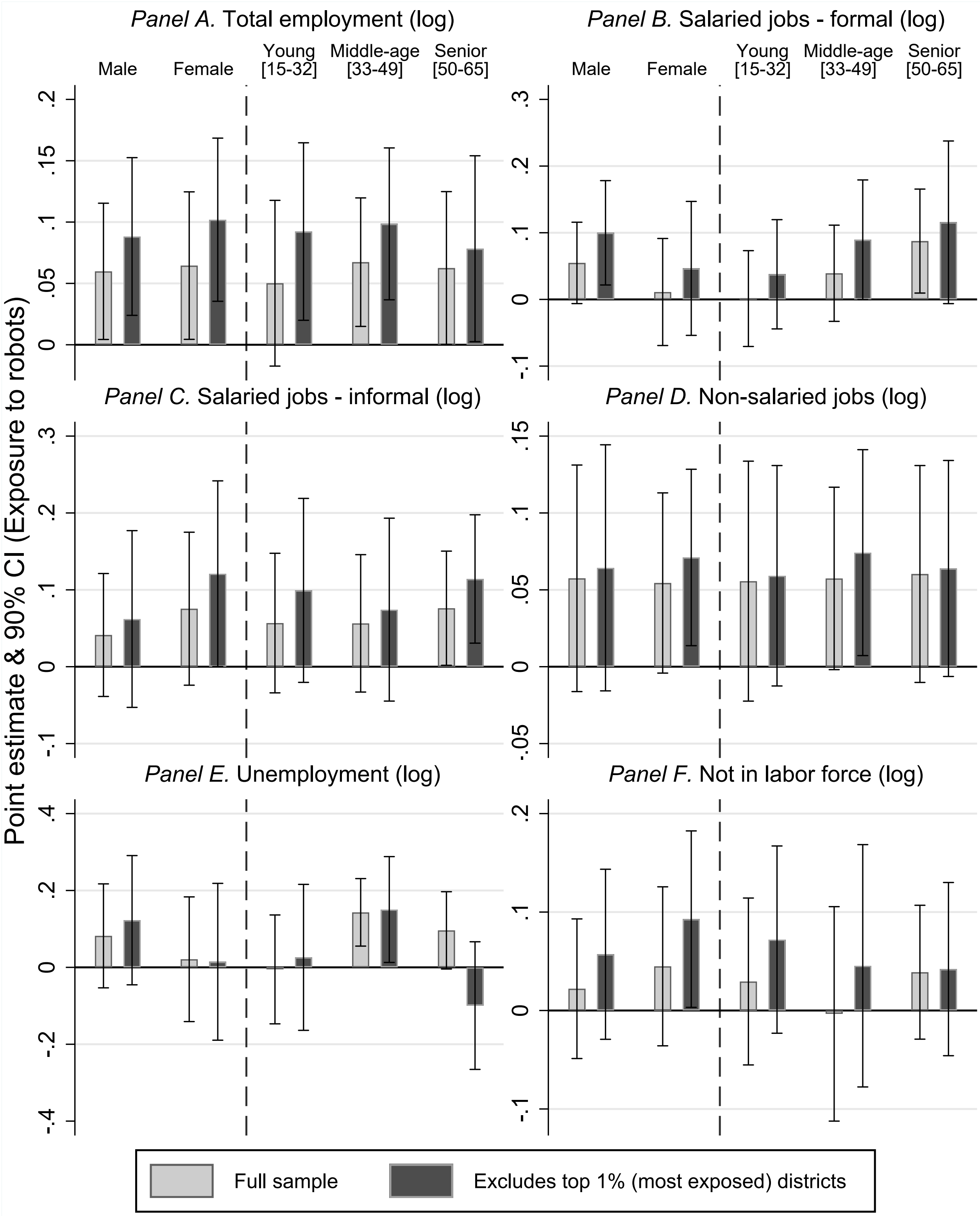
Notes. The figure presents the correlation between the average annual change in exposure to robots in Vietnamese districts during 2014-2020 and average annual change in exposure to robots in calculated using the average industry robot adoption across 56 countries. Exposure to robots is measured as the interaction between the 2011 industry employment composition in each district and robot adoption by industry-year (in Viet Nam and the world). Bubble size represents 2011 district's population. The dotted line corresponds to the linear regression coefficient, excluding the 1 percent districts with the highest exposure to robots in Viet Nam (these districts are labeled with numbers).

Fig. 6: Heterogeneous effects of robot adoption on employment by education (2SLS)



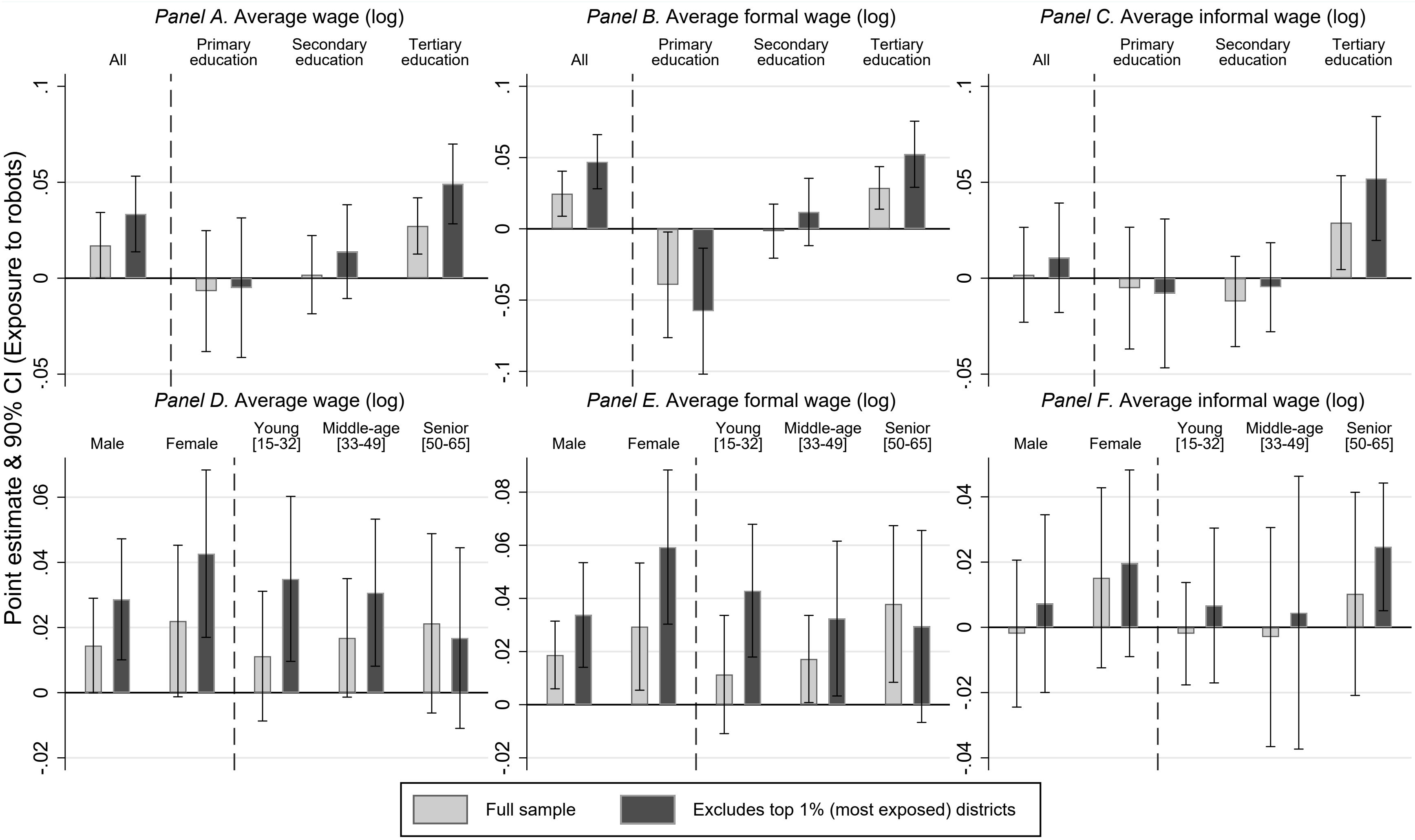
Notes. The figures present estimates of the heterogeneous effects of exposure to robots on employment outcomes across sub-population groups based on education. Preferred specifications (columns 4 and 5 of Table 1).

Fig. 7: Heterogeneous effects of robot adoption on employment by sex and age (2SLS)



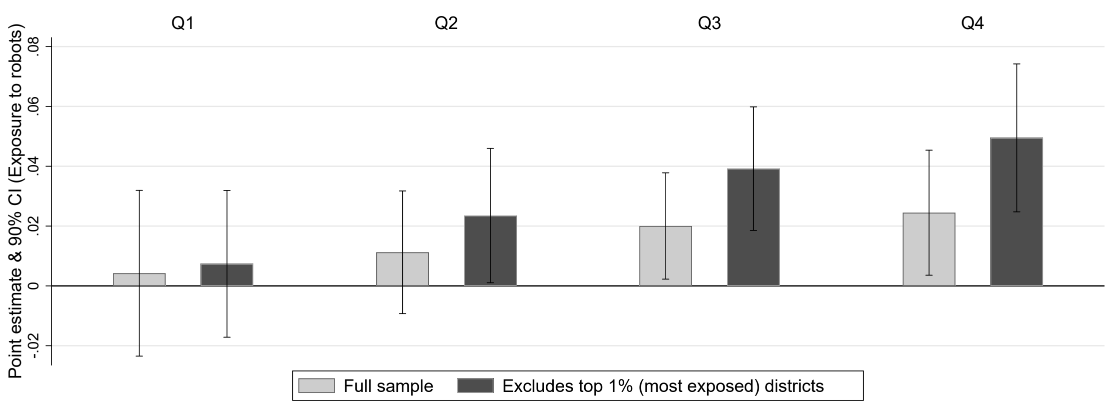
Notes. The figures present estimates of the heterogeneous effects of exposure to robots on employment outcomes across sub-population groups based on sex and age. Preferred specifications (columns 4 and 5 of Table 1).

Fig. 8: Heterogeneous effects of robot adoption on wages by education, sex and age (2SLS)



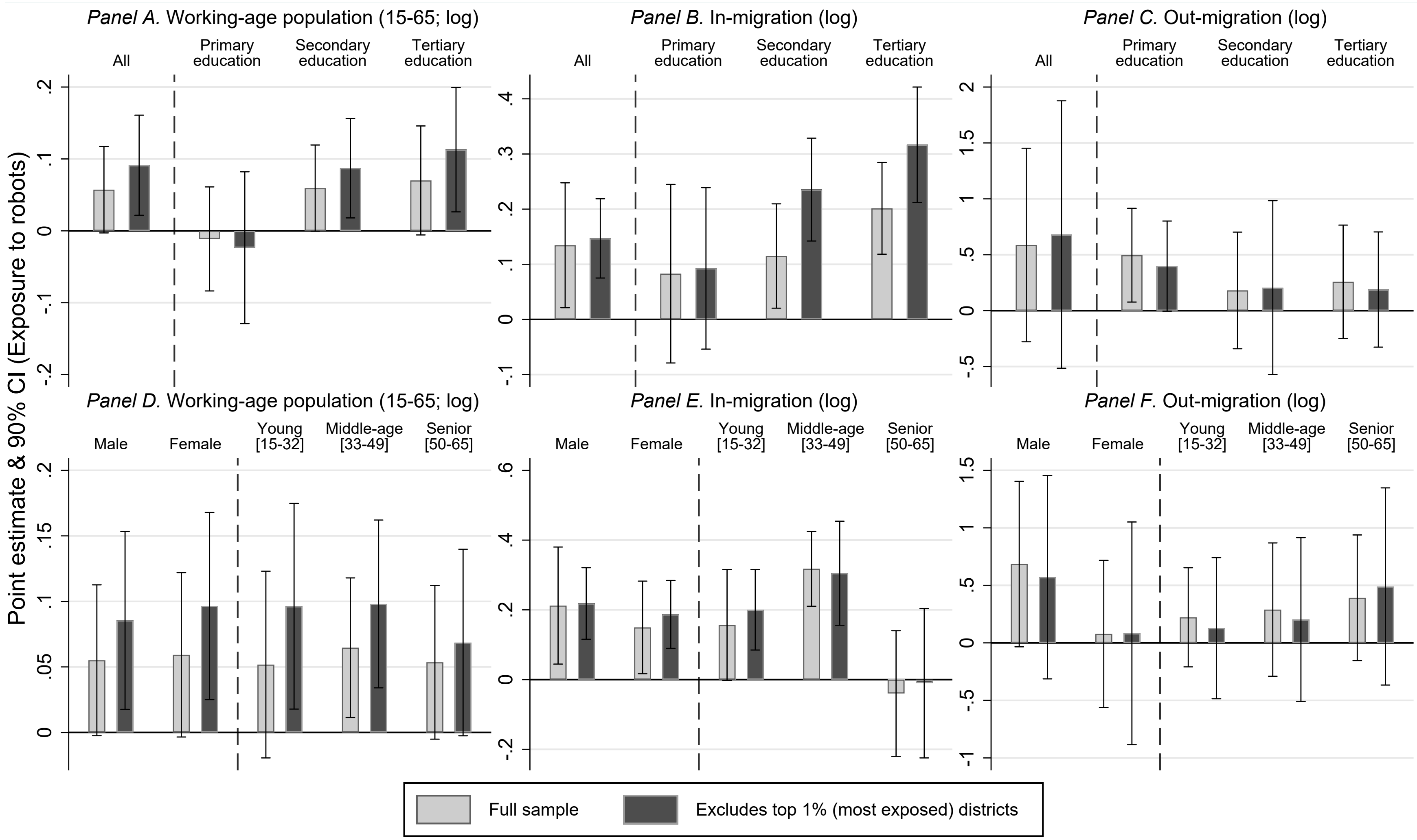
Notes. The figures present estimates of the heterogeneous effects of exposure to robots on wages across sub-population groups based on education, sex and age. Preferred specifications (columns 4 and 5 of Table 1).

Fig. 9: Heterogeneous effects of robot adoption on wages by quartiles (2SLS)



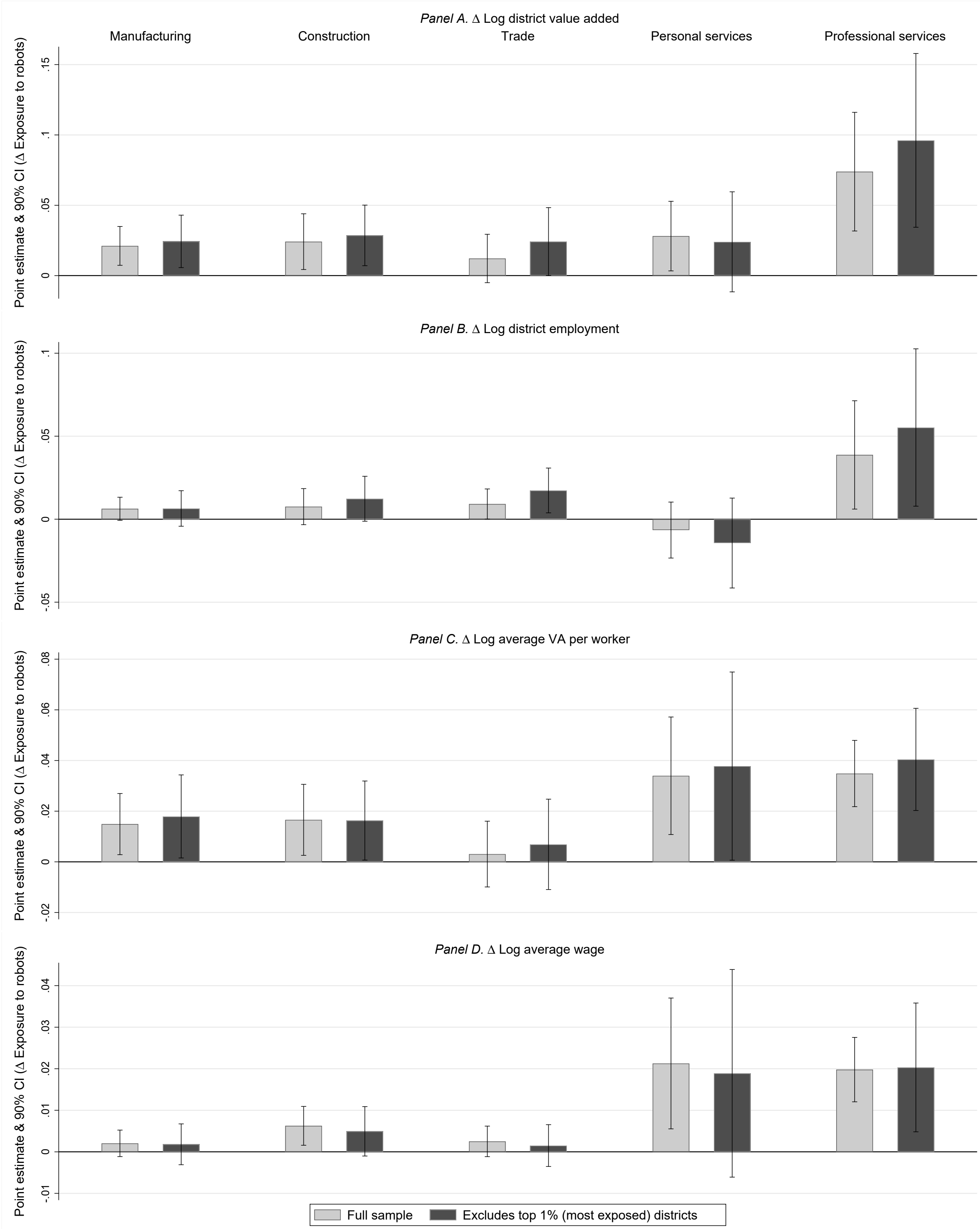
Notes. The figures present estimates of the heterogeneous effects of exposure to robots on wages of workers in different wage quartiles. Preferred specifications (columns 4 and 5 of Table 1).

Fig. 10: Heterogeneous effects of robot adoption on population dynamics by education, sex and age (2SLS)



Notes. The figures present estimates of the heterogeneous effects of exposure to robots on population dynamics across sub-population groups based on education, sex and age. Preferred specifications (columns 4 and 5 of Table 1).

Fig. 11: Heterogeneous effects of robot adoption on registered firm outcomes by industry



Notes. 2SLS. Regressions in changes (2011 vs. 2019). Preferred specifications. Weights correspond to district's employment in 2011. Source: VES.

Table 1: The effects of robot adoption on labor market outcomes (2SLS)

	(1)	(2)	(3)	(4)	(5)
Panel A. First-stage regression					
Exposure to robots (world)	4.010***	3.853***	3.760***	3.870***	3.740***
	(0.339)	(0.398)	(0.359)	(0.341)	(0.327)
KP F-stat	136.5	90.0	103.9	121.2	123.2
R-squared	0.815	0.831	0.855	0.858	0.827
Panel B. Employment outcomes					
B.1. Total Employment (log)					
Exposure to robots	0.082***	0.064**	0.055**	0.062*	0.095**
	(0.022)	(0.027)	(0.027)	(0.035)	(0.039)
B.1a. Salaried jobs - formal (log)					
Exposure to robots	0.070***	0.026	0.017	0.031	0.070
	(0.025)	(0.033)	(0.034)	(0.041)	(0.053)
B.1b. Salaried jobs - informal (log)					
Exposure to robots	0.039	0.043	0.042	0.060	0.095
	(0.033)	(0.039)	(0.044)	(0.053)	(0.070)
B.1c. Non-salaried jobs (log)					
Exposure to robots	0.055**	0.064**	0.053*	0.055	0.067*
	(0.025)	(0.027)	(0.027)	(0.040)	(0.040)
B.2. Unemployment (log)					
Exposure to robots	0.103*	0.034	0.036	0.029	0.063
	(0.061)	(0.071)	(0.076)	(0.082)	(0.102)
Panel C. Wage outcomes					
B.5. Average wage (log)					
Exposure to robots	0.001	0.016**	0.015*	0.017	0.033***
	(0.007)	(0.007)	(0.008)	(0.010)	(0.012)
B.6. Average formal wage (log)					
Exposure to robots	0.012**	0.024***	0.020**	0.025**	0.047***
	(0.006)	(0.008)	(0.008)	(0.010)	(0.012)
C.1. Average informal wage (log)					
Exposure to robots	−0.004	0.005	0.004	0.002	0.011
	(0.012)	(0.011)	(0.013)	(0.015)	(0.017)
Number of districts	680	680	680	680	673
Observations	4696	4696	4696	4696	4647
Specification details:					
District FE	✓	✓	✓	✓	✓
Subregion × year FE	✓	✓	✓	✓	✓
Demographics		✓	✓	✓	✓
Industry shares		✓	✓	✓	✓
Labor market conditions			✓	✓	✓
Trade with China				✓	✓

Notes. The table presents estimates of the effects of exposure to robots on local labor market outcomes in Viet Nam during 2014–2020. All specifications include district and subregion × year fixed effects. Column 2 adds controls for initial differences in demographics and industry composition. Column 3 adds controls for initial differences in labor market conditions. Column 4 controls for bilateral trade flows with China. All regressions are weighted by population in 2011. Column 5 excludes the top 1 percent districts with the highest exposure to robots. Standard errors that are robust against heteroskedasticity and correlation within provinces are in parentheses. Significance at the 1, 5, and 10 percent levels denoted with ***, **, and *.

Table 2: The effects of robot adoption on population dynamics (2SLS)

	(1)	(2)	(3)	(4)	(5)
Panel A. Population					
A.1. Total population (log)					
Exposure to robots	0.074***	0.063**	0.051*	0.057	0.089**
	(0.021)	(0.027)	(0.028)	(0.035)	(0.041)
A.1a. Working-age population (15-65; log)					
Exposure to robots	0.081***	0.064**	0.052*	0.057	0.091**
	(0.023)	(0.029)	(0.029)	(0.037)	(0.042)
A.1b. Non-working age population (0-14,+65; log))					
Exposure to robots	0.057***	0.062***	0.048*	0.054*	0.085**
	(0.019)	(0.023)	(0.026)	(0.032)	(0.038)
A.2. Labor force participants (log)					
Exposure to robots	0.083***	0.064**	0.054**	0.061*	0.094**
	(0.022)	(0.027)	(0.027)	(0.035)	(0.040)
A.3a. Not in labor force: school aged (15-24; log)					
Exposure to robots	0.074**	0.040	0.023	0.030	0.064
	(0.031)	(0.042)	(0.043)	(0.052)	(0.062)
A.3b. Not in labor force: prime aged (25-64; log)					
Exposure to robots	0.030	0.043	0.026	0.023	0.058
	(0.028)	(0.036)	(0.042)	(0.048)	(0.055)
Panel B. Migrations					
B.1. In-migrantion (log)					
Exposure to robots	0.166**	0.141***	0.134***	0.129*	0.141***
	(0.068)	(0.053)	(0.047)	(0.070)	(0.042)
B.2. Out-migrantion (log)					
Exposure to robots	−0.020	0.053	0.099	0.070	−0.068
	(0.078)	(0.101)	(0.109)	(0.092)	(0.097)
Number of districts	680	680	680	680	673
Observations	4696	4696	4696	4696	4647
Specification details:					
District FE	✓	✓	✓	✓	✓
Subregion × year FE	✓	✓	✓	✓	✓
Demographics		✓	✓	✓	✓
Industry shares		✓	✓	✓	✓
Labor market conditions			✓	✓	✓
Trade with China				✓	✓

Notes. The table presents estimates of the effects of exposure to robots on population outcomes in Viet Nam during 2014–2020. All specifications include district and subregion × year fixed effects. Column 2 adds controls for initial differences in demographics and industry composition. Column 3 adds controls for initial differences in labor market conditions. Column 4 controls for bilateral trade flows with China. All regressions are weighted by population in 2011. Column 5 excludes the top 1 percent districts with the highest exposure to robots. Standard errors that are robust against heteroskedasticity and correlation within provinces are in parentheses. Significance at the 1, 5, and 10 percent levels denoted with ***, **, and *.

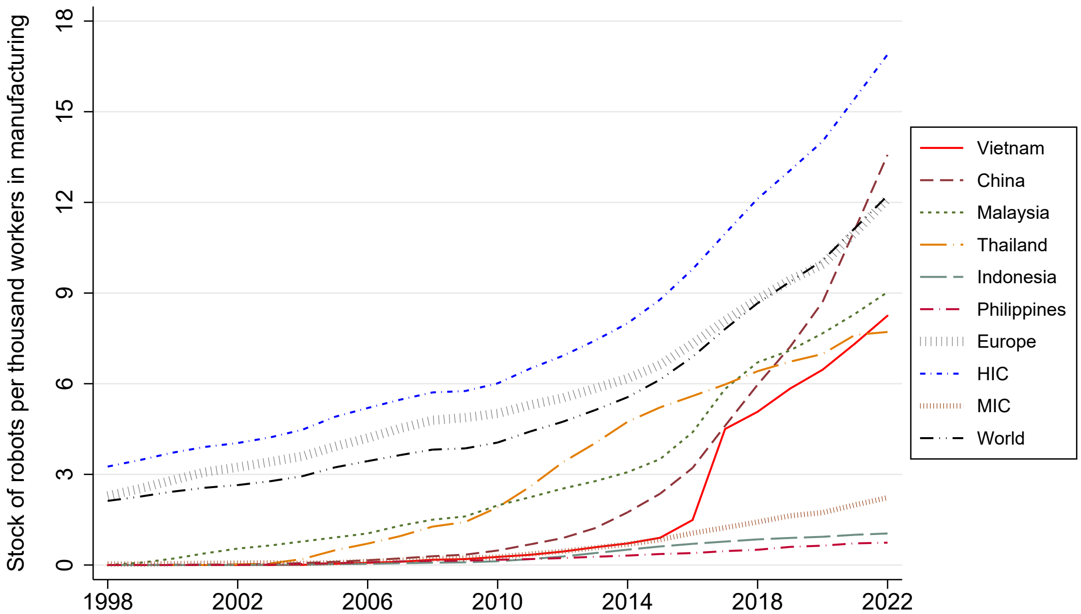
Table 3: The effects of robot adoption on registered firm outcomes (2011 vs. 2019)

	(1)	(2)	(3)	(4)	(5)
1. Δ Log district value added					
Δ Exposure to robots	0.051***	0.027***	0.025***	0.026***	0.029***
	(0.007)	(0.009)	(0.007)	(0.007)	(0.011)
2. Δ Log district employment					
Δ Exposure to robots	0.025***	0.012**	0.009**	0.009**	0.010**
	(0.003)	(0.005)	(0.004)	(0.004)	(0.005)
3. Δ Log average VA per worker					
Δ Exposure to robots	0.021***	0.011***	0.009***	0.010***	0.015***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.005)
4. Δ Log average wage					
Δ Exposure to robots	0.012***	0.004**	0.003	0.003	0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)
5. Δ Log district exports					
Δ Exposure to robots	0.015	0.068**	0.070**	0.075**	0.083**
	(0.020)	(0.033)	(0.033)	(0.034)	(0.042)
6. Δ Log district imports					
Δ Exposure to robots	0.007	0.088***	0.089***	0.100***	0.134***
	(0.022)	(0.024)	(0.026)	(0.028)	(0.038)
KP F-stat	34.8	30.8	32.6	32.0	43.2
Observations	674	674	674	674	667
Specification details:					
Subregion FE	✓	✓	✓	✓	✓
Demographics		✓	✓	✓	✓
Industry shares		✓	✓	✓	✓
Labor market conditions			✓	✓	✓
Trade with China				✓	✓

Notes. 2SLS. Regressions in changes: 2011 vs. 2019. Same specifications as in main regression analysis. All specifications control for baseline (2011) differences in log imports and log exports. Weights correspond to district's employment in 2011. Source: VES.

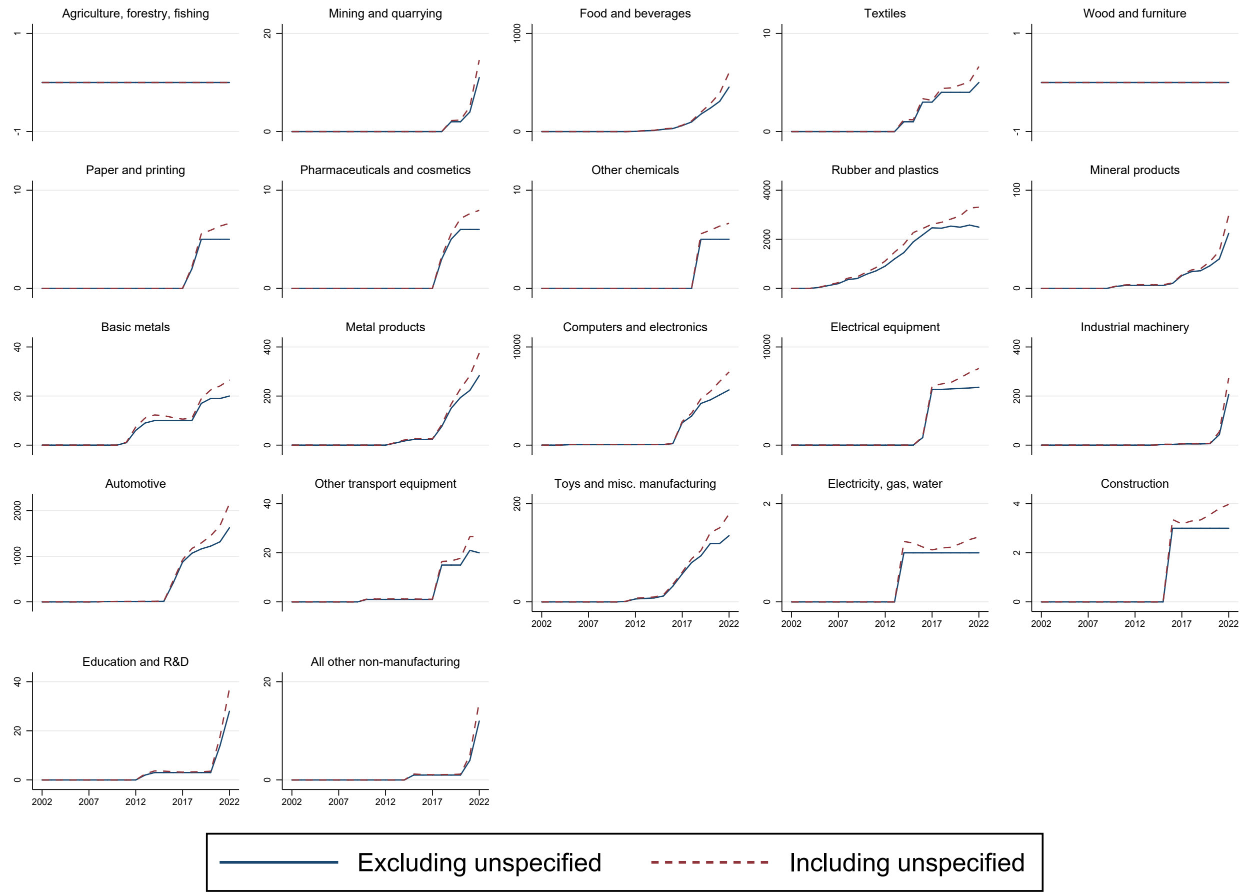
VII Appendix. Additional tables and figures

Fig. B1: Robot adoption trends



Notes. This figure shows the evolution of the stock of robots per thousand workers (in manufacturing industries) in Viet Nam and different countries/groups between 1998 and 2022. Sources: IFR and OECD.

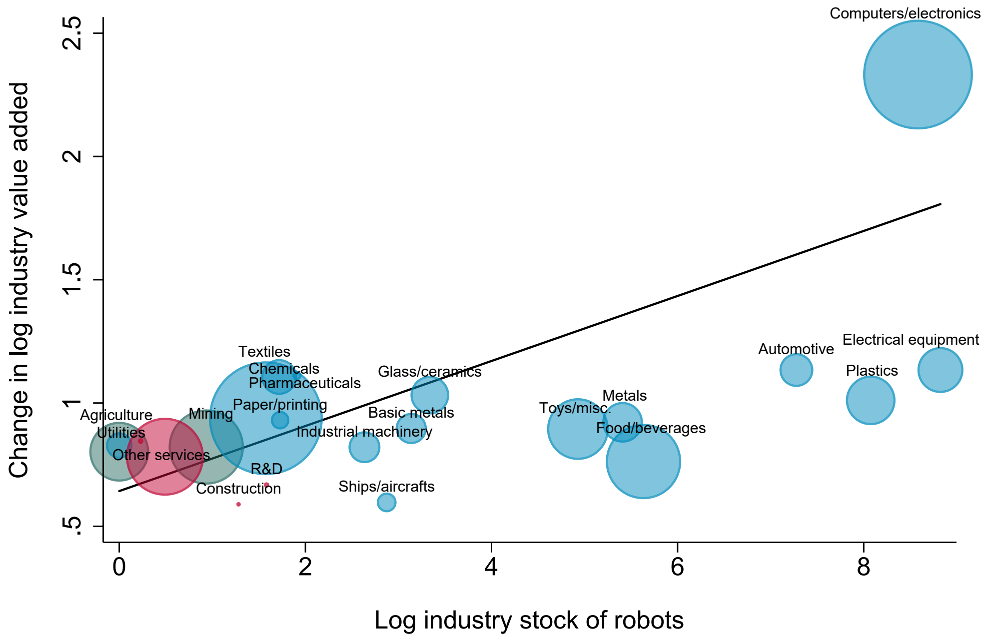
Fig. B2: Evolution of the stock of industrial robots in Viet Nam by industry



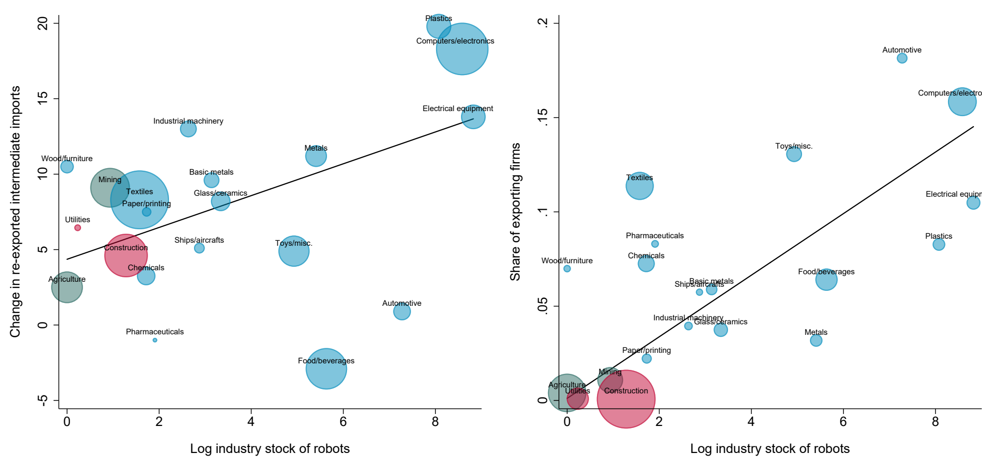
Notes. The figure presents the evolution of the stock of robots in Viet Nam by industry between 2002 and 2022. The dotted lines includes robots that are unspecified (i.e. missing industry) according to the observed distribution of robots in each industry-year. Source: International Federation of Robotics (IFR).

Fig. B3: Industry outcomes and robot adoption in Viet Nam

(a) Value added

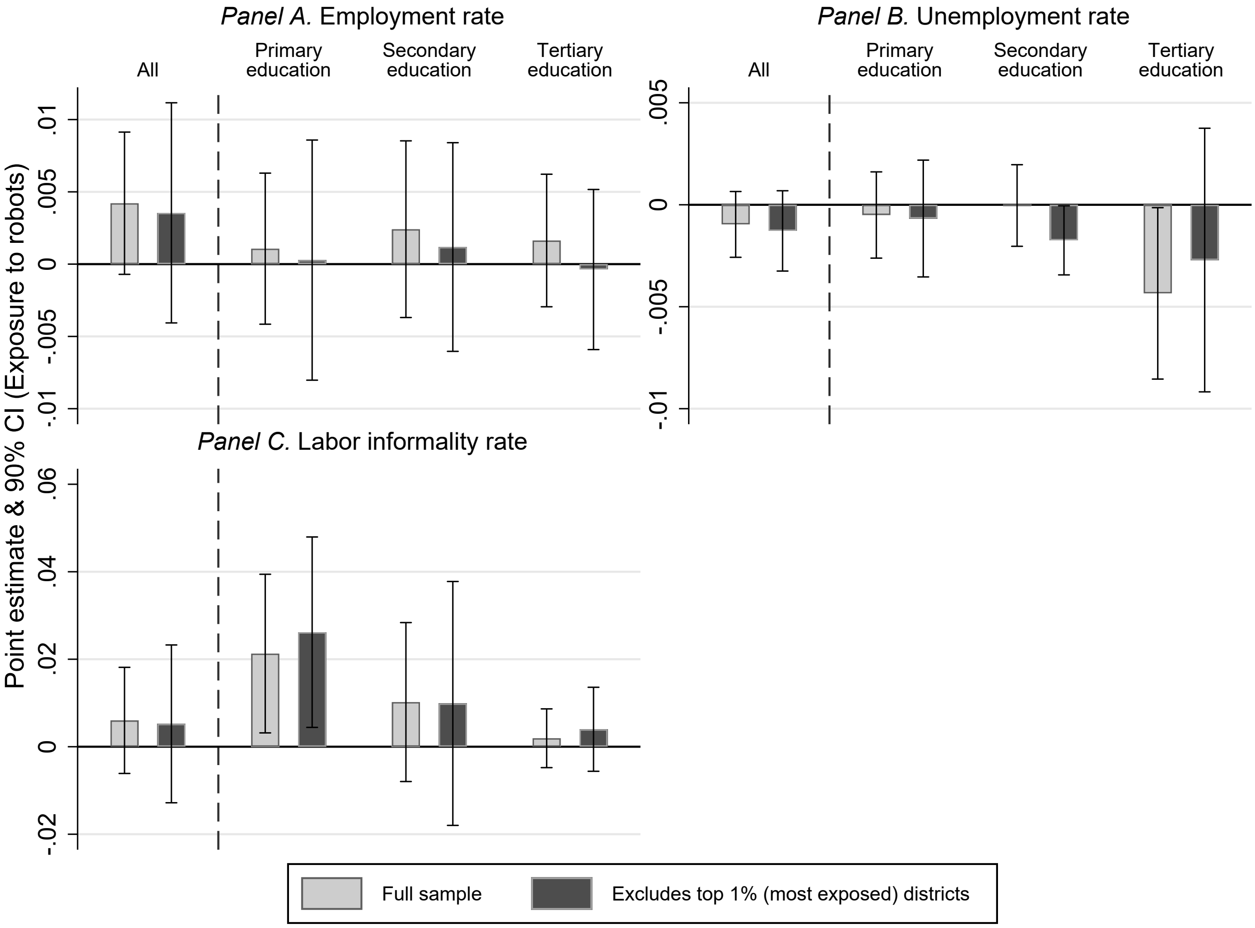


(b) Trade orientation



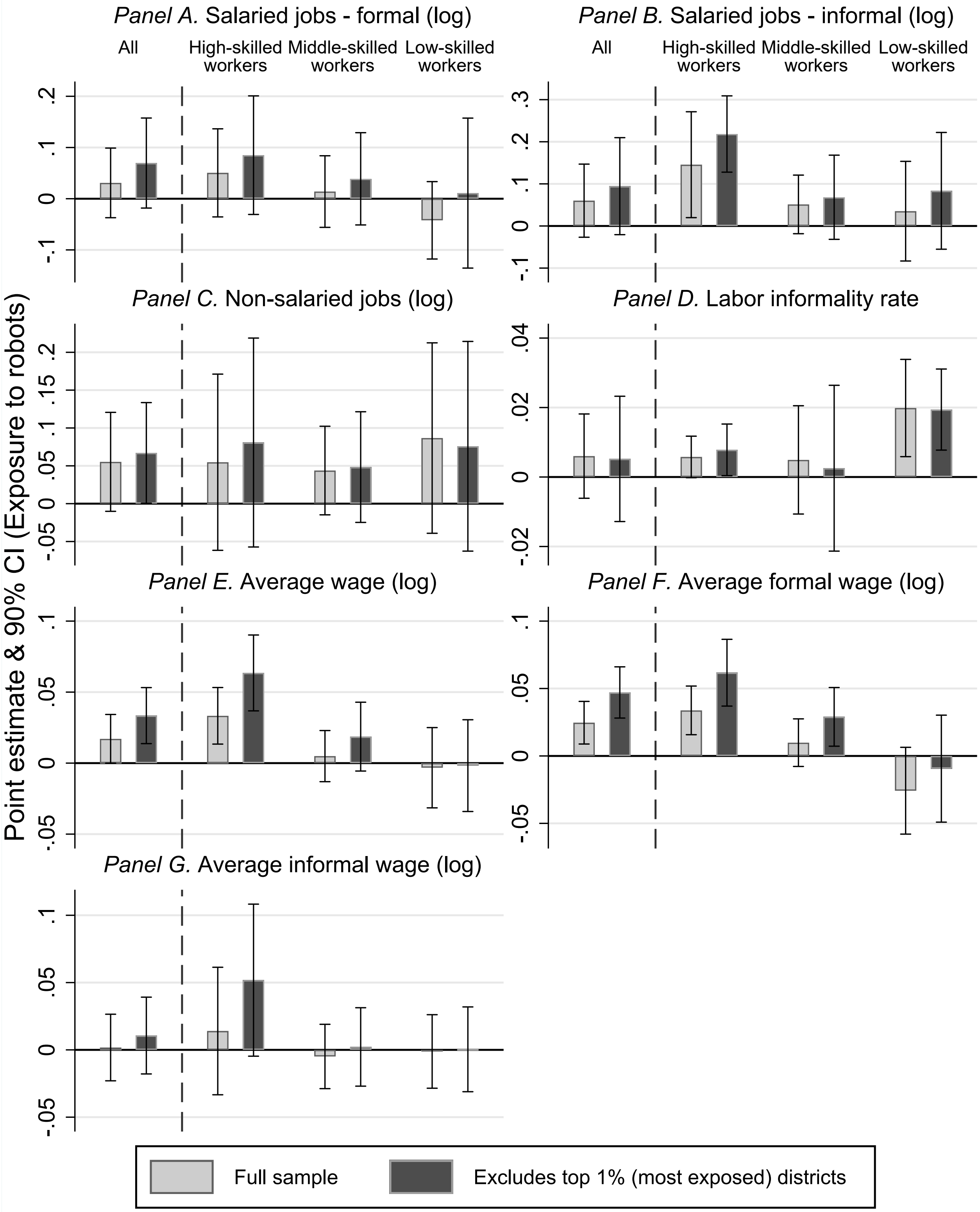
Notes. Top panel shows the correlation between the 2010-2020 change in log industry value added and the log stock of robots in 2020. Bubble size (in panel a) represents industry exports. Bottom left panel shows the correlation between the 2010-2020 change in re-exported intermediate imports, as a share of total intermediate imports, and the log stock of robots in 2020. Bottom right panel shows the share of exporting firms in each industry and the log stock of robots in 2020. Bubble size (in panel b) represents industry value added. $\rho1$ ($\rho2$) shows the (weighted) correlation coefficient and $\rho1$ ($\rho4$) shows the (weighted) correlation coefficient for manufacturing industries only; p-values are in parenthesis. Sources: IFR and OECD.

Fig. B4: Heterogeneous effects of robot adoption on employment rates by educational skill level (2SLS)



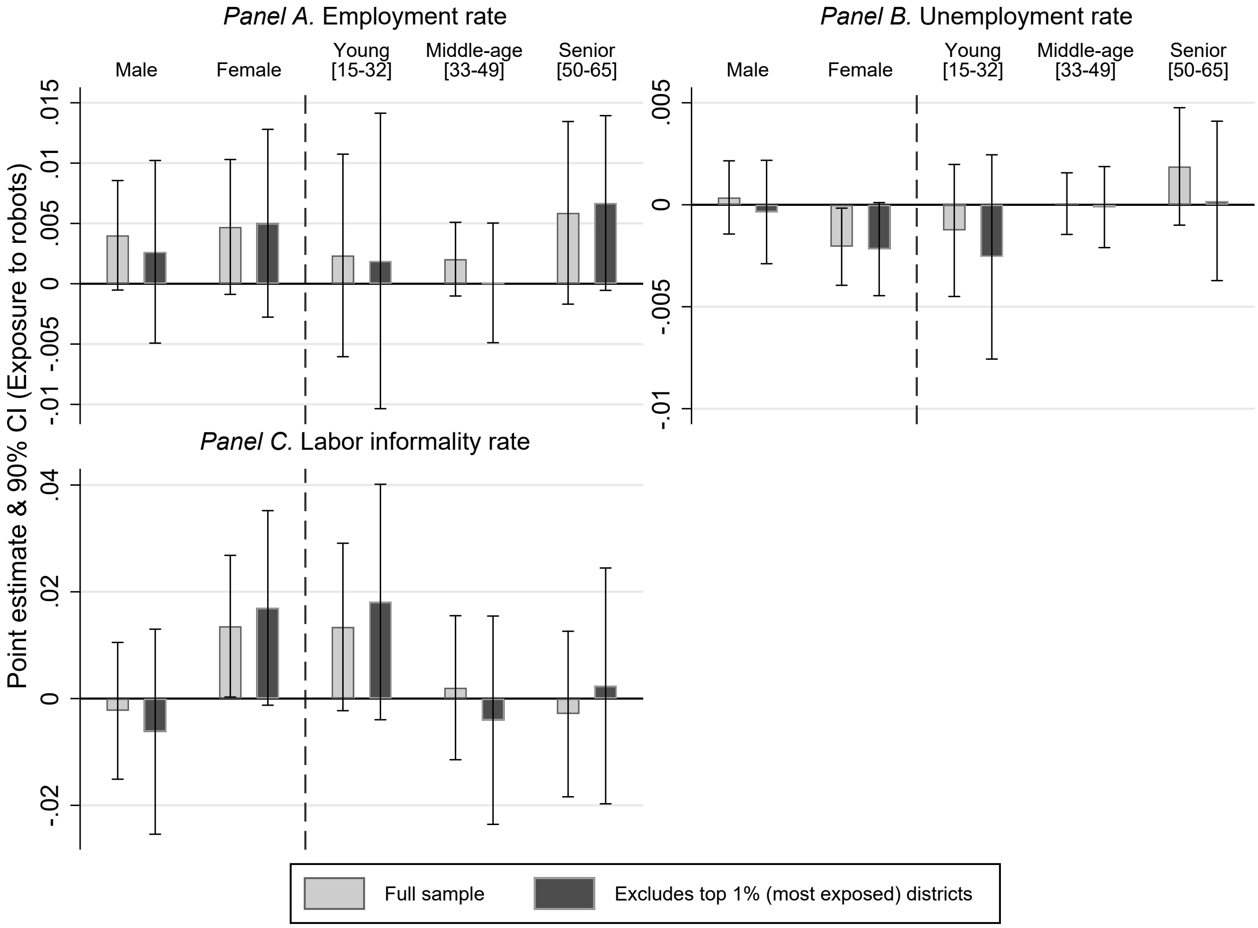
Notes. The figures present estimates of the heterogeneous effects of exposure to robots on employment outcomes across sub-population groups based on education. Preferred specifications plotted (corresponding to columns 4 and 5 of Table 1).

Fig. B5: Heterogeneous effects of robot adoption on employment outcomes by occupational skill level (2SLS)



Notes. The figures present estimates of the heterogeneous effects of exposure to robots on employment outcomes across sub-population groups based on occupational skills. Occupational skill levels are defined through followed ILO's 1-digit major occupational groups. Preferred specifications plotted (corresponding to columns 4 and 5 of Table 1).

Fig. B6: Heterogeneous effects of robot adoption on employment outcomes by gender and age (2SLS)



Notes. The figures present estimates of the heterogeneous effects of exposure to robots on employment outcomes across subpopulation groups based on gender and age. Preferred specifications (columns 4 and 5 of Table 1).

Table B1: Descriptive statistics

	2011	2014	2017	2020
Panel A. Exposure to robots				
Exposure to robots	0.035	0.068***	0.462***	0.774***
	(0.079)	(0.143)	(0.923)	(1.393)
Exposure to robots (world)	0.302	0.366***	0.529***	0.721***
	(0.292)	(0.352)	(0.597)	(0.766)
Panel B. Labor market outcomes				
Employment rate	0.802	0.808*	0.792***	0.756***
	(0.090)	(0.090)	(0.091)	(0.096)
Unemployment rate	0.019	0.014***	0.021***	0.023
	(0.017)	(0.013)	(0.018)	(0.020)
Labor informality rate	0.606	0.607	0.532***	0.462***
	(0.196)	(0.188)	(0.193)	(0.186)
Total labor income (million VND)	102.1	195.3*	195.1	234.5
	(116.7)	(351.1)	(234.5)	(346.8)
Average labor income (VND)	2500.3	2984.7***	3363.9***	3844.6***
	(709.3)	(792.3)	(839.0)	(912.7)
Average hourly wage (VND)	12.9	17.1***	19.2***	22.5***
	(3.6)	(5.6)	(5.6)	(6.5)
Panel C. Demographic conditions and employment structure				
Population (thousands)	129.2	132.6	135.3	141.0
	(67.0)	(89.4)	(80.7)	(111.7)
Share in urban areas	0.317	0.323**	0.341***	0.358
	(0.353)	(0.408)	(0.367)	(0.382)
Share migrants	0.014	0.011***	0.014***	0.012*
	(0.022)	(0.011)	(0.022)	(0.018)
Share primary education	0.381	0.368	0.337	0.311
	(0.230)	(0.219)	(0.207)	(0.202)
Share secondary education	0.477	0.461***	0.464**	0.472
	(0.179)	(0.163)	(0.149)	(0.142)
Share tertiary education	0.143	0.171	0.199***	0.217
	(0.112)	(0.126)	(0.123)	(0.131)
Share child (0–15)	0.235	0.236***	0.238***	0.239
	(0.047)	(0.042)	(0.041)	(0.043)
Share middle-age (21–55)	0.519	0.515***	0.506	0.502**
	(0.048)	(0.043)	(0.045)	(0.053)
Share old-age (+56)	0.139	0.163***	0.172***	0.189***
	(0.046)	(0.050)	(0.054)	(0.060)
Share primary	0.469	0.449	0.380***	0.308***
	(0.281)	(0.275)	(0.264)	(0.252)
Share manufacturing	0.141	0.147	0.181***	0.213**
	(0.121)	(0.115)	(0.139)	(0.155)
Share services	0.389	0.404	0.439***	0.478**
	(0.214)	(0.218)	(0.204)	(0.204)
Share female in manufacturing	0.475	0.495	0.516***	0.512
	(0.170)	(0.168)	(0.154)	(0.141)
Share salaried jobs	0.358	0.369*	0.446***	0.506***
	(0.182)	(0.177)	(0.182)	(0.177)
Female employment rate	0.766	0.776*	0.757***	0.708***
	(0.119)	(0.118)	(0.115)	(0.121)
Employment share in FOEs	0.034	0.038	0.055***	0.074***
	(0.071)	(0.069)	(0.094)	(0.117)
Employment share in DOEs	0.087	0.094	0.135***	0.177***
	(0.088)	(0.090)	(0.119)	(0.133)
Number of districts	680	641	678	674

Notes. The table presents descriptive statistics for Vietnamese local labor markets (districts) in 2011, 2014, 2017 and 2020. Mean and standard deviation (in parenthesis). All statistics, except demographic composition, correspond to the sample of adults (i.e. population of working age, 16 to 65 years old). All statistics are weighted by district's population.

Table B2: Descriptive statistics for registered enterprises (district average)

	2011	2014	2017	2020
Enterprise value-added	165400	185046	273204***	283073
	(513014)	(533878)	(716664)	(720454)
Enterprise employment	13103	14228	16593	16151
	(29145)	(30948)	(34787)	(33009)
Enterprise value-added per worker	12623	13011	16375***	17339
	(7359)	(6547)	(6720)	(6460)
Enterprise wage (per-worker average)	8644	9264*	11868***	13301***
	(2466)	(2216)	(3023)	(3465)
Number of observations	693	693	693	685

Notes. The table presents descriptive statistics for Vietnamese enterprises, at the district-average level, in 2011, 2014, 2017 and 2020. Mean and standard deviation (in parenthesis). Statistics correspond to the full sample of registered firms as captured in the Viet Nam Enterprise Survey (VES). Statistics for average value-added per worker and average wage are weighted by district's employment. Enterprise value-added and wages are expressed in '000 Viet Nam Dong.

Table B3: Balance tests

	Change in exposure to robots			Change in exposure to robots (world)		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Labor market outcomes (year 2011)						
Employment rate	-0.043^{**}	-0.006^{*}	-0.015^{***}	-0.330^{**}	-0.045^{*}	-0.106^{***}
	(0.020)	(0.003)	(0.005)	(0.135)	(0.023)	(0.033)
Unemployment rate	0.005^{**}	-0.004^{**}	-0.004	0.039^{**}	-0.030^{***}	-0.038^{**}
	(0.002)	(0.002)	(0.003)	(0.017)	(0.009)	(0.019)
Labor informality rate	-0.265^{***}	-0.007	-0.018^{*}	-1.389^{***}	-0.032	-0.079
	(0.040)	(0.007)	(0.009)	(0.345)	(0.031)	(0.055)
Log average hourly wage	0.187^{**}	0.044^{**}	0.040	0.833^{***}	0.138^{**}	0.060
	(0.075)	(0.017)	(0.027)	(0.308)	(0.069)	(0.095)
Log average labor income	0.254^{***}	-0.008	0.008	1.177^{***}	-0.015	0.080
	(0.078)	(0.016)	(0.018)	(0.352)	(0.070)	(0.089)
Log total labor income	1.238^{***}	0.012	0.065	6.177^{***}	0.135	0.355
	(0.266)	(0.051)	(0.075)	(1.812)	(0.213)	(0.271)
Panel B. Demographic, industry, and economic conditions (year 2011)						
Log population	0.305^{**}	0.036	0.019	1.367^{*}	0.050	0.040
	(0.135)	(0.050)	(0.056)	(0.753)	(0.213)	(0.196)
Share in urban areas	0.298^{***}	0.054	0.005	1.678^{***}	0.135	0.061
	(0.078)	(0.091)	(0.068)	(0.600)	(0.368)	(0.264)
Share migrants	0.026^{***}	0.003	0.001	0.120^{***}	0.014	-0.036
	(0.007)	(0.008)	(0.011)	(0.037)	(0.056)	(0.026)
Share primary education	-0.155^{***}	-0.000	0.000	-0.795^{***}	-0.000	-0.000
	(0.049)	(0.000)	(0.000)	(0.305)	(0.000)	(0.000)
Share secondary education	0.093^{***}	-0.000	0.000	0.385^{**}	-0.000	-0.000
	(0.034)	(0.000)	(0.000)	(0.175)	(0.000)	(0.000)
Share tertiary education	0.062^{**}	-0.000	0.000	0.411^{**}	-0.000	-0.000
	(0.026)	(0.000)	(0.000)	(0.180)	(0.000)	(0.000)
Share child (0–15)	-0.022^{**}	0.000	0.002	-0.122^{*}	0.021^{*}	0.042^{***}
	(0.011)	(0.003)	(0.005)	(0.064)	(0.012)	(0.016)
Share middle-age (21–55)	0.049^{***}	-0.000	0.002	0.246^{***}	0.026^{**}	0.054^{***}
	(0.012)	(0.002)	(0.003)	(0.070)	(0.012)	(0.021)
Share old-age (+55)	-0.034^{***}	-0.010^{***}	-0.008^{*}	-0.137^{***}	-0.020	-0.006
	(0.008)	(0.003)	(0.004)	(0.032)	(0.017)	(0.030)
Share females	0.009^{*}	-0.004	-0.006	0.046	-0.025	-0.022
	(0.005)	(0.005)	(0.006)	(0.030)	(0.019)	(0.025)
Share primary sector	-0.356^{***}	-0.000	0.000	-2.022^{***}	-0.000	0.000
	(0.066)	(0.000)	(0.000)	(0.558)	(0.000)	(0.000)
Share manufacturing	0.248^{***}	-0.000	0.000	1.245^{***}	-0.000	0.000
	(0.030)	(0.000)	(0.000)	(0.232)	(0.000)	(0.000)
Share services	0.108^{**}	-0.000	0.000	0.777^{**}	-0.000	0.000
	(0.053)	(0.000)	(0.000)	(0.361)	(0.000)	(0.000)
Share female in manufacturing	0.023	-0.010	-0.025	0.017	-0.162	-0.311^{*}
	(0.026)	(0.029)	(0.037)	(0.107)	(0.139)	(0.184)
Share salaried jobs	0.260^{***}	-0.001	-0.013^{*}	1.341^{***}	-0.013	-0.068^{*}
	(0.036)	(0.006)	(0.008)	(0.322)	(0.025)	(0.035)
Share self-employment	0.007	0.049^{**}	0.057	-0.027	0.094	0.076
	(0.026)	(0.023)	(0.039)	(0.116)	(0.115)	(0.193)
Female employment rate	-0.042^{*}	0.003	0.014^{**}	-0.368^{**}	0.012	0.074^{*}
	(0.022)	(0.005)	(0.007)	(0.146)	(0.030)	(0.044)
Employment share in FOEs	0.157^{***}	0.057^{***}	0.053^{**}	0.580^{***}	0.161^{*}	0.191^{*}
	(0.035)	(0.015)	(0.021)	(0.197)	(0.087)	(0.100)
Employment share in DOEs	0.116^{***}	0.038^{***}	0.054^{***}	0.704^{***}	0.231^{***}	0.298^{***}
	(0.022)	(0.009)	(0.012)	(0.126)	(0.038)	(0.093)
Exposure to China's import comp.	-0.623^{***}	0.132^{***}	0.129^{**}	-3.401^{***}	0.911^{***}	1.105^{***}
	(0.170)	(0.037)	(0.052)	(1.260)	(0.156)	(0.198)
Exposure to job routinization	-0.099^{**}	0.012	0.021	-0.626^{**}	0.131^{**}	0.209^{***}
	(0.044)	(0.014)	(0.020)	(0.278)	(0.057)	(0.071)
Observations	680	680	673	680	680	673
Specification details:						
Subregion FE	✓	✓	✓	✓	✓	✓
Full controls		✓	✓		✓	✓
Excludes top 1%			✓			✓

Notes. The table presents regression estimates of district's initial characteristics (year 2011) on the 2015-2020 change in exposure to robots (ER). ER is measured as the interaction between the 2011 employment composition by industry in each district and robot adoption by industry-year in Viet Nam (columns 1-3) or average robot adoption by industry-year across 56 countries (columns 4-6). All regressions are weighted by population in 2011 and control for subregion dummies. Columns 3 and 6 exclude the 1 percent districts with the highest exposure to robots. Columns 2-3 and 5-6 control for the full set of demographic, labor market, and economic characteristics of districts in 2011, while excluding the corresponding outcome variable. Standard errors that are robust against heteroskedasticity and correlation within provinces are in parentheses.

Table B4: Pre-trend tests

	ΔER_l		ΔER_l^{World}	
	(1)	(2)	(3)	(4)
Panel A. 2011-2014 change in labor market outcomes				
Employment rate	−0.009	−0.005	−0.014	0.004
	(0.006)	(0.007)	(0.029)	(0.042)
Unemployment rate	0.000	0.000	0.004	0.003
	(0.001)	(0.002)	(0.007)	(0.013)
Labor informality rate	−0.015**	−0.025*	−0.027	−0.016
	(0.008)	(0.013)	(0.038)	(0.056)
Log average hourly wage	0.000	−0.003	−0.037	−0.037
	(0.020)	(0.022)	(0.079)	(0.097)
Log average labor income	0.014	0.026*	−0.028	0.033
	(0.014)	(0.015)	(0.076)	(0.079)
Log total labor income	−0.022	0.020	−0.254	−0.323
	(0.106)	(0.141)	(0.533)	(0.753)
Panel B. 2011-2014 change in demographic, industry, and economic conditions				
Log population	−0.069	−0.066	−0.317	−0.400
	(0.096)	(0.130)	(0.539)	(0.773)
Share in urban areas	−0.033	−0.063**	−0.369	−0.630***
	(0.040)	(0.031)	(0.229)	(0.198)
Share migrants	0.001	0.002	0.010*	0.017***
	(0.002)	(0.001)	(0.006)	(0.006)
Share primary education	0.001	−0.015	0.044	−0.019
	(0.015)	(0.024)	(0.084)	(0.147)
Share secondary education	0.028	0.029	0.164*	0.166
	(0.020)	(0.025)	(0.090)	(0.123)
Share tertiary education	0.011*	0.014	0.033	0.048
	(0.006)	(0.009)	(0.023)	(0.031)
Share child (0–15)	0.011	0.010	0.076*	0.071
	(0.008)	(0.011)	(0.039)	(0.059)
Share middle-age (21–55)	0.019	0.014	0.125	0.114
	(0.019)	(0.026)	(0.091)	(0.146)
Share old-age (+56)	0.005	0.001	0.007	−0.018
	(0.007)	(0.010)	(0.033)	(0.049)
Share females	0.020	0.014	0.117	0.092
	(0.019)	(0.026)	(0.089)	(0.138)
Share primary sector	−0.022	−0.045	−0.025	−0.098
	(0.021)	(0.029)	(0.104)	(0.135)
Share manufacturing	0.027	0.042***	0.155***	0.223***
	(0.017)	(0.015)	(0.056)	(0.059)
Share services	0.034***	0.030	0.111	0.069
	(0.012)	(0.021)	(0.073)	(0.140)
Share female in manufacturing	−0.003	−0.023	0.041	−0.078
	(0.026)	(0.032)	(0.131)	(0.156)
Share salaried jobs	0.029	0.035	0.117	0.099
	(0.019)	(0.024)	(0.085)	(0.126)
Female employment rate	−0.015*	−0.010	−0.040	−0.022
	(0.008)	(0.009)	(0.036)	(0.046)
Employment share in FOEs	0.006	0.007	0.006	−0.014
	(0.013)	(0.011)	(0.055)	(0.053)
Employment share in DOEs	0.002	0.007	−0.016	0.015
	(0.007)	(0.007)	(0.036)	(0.030)
Observations	680	673	680	673
Specification details:				
Full controls	✓	✓	✓	✓
Excludes top 1%		✓		✓

Notes. The table presents regression estimates of past changes (2011-2014) in local labor market outcomes on the 2015-2020 change in exposure to robots (ER). ER is measured as the interaction between the 2011 employment composition by industry in each district and robot adoption by industry-year in Viet Nam (columns 1-3) or average robot adoption by industry-year across 56 countries (columns 4-6). All regressions are weighted by population in 2011 and control for subregion dummies. Columns 3 and 6 exclude the 1 percent districts with the highest exposure to robots. Columns 2-3 and 5-6 control for the full set of demographic, labor market, and economic characteristics of districts in 2011. Standard errors that are robust against heteroskedasticity and correlation within provinces are in parentheses.

Table B5: The effects of robot adoption on employment rates (2SLS)

	(1)	(2)	(3)	(4)	(5)
A.1. Employment rate					
Exposure to robots	0.002	0.001	0.003	0.004	0.004
	(0.002)	(0.003)	(0.003)	(0.003)	(0.005)
A.2. Unemployment rate					
Exposure to robots	0.000	−0.000	−0.000	−0.001	−0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
A.3. Labor informality rate					
Exposure to robots	−0.007	0.003	0.006	0.006	0.005
	(0.005)	(0.007)	(0.007)	(0.007)	(0.011)
Number of districts	680	680	680	680	673
Observations	4696	4696	4696	4696	4647
Specification details:					
District FE	✓	✓	✓	✓	✓
Subregion × year FE	✓	✓	✓	✓	✓
Demographics		✓	✓	✓	✓
Industry shares		✓	✓	✓	✓
Labor market conditions			✓	✓	✓
Trade with China				✓	✓

Notes. The table presents estimates of the effects of exposure to robots on employment rates in Viet Nam during 2014–2020. Labor informality rate is the share of salaried workers that are not contributing to the pension system. All specifications include district and subregion × year fixed effects. Column 2 adds controls for initial differences in demographics and industry composition. Column 3 adds controls for initial differences in labor market conditions. Column 4 controls for bilateral trade flows with China. All regressions are weighted by population in 2011. Column 5 excludes the top 1 percent districts with the highest exposure to robots. Standard errors that are robust against heteroskedasticity and correlation within provinces are in parentheses. Significance at the 1, 5, and 10 percent levels denoted with ***, **, and *.

Table B6: The effects of robot adoption on employment composition by ownership structure (2SLS)

	(1)	(2)	(3)	(4)	(5)
1. Public sector					
Exposure to robots	-0.005^{**}	-0.000	-0.000	-0.000	0.002
	(0.002)	(0.003)	(0.003)	(0.003)	(0.005)
2. Domestic private firms					
Exposure to robots	0.001	-0.011^{***}	-0.013^{***}	-0.013^{***}	-0.011
	(0.005)	(0.003)	(0.004)	(0.005)	(0.008)
3. Foreign owned enterprises					
Exposure to robots	0.017^{***}	0.013^{*}	0.013^{**}	0.013^{**}	0.019^{***}
	(0.005)	(0.007)	(0.006)	(0.006)	(0.006)
Number of districts	680	680	680	680	673
Observations	4696	4696	4696	4696	4647
Specification details:					
District FE	✓	✓	✓	✓	✓
Subregion × year FE	✓	✓	✓	✓	✓
Demographics		✓	✓	✓	✓
Industry shares		✓	✓	✓	✓
Labor market conditions			✓	✓	✓
Imports from China				✓	✓

Notes. The table presents estimates of the effects of exposure to robots on local labor market outcomes in Viet Nam during 2014–2020. Exposure to robots is measured as the interaction between the 2011 employment composition by industry in each district and robot adoption by industry-year in Viet Nam, and it is instrumented with Exposure to robots (world) that uses the average robot adoption by industry-year across 54 countries. Columns 1-5 present regressions weighted by population in 2011. Column 6 excludes the 1 percent districts with the highest exposure to robots. Column 7 presents unweighted regressions. All specifications include district, district trends and subregion × year fixed effects. Column 2 adds demographic characteristics of districts in 2011 (log population; share in urban areas; share of migrants; shares of population with primary, secondary, and tertiary education; shares of population under ages 21-55 and older than 56; and share of females). Column 3 adds the shares of employment in primary, manufacturing, services, and the female share of manufacturing employment. Column 4 adds economic characteristics of districts in 2011 (employment rate, unemployment rate, labor informality rate, share of salaried employment, share of self-employment, female employment rate, exposure to job routinization, log average hourly wage, log average labor income, and log total labor income). Columns 5-7 add controls for trade with China, calculated as the interaction between 2011's industry employment composition in each district and the level and 2000–2010 change in log industry imports (from) and exports (to) China. Standard errors that are robust against heteroskedasticity and correlation within provinces are in parentheses. Significance at the 1, 5, and 10 percent levels denoted with ***, **, and *.

Table B7: Spillover effects of robot adoption on employment and wages (2SLS)

	Nearby locations (<20km)		Nearby locations (<30km)		Nearby locations (<40km)	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Employment outcomes						
A.1. Total Employment (log)						
ER (own district)	0.057	0.093*	0.051	0.080*	0.051	0.079*
	(0.039)	(0.048)	(0.038)	(0.047)	(0.037)	(0.046)
ER (nearby districts)	0.035	0.009	0.086	0.065	0.094	0.075
	(0.063)	(0.070)	(0.056)	(0.061)	(0.059)	(0.064)
A.1a. Salaried jobs - formal (log)						
ER (own district)	0.031	0.079	0.030	0.077	0.026	0.068
	(0.045)	(0.064)	(0.045)	(0.063)	(0.044)	(0.062)
ER (nearby districts)	0.000	−0.038	0.005	−0.033	0.043	0.010
	(0.081)	(0.095)	(0.085)	(0.096)	(0.087)	(0.097)
A.1b. Salaried jobs - informal (log)						
ER (own district)	0.066	0.110	0.059	0.096	0.057	0.091
	(0.056)	(0.076)	(0.055)	(0.076)	(0.055)	(0.078)
ER (nearby districts)	−0.038	−0.060	0.012	−0.004	0.028	0.016
	(0.096)	(0.101)	(0.083)	(0.089)	(0.094)	(0.104)
A.1c. Non-salaried jobs (log)						
ER (own district)	0.047	0.056	0.039	0.041	0.043	0.046
	(0.047)	(0.054)	(0.045)	(0.052)	(0.043)	(0.048)
ER (nearby districts)	0.050	0.040	0.122**	0.114*	0.108*	0.103*
	(0.068)	(0.073)	(0.058)	(0.058)	(0.059)	(0.062)
Panel B. Wage outcomes						
B.1. Average wage (log)						
ER (own district)	0.011	0.025**	0.012	0.026**	0.012	0.026**
	(0.010)	(0.013)	(0.010)	(0.011)	(0.010)	(0.012)
ER (nearby districts)	0.042**	0.032*	0.039***	0.032**	0.043***	0.034**
	(0.017)	(0.019)	(0.013)	(0.015)	(0.015)	(0.017)
B.1a. Average formal wage (log)						
ER (own district)	0.018*	0.039***	0.018*	0.038***	0.019**	0.038***
	(0.010)	(0.014)	(0.010)	(0.012)	(0.009)	(0.012)
ER (nearby districts)	0.045**	0.031	0.052***	0.042**	0.054***	0.043**
	(0.022)	(0.025)	(0.020)	(0.021)	(0.019)	(0.021)
B.1b. Average informal wage (log)						
ER (own district)	−0.003	0.003	−0.001	0.006	−0.001	0.006
	(0.015)	(0.019)	(0.015)	(0.018)	(0.015)	(0.018)
ER (nearby districts)	0.035*	0.030	0.023	0.019	0.026	0.020
	(0.019)	(0.023)	(0.016)	(0.019)	(0.019)	(0.022)
KP F-stat	52.0	76.3	59.3	75.9	62.6	84.2
Number of districts	680	673	680	673	680	673
Observations	4696	4647	4696	4647	4696	4647
Specification details:						
Full controls	✓	✓	✓	✓	✓	✓
Excludes top 1%		✓		✓		✓

Notes. This table reports estimates of the effects of robot exposure on registered firm outcomes in Viet Nam during 2014–2020, accounting for exposure in both own and nearby districts. Nearby robot exposure is defined as the population-weighted average exposure of districts within a 20 km (columns 1-2), 30 km (columns 3-4) and 40 km radius (columns 5-6). Own and nearby exposure are treated as endogenous and are instrumented using baseline shift-share IVs. other specifications follow the fully specified model in the main manuscript.

Table B8: Spillover effects of robot adoption on population and migration dynamics (2SLS)

	Nearby locations (<20km)		Nearby locations (<30km)		Nearby locations (<40km)	
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel C. Population					
C.1. Working-age population (15-65; log)						
ER (own district)	0.051	0.088*	0.047	0.078	0.047	0.077
	(0.041)	(0.051)	(0.040)	(0.049)	(0.039)	(0.049)
ER (nearby districts)	0.040	0.013	0.084	0.060	0.092	0.070
	(0.061)	(0.067)	(0.054)	(0.058)	(0.057)	(0.062)
C.2. Labor force participants (log)						
ER (own district)	0.056	0.091*	0.050	0.078	0.050	0.078*
	(0.040)	(0.049)	(0.039)	(0.048)	(0.038)	(0.047)
ER (nearby districts)	0.037	0.011	0.089	0.068	0.097	0.078
	(0.063)	(0.070)	(0.056)	(0.061)	(0.059)	(0.064)
C.3. Total in-migration (log)						
ER (own district)	0.122	0.130***	0.122	0.133***	0.119	0.124***
	(0.076)	(0.050)	(0.076)	(0.049)	(0.074)	(0.045)
ER (nearby districts)	0.059	0.046	0.066	0.039	0.105	0.090
	(0.117)	(0.123)	(0.120)	(0.127)	(0.118)	(0.118)
C.4. Total out-migration (log)						
ER (own district)	0.089	−0.061	0.072	−0.079	0.063	−0.098
	(0.095)	(0.106)	(0.096)	(0.105)	(0.095)	(0.105)
ER (nearby districts)	−0.129	−0.027	−0.010	0.050	0.067	0.150
	(0.204)	(0.225)	(0.221)	(0.234)	(0.197)	(0.208)
KP F-stat	52.0	76.3	59.3	75.9	62.6	84.2
Number of districts	680	673	680	673	680	673
Observations	4696	4647	4696	4647	4696	4647
Specification details:						
Full controls	✓	✓	✓	✓	✓	✓
Excludes top 1%		✓		✓		✓

Notes. This table reports estimates of the effects of robot exposure on registered firm outcomes in Viet Nam during 2014–2020, accounting for exposure in both own and nearby districts. Nearby robot exposure is defined as the population-weighted average exposure of districts within a 20 km (columns 1-2), 30 km (columns 3-4) and 40 km radius (columns 5-6). Own and nearby exposure are treated as endogenous and are instrumented using baseline shift-share IVs. other specifications follow the fully specified model in the main manuscript.

Table B9: Robustness to control for Pre-trends

	Demographics		Demographics + Industry shares		Demographics + Industry shares + Labor market cond.	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Employment outcomes						
A.1. Total Employment (log)						
Exposure to robots	0.033	0.064**	0.028	0.059**	0.028	0.057**
	(0.022)	(0.027)	(0.020)	(0.023)	(0.019)	(0.023)
A.1a. Salaried jobs - formal (log)						
Exposure to robots	0.005	0.048	−0.008	0.029	−0.011	0.025
	(0.031)	(0.034)	(0.027)	(0.034)	(0.028)	(0.037)
A.1b. Salaried jobs - informal (log)						
Exposure to robots	0.031	0.061*	0.066***	0.097***	0.065***	0.087***
	(0.028)	(0.033)	(0.023)	(0.031)	(0.020)	(0.028)
A.1c. Non-salaried jobs (log)						
Exposure to robots	0.022	0.029	0.019	0.026	0.018	0.023
	(0.020)	(0.034)	(0.017)	(0.029)	(0.015)	(0.029)
A.2. Unemployment (log)						
Exposure to robots	−0.018	0.006	−0.006	0.021	0.000	0.018
	(0.061)	(0.084)	(0.056)	(0.074)	(0.043)	(0.047)
Panel B. Wage outcomes						
B.1. Average wage (log)						
Exposure to robots	0.015	0.030**	0.009	0.025**	0.005	0.023**
	(0.011)	(0.012)	(0.011)	(0.012)	(0.010)	(0.010)
B.1a. Average formal wage (log)						
Exposure to robots	0.021*	0.043***	0.013	0.036***	0.008	0.030***
	(0.011)	(0.012)	(0.011)	(0.012)	(0.010)	(0.011)
B.1b. Average informal wage (log)						
Exposure to robots	0.001	0.009	−0.002	0.006	−0.002	0.008
	(0.014)	(0.016)	(0.016)	(0.017)	(0.014)	(0.016)
Panel C. Population						
C.1. Working-age population (15-65; log)						
Exposure to robots	0.027	0.058**	0.024	0.056***	0.024	0.053**
	(0.020)	(0.024)	(0.019)	(0.022)	(0.019)	(0.022)
C.2. Labor force participants (log)						
Exposure to robots	0.032	0.063**	0.027	0.057**	0.027	0.056**
	(0.021)	(0.026)	(0.020)	(0.023)	(0.019)	(0.023)
C.3. Total in-migration (log)						
Exposure to robots	0.128**	0.196***	0.113**	0.180***	0.104**	0.171***
	(0.050)	(0.047)	(0.051)	(0.052)	(0.051)	(0.051)
C.4. Total out-migration (log)						
Exposure to robots	0.045	−0.096	0.026	−0.160	0.051	−0.134
	(0.093)	(0.096)	(0.093)	(0.100)	(0.089)	(0.098)
KP F-stat	100.9	102.6	100.5	114.6	103.7	120.2
Number of districts	680	673	680	673	680	673
Observations	4696	4647	4696	4647	4696	4647
Specification details:						
Full controls	✓	✓	✓	✓	✓	✓
Excludes top 1%		✓	✓		✓	✓

Notes. The table presents 2SLS estimates of the effects of exposure to robots on labor market outcomes and population dynamics in Viet Nam during 2014–2020. All specifications include full controls (as in columns 4 and 5 of Tables 1 and 2). Columns 1 and 2 control for differential pre-trends in demographic conditions. Columns 3 and 4 add controls for differential pre-trends in industry composition. Columns 5 and 6 add controls for differential pre-trends in labor market conditions (i.e., including all the variables reported in Table B4). Even columns exclude the 1 percent districts with the highest exposure to robots.

Table B10: Robustness to control for FOEs and SEZs

	SEZs share in Y, L, and K		FOEs share in Y, L, and K		SEZs and FOEs shares in Y, L, and K	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Employment outcomes						
A.1. Total Employment (log)						
Exposure to robots	0.059*	0.091**	0.060*	0.094**	0.057*	0.090**
	(0.035)	(0.040)	(0.033)	(0.037)	(0.032)	(0.037)
A.1a. Salaried jobs - formal (log)						
Exposure to robots	0.022	0.061	0.025	0.066	0.018	0.057
	(0.041)	(0.056)	(0.040)	(0.052)	(0.040)	(0.053)
A.1b. Salaried jobs - informal (log)						
Exposure to robots	0.059	0.094	0.062	0.097	0.062	0.096
	(0.051)	(0.070)	(0.049)	(0.067)	(0.047)	(0.066)
A.1c. Non-salaried jobs (log)						
Exposure to robots	0.052	0.064	0.054	0.066*	0.051	0.063*
	(0.039)	(0.041)	(0.038)	(0.038)	(0.037)	(0.037)
A.2. Unemployment (log)						
Exposure to robots	0.024	0.054	0.032	0.063	0.026	0.055
	(0.080)	(0.105)	(0.079)	(0.101)	(0.077)	(0.102)
Panel B. Wage outcomes						
B.1. Average wage (log)						
Exposure to robots	0.016	0.032***	0.016	0.031**	0.015	0.030**
	(0.011)	(0.012)	(0.011)	(0.013)	(0.011)	(0.013)
B.1a. Average formal wage (log)						
Exposure to robots	0.024**	0.046***	0.023**	0.045***	0.023**	0.045***
	(0.010)	(0.012)	(0.010)	(0.012)	(0.010)	(0.013)
B.1b. Average informal wage (log)						
Exposure to robots	0.001	0.010	0.001	0.010	0.001	0.009
	(0.015)	(0.018)	(0.015)	(0.018)	(0.016)	(0.018)
Panel C. Population						
C.1. Working-age population (15-65; log)						
Exposure to robots	0.054	0.087**	0.056	0.091**	0.053	0.087**
	(0.036)	(0.043)	(0.035)	(0.040)	(0.034)	(0.040)
C.2. Labor force participants (log)						
Exposure to robots	0.057	0.090**	0.059*	0.092**	0.056*	0.089**
	(0.035)	(0.041)	(0.034)	(0.038)	(0.033)	(0.038)
C.3. Total in-migration (log)						
Exposure to robots	0.118*	0.132***	0.130*	0.150***	0.122*	0.144***
	(0.067)	(0.044)	(0.072)	(0.045)	(0.068)	(0.045)
C.4. Total out-migration (log)						
Exposure to robots	0.077	−0.061	0.069	−0.067	0.077	−0.057
	(0.089)	(0.096)	(0.088)	(0.094)	(0.086)	(0.096)
KP F-stat	126.4	128.3	124.8	120.7	125.7	122.8
Number of districts	680	673	680	673	680	673
Observations	4696	4647	4696	4647	4696	4647
Specification details:						
Full controls	✓	✓	✓	✓	✓	✓
Excludes top 1%		✓	✓		✓	✓

Notes. The table presents 2SLS estimates of the effects of exposure to robots on labor market outcomes and population dynamics in Viet Nam during 2014–2020. All specifications include full controls (as in columns 4 and 5 of Tables 1 and 2). Columns 1 and 2 control for initial differences in SEZs participation in production, employment, and capital. Columns 3 and 4 control for initial differences in FOEs participation in production, employment, and capital. Columns 5 and 6 control for both initial differences in SEZs and FOEs participation in production, employment, and capital. Even columns exclude the 1 percent districts with the highest exposure to robots.

Table B11: Robustness to control for FOEs and SEZs (augmented)

	SEZs & FOEs sh. in Y, L, and K		SEZs & FOEs sh. in Y, L, and K + Dummy SEZs		SEZs & FOEs sh. in Y, L, and K + D_SEZs + N_SEZs	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Employment outcomes						
A.1. Total Employment (log)						
Exposure to robots	0.057*	0.090**	0.057*	0.090**	0.056*	0.091**
	(0.032)	(0.037)	(0.033)	(0.037)	(0.033)	(0.039)
A.1a. Salaried jobs - formal (log)						
Exposure to robots	0.018	0.057	0.019	0.057	0.014	0.050
	(0.040)	(0.053)	(0.040)	(0.055)	(0.041)	(0.056)
A.1b. Salaried jobs - informal (log)						
Exposure to robots	0.062	0.096	0.062	0.097	0.061	0.099
	(0.047)	(0.066)	(0.047)	(0.065)	(0.047)	(0.066)
A.1c. Non-salaried jobs (log)						
Exposure to robots	0.051	0.063*	0.051	0.063*	0.054	0.071*
	(0.037)	(0.037)	(0.037)	(0.036)	(0.037)	(0.038)
A.2. Unemployment (log)						
Exposure to robots	0.026	0.055	0.024	0.054	0.022	0.051
	(0.077)	(0.102)	(0.077)	(0.100)	(0.077)	(0.102)
Panel B. Wage outcomes						
B.1. Average wage (log)						
Exposure to robots	0.015	0.030**	0.015	0.030**	0.015	0.029**
	(0.011)	(0.013)	(0.011)	(0.013)	(0.011)	(0.014)
B.1a. Average formal wage (log)						
Exposure to robots	0.023**	0.045***	0.023**	0.045***	0.022**	0.044***
	(0.010)	(0.013)	(0.010)	(0.013)	(0.010)	(0.014)
B.1b. Average informal wage (log)						
Exposure to robots	0.001	0.009	0.001	0.009	0.002	0.011
	(0.016)	(0.018)	(0.016)	(0.019)	(0.015)	(0.019)
Panel C. Population						
C.1. Working-age population (15-65; log)						
Exposure to robots	0.053	0.087**	0.053	0.087**	0.051	0.086**
	(0.034)	(0.040)	(0.034)	(0.040)	(0.035)	(0.041)
C.2. Labor force participants (log)						
Exposure to robots	0.056*	0.089**	0.056*	0.089**	0.055	0.089**
	(0.033)	(0.038)	(0.033)	(0.038)	(0.034)	(0.039)
C.3. Total in-migration (log)						
Exposure to robots	0.122*	0.144***	0.123*	0.143***	0.118*	0.151***
	(0.068)	(0.045)	(0.069)	(0.045)	(0.068)	(0.047)
C.4. Total out-migration (log)						
Exposure to robots	0.077	−0.057	0.075	−0.063	0.057	−0.081
	(0.086)	(0.096)	(0.087)	(0.098)	(0.085)	(0.099)
KP F-stat	125.7	122.8	125.3	126.9	125.8	130.5
Number of districts	680	673	680	673	680	673
Observations	4696	4647	4696	4647	4696	4647
Specification details:						
Full controls	✓	✓	✓	✓	✓	✓
Excludes top 1%		✓	✓		✓	✓

Notes. The table presents 2SLS estimates of the effects of exposure to robots on labor market outcomes and population dynamics in Viet Nam during 2014–2020. All specifications include full controls (as in columns 4 and 5 of Tables 1 and 2). Columns 1 and 2 control for initial differences in SEZs and FOEs participation in production, employment, and capital. Columns 3 and 4 add controls for initial differences in SEZs presence, and columns 5 and 6 control also for the number of SEZs established in each district, using data on SEZs establishment from Tafese et al. (2025). Even columns exclude the 1 percent districts with the highest exposure to robots.

Table B12: Robustness to covariates selected by LASSO

	Baseline covariates		Baseline + SEZs + FOEs		Baseline + SEZs + FOEs + Pre-trends	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Employment outcomes						
A.1. Total Employment (log)						
Exposure to robots	0.037*	0.095***	0.039*	0.093***	0.039*	0.093***
	(0.020)	(0.031)	(0.020)	(0.032)	(0.021)	(0.033)
A.1a. Salaried jobs - formal (log)						
Exposure to robots	−0.044	−0.015	−0.035	−0.025	−0.035	−0.025
	(0.029)	(0.043)	(0.031)	(0.047)	(0.030)	(0.047)
A.1b. Salaried jobs - informal (log)						
Exposure to robots	0.019	0.015	0.018	0.010	0.019	0.012
	(0.035)	(0.053)	(0.035)	(0.055)	(0.035)	(0.056)
A.1c. Non-salaried jobs (log)						
Exposure to robots	0.054**	0.068**	0.055**	0.066**	0.055**	0.066**
	(0.024)	(0.029)	(0.024)	(0.031)	(0.025)	(0.031)
A.2. Unemployment (log)						
Exposure to robots	0.045	0.054	0.043	0.047	0.044	0.049
	(0.069)	(0.101)	(0.069)	(0.103)	(0.069)	(0.103)
Panel B. Wage outcomes						
B.1. Average wage (log)						
Exposure to robots	0.010	0.020**	0.008	0.018**	0.009	0.019**
	(0.009)	(0.008)	(0.009)	(0.009)	(0.009)	(0.008)
B.1a. Average formal wage (log)						
Exposure to robots	0.024***	0.044***	0.024***	0.044***	0.024***	0.045***
	(0.008)	(0.010)	(0.008)	(0.009)	(0.008)	(0.009)
B.1b. Average informal wage (log)						
Exposure to robots	−0.003	−0.001	−0.003	−0.002	−0.003	−0.002
	(0.015)	(0.014)	(0.016)	(0.014)	(0.016)	(0.014)
Panel C. Population						
*C.1.*Working-age population (15-65; log)						
Exposure to robots	0.036	0.065**	0.038	0.063*	0.038	0.063*
	(0.023)	(0.031)	(0.024)	(0.033)	(0.024)	(0.033)
*C.2.*Labor force participants (log)						
Exposure to robots	0.040**	0.095***	0.039*	0.093***	0.039*	0.062**
	(0.020)	(0.032)	(0.021)	(0.033)	(0.021)	(0.028)
C.3. Total in-migration (log)						
Exposure to robots	0.094**	0.083*	0.104***	0.066	0.102***	0.063
	(0.038)	(0.047)	(0.036)	(0.049)	(0.035)	(0.048)
C.4. Total out-migration (log)						
Exposure to robots	0.059	−0.000	0.032	0.018	0.025	0.011
	(0.080)	(0.102)	(0.081)	(0.112)	(0.079)	(0.107)
KP F-stat						
Number of districts	680	673	680	673	663	656
Observations	4696	4647	4696	4647	4578	4529
Specification details:						
Full controls	✓	✓	✓	✓	✓	✓
Excludes top 1%		✓		✓		✓

Notes. The table presents 2SLS estimates of the effects of exposure to robots on labor market outcomes and population dynamics in Viet Nam during 2014–2020.; following the two-step LASSO procedure (Belloni et al., 2014). Columns 1 and 2 include all the baseline covariates (demographics, industry composition, labor market conditions, and trade exposure variables). Columns 3 and 4 add controls for initial differences in SEZs and FOEs participation in economic activity. Columns 5 and 6 incorporate controls for differential pre-trends in all the variables reported in Table B4. Even columns exclude the 1 percent districts with the highest exposure to robots.

Table B13: Robustness to excluding key industries

	Excluding Computers & Electronics		Excluding Electrical equipment		Excluding Automotive		Excluding Rubber & plastics	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Employment outcomes								
A.1. Total Employment (log)								
Exposure to robots	0.085*	0.176**	0.089*	0.116**	0.065*	0.076*	0.048	0.065*
	(0.050)	(0.070)	(0.047)	(0.050)	(0.036)	(0.041)	(0.032)	(0.034)
A.1a. Salaried jobs - formal (log)								
Exposure to robots	0.051	0.153*	0.055	0.096	0.014	0.022	0.019	0.044
	(0.054)	(0.086)	(0.060)	(0.070)	(0.047)	(0.058)	(0.041)	(0.052)
A.1b. Salaried jobs - informal (log)								
Exposure to robots	0.086	0.191*	0.081	0.118	0.083	0.089	0.042	0.054
	(0.069)	(0.116)	(0.081)	(0.096)	(0.052)	(0.063)	(0.050)	(0.065)
A.1c. Non-salaried jobs (log)								
Exposure to robots	0.075	0.125*	0.072	0.070	0.060	0.066*	0.037	0.028
	(0.051)	(0.075)	(0.059)	(0.052)	(0.037)	(0.035)	(0.037)	(0.032)
A.2. Unemployment (log)								
Exposure to robots	0.032	0.122	0.038	0.081	0.046	0.027	0.014	0.031
	(0.094)	(0.158)	(0.133)	(0.147)	(0.071)	(0.078)	(0.089)	(0.108)
Panel B. Wage outcomes								
B.1. Average wage (log)								
Exposure to robots	0.022**	0.042**	0.025	0.044***	0.021*	0.039***	0.016	0.034**
	(0.011)	(0.016)	(0.018)	(0.017)	(0.012)	(0.013)	(0.013)	(0.015)
B.1a. Average formal wage (log)								
Exposure to robots	0.030**	0.062***	0.037**	0.063***	0.034***	0.056***	0.022*	0.045***
	(0.013)	(0.020)	(0.016)	(0.015)	(0.011)	(0.013)	(0.012)	(0.014)
B.1b. Average informal wage (log)								
Exposure to robots	0.009	0.017	−0.001	0.008	−0.002	0.014	0.003	0.015
	(0.016)	(0.025)	(0.023)	(0.023)	(0.015)	(0.016)	(0.016)	(0.017)
Panel C. Population								
C.1. Working-age population (15-65; log)								
Exposure to robots	0.080	0.173**	0.084*	0.114**	0.058	0.068*	0.042	0.060*
	(0.053)	(0.076)	(0.050)	(0.053)	(0.036)	(0.040)	(0.033)	(0.036)
C.2. Labor force participants (log)								
Exposure to robots	0.083*	0.174**	0.087*	0.114**	0.065*	0.075*	0.047	0.064*
	(0.050)	(0.070)	(0.048)	(0.050)	(0.037)	(0.041)	(0.033)	(0.034)
C.3. Total in-migration (log)								
Exposure to robots	0.118*	0.187***	0.186*	0.170***	0.195**	0.193**	0.129*	0.110**
	(0.071)	(0.064)	(0.101)	(0.061)	(0.092)	(0.083)	(0.070)	(0.049)
C.4. Total out-migration (log)								
Exposure to robots	0.120	−0.048	0.073	−0.091	0.107	−0.014	0.077	−0.059
	(0.102)	(0.165)	(0.147)	(0.134)	(0.113)	(0.118)	(0.099)	(0.099)
KP F-stat	195.0	361.4	34.2	55.5	420.5	385.0	98.2	89.7
Number of districts	680	673	680	673	680	673	680	673
Observations	4696	4647	4696	4647	4696	4647	4696	4647
Specification details:								
Full controls	✓	✓	✓	✓	✓	✓	✓	✓
Excludes top 1%		✓		✓		✓		✓

Notes. The table presents 2SLS estimates of the effects of exposure to robots on labor market outcomes and population dynamics in Viet Nam during 2014–2020. All specifications include full controls (as in columns 4 and 5 of Tables 1 and 2). Columns 1-2, 3-4, 5-6, and 7-8, exclude computers and electronics, electrical equipment, automotive, and rubber and plastics, respectively, from the computation of robot exposure variables. Even columns exclude the 1 percent districts with the highest exposure to robots.

Table B14: Robustness to excluding most exposed districts

	Excluding Top 5 (1)	Excluding Top 10 (2)	Excluding Top 15 (3)	Excluding Top 20 (4)	Excluding Top 25 (5)	Excluding Top 30 (6)
Panel A. Employment outcomes						
A.1. Total Employment (log)						
Exposure to robots	0.082**	0.119**	0.141**	0.170**	0.171**	0.160**
	(0.036)	(0.056)	(0.066)	(0.073)	(0.082)	(0.064)
A.1a. Salaried jobs - formal (log)						
Exposure to robots	0.059	0.084	0.101	0.119	0.117	0.090
	(0.050)	(0.069)	(0.081)	(0.100)	(0.103)	(0.094)
A.1b. Salaried jobs - informal (log)						
Exposure to robots	0.086	0.101	0.125	0.182**	0.172**	0.178**
	(0.062)	(0.087)	(0.099)	(0.088)	(0.087)	(0.077)
A.1c. Non-salaried jobs (log)						
Exposure to robots	0.049	0.103*	0.122*	0.130	0.113	0.091
	(0.040)	(0.061)	(0.072)	(0.085)	(0.090)	(0.067)
A.2. Unemployment (log)						
Exposure to robots	0.047	0.096	0.163	0.279**	0.235**	0.262**
	(0.090)	(0.134)	(0.143)	(0.119)	(0.104)	(0.117)
Panel B. Wage outcomes						
B.1. Average wage (log)						
Exposure to robots	0.028**	0.038***	0.049***	0.047***	0.064***	0.056***
	(0.012)	(0.012)	(0.012)	(0.014)	(0.018)	(0.019)
B.1a. Average formal wage (log)						
Exposure to robots	0.041***	0.052***	0.069***	0.071***	0.086***	0.085***
	(0.012)	(0.013)	(0.014)	(0.017)	(0.023)	(0.025)
B.1b. Average informal wage (log)						
Exposure to robots	0.004	0.011	0.013	0.012	0.039**	0.029
	(0.017)	(0.019)	(0.021)	(0.025)	(0.019)	(0.021)
Panel C. Population						
C.1. Working-age population (15-65; log)						
Exposure to robots	0.078**	0.115*	0.139**	0.175**	0.166**	0.155**
	(0.038)	(0.061)	(0.070)	(0.077)	(0.079)	(0.064)
C.2. Labor force participants (log)						
Exposure to robots	0.081**	0.117**	0.140**	0.170**	0.171**	0.160**
	(0.036)	(0.057)	(0.066)	(0.073)	(0.081)	(0.064)
C.3. Total in-migration (log)						
Exposure to robots	0.095**	0.166***	0.148***	0.259**	0.404***	0.506***
	(0.043)	(0.050)	(0.055)	(0.124)	(0.150)	(0.168)
C.4. Total out-migration (log)						
Exposure to robots	−0.063	−0.062	−0.034	0.076	0.112	0.139
	(0.100)	(0.124)	(0.140)	(0.173)	(0.224)	(0.236)
KP F-stat	90.4	133.2	177.7	117.7	76.4	105.5
Number of districts	675	670	665	660	655	650
Observations	4661	4626	4592	4557	4522	4488

Notes. The table presents 2SLS estimates of the effects of exposure to robots on labor market outcomes and population dynamics in Viet Nam during 2014–2020. All specifications include full controls (as in columns 4 and 5 of Tables 1 and 2). Columns 1 to 6 exclude the top 5, 10, 15, 20, 25, and 30 districts with the highest exposure to robots.

Table B15: Robustness to alternative definitions of the IV

	High-robot countries		High-income countries		Middle-income countries		Weighted* World	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Employment outcomes								
A.1. Total Employment (log)								
Exposure to robots	0.055	0.078*	0.061*	0.091**	0.082*	0.154***	0.058*	0.084**
	(0.036)	(0.041)	(0.034)	(0.039)	(0.045)	(0.058)	(0.033)	(0.036)
A.1a. Salaried jobs - formal (log)								
Exposure to robots	0.018	0.044	0.028	0.064	0.064	0.154**	0.023	0.054
	(0.042)	(0.054)	(0.041)	(0.053)	(0.052)	(0.068)	(0.039)	(0.051)
A.1b. Salaried jobs - informal (log)								
Exposure to robots	0.054	0.075	0.060	0.092	0.067	0.151	0.056	0.079
	(0.052)	(0.066)	(0.052)	(0.069)	(0.068)	(0.109)	(0.049)	(0.062)
A.1c. Non-salaried jobs (log)								
Exposure to robots	0.049	0.054	0.053	0.062	0.074	0.116*	0.052	0.061*
	(0.041)	(0.039)	(0.039)	(0.039)	(0.051)	(0.067)	(0.037)	(0.035)
A.2. Unemployment (log)								
Exposure to robots	0.023	0.038	0.029	0.058	0.031	0.120	0.029	0.052
	(0.084)	(0.103)	(0.081)	(0.101)	(0.098)	(0.149)	(0.078)	(0.094)
Panel B. Wage outcomes								
B.1. Average wage (log)								
Exposure to robots	0.015	0.032**	0.017	0.033***	0.020**	0.035***	0.016	0.033***
	(0.011)	(0.013)	(0.011)	(0.012)	(0.010)	(0.012)	(0.011)	(0.012)
B.1a. Average formal wage (log)								
Exposure to robots	0.023**	0.043***	0.025**	0.047***	0.024**	0.047***	0.024**	0.045***
	(0.010)	(0.012)	(0.010)	(0.012)	(0.010)	(0.013)	(0.010)	(0.012)
B.1b. Average informal wage (log)								
Exposure to robots	0.001	0.014	0.002	0.011	0.003	0.005	0.002	0.012
	(0.015)	(0.016)	(0.015)	(0.017)	(0.017)	(0.023)	(0.015)	(0.016)
Panel C. Population								
C.1. Working-age population (15-65; log)								
Exposure to robots	0.048	0.072*	0.056	0.087**	0.080	0.155**	0.052	0.079**
	(0.037)	(0.042)	(0.036)	(0.042)	(0.049)	(0.065)	(0.034)	(0.038)
C.2. Labor force participants (log)								
Exposure to robots	0.054	0.077*	0.060*	0.090**	0.080*	0.152***	0.057*	0.083**
	(0.037)	(0.042)	(0.035)	(0.039)	(0.046)	(0.058)	(0.033)	(0.037)
C.3. Total in-migration (log)								
Exposure to robots	0.127*	0.116**	0.133*	0.143***	0.094	0.127**	0.136*	0.139***
	(0.073)	(0.048)	(0.071)	(0.042)	(0.065)	(0.056)	(0.069)	(0.045)
C.4. Total out-migration (log)								
Exposure to robots	0.080	−0.038	0.079	−0.054	0.009	−0.186*	0.074	−0.067
	(0.096)	(0.103)	(0.093)	(0.098)	(0.101)	(0.109)	(0.092)	(0.095)
KP F-stat	187.6	167.0	131.8	136.5	104.5	127.0	144.5	138.1
Number of districts	680	673	680	673	680	673	680	673
Observations	4696	4647	4696	4647	4696	4647	4696	4647
Specification details:								
Full controls	✓	✓	✓	✓	✓	✓	✓	✓
Excludes top 1%		✓		✓		✓		✓

Notes. The table presents 2SLS estimates of the effects of exposure to robots on labor market outcomes and population dynamics in Viet Nam during 2014–2020. All specifications include full controls (as in columns 4 and 5 of Tables 1 and 2). Columns 1-2, 3-4, 5-6, and 7-8, compute the robot exposure variable (IV) using different subset of countries: (i) high-robot countries (defined as the top 15 countries with highest robots per thousand workers in 2020); (ii) high-income countries; (iii) middle-income economies; and (iv) all countries weighted by the ratio of population above 56 years old to middle-age population (21-55); respectively. Even columns exclude the 1 percent districts with the highest exposure to robots.

Table B16: Regressions in changes

	2014–2020		2014–2019		2015–2020		2015–2019	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Employment outcomes								
A.1. Total Employment (log)								
Exposure to robots	0.086	0.112*	0.102	0.141	0.036**	0.049**	0.037***	0.050**
	(0.065)	(0.068)	(0.083)	(0.090)	(0.016)	(0.021)	(0.013)	(0.020)
A.1a. Salaried jobs - formal (log)								
Exposure to robots	0.034	0.060	0.020	0.063	0.029	0.040	0.023	0.042
	(0.065)	(0.071)	(0.094)	(0.098)	(0.033)	(0.036)	(0.038)	(0.048)
A.1b. Salaried jobs - informal (log)								
Exposure to robots	0.066	0.136	0.090	0.145	0.057***	0.056**	0.061**	0.020
	(0.092)	(0.100)	(0.121)	(0.145)	(0.019)	(0.027)	(0.027)	(0.033)
A.1c. Non-salaried jobs (log)								
Exposure to robots	0.096	0.091	0.087	0.108	0.035	0.034	0.009	0.023
	(0.073)	(0.077)	(0.070)	(0.094)	(0.021)	(0.026)	(0.027)	(0.031)
A.2. Unemployment (log)								
Exposure to robots	0.070	0.217	0.139	0.235	−0.087	−0.126**	−0.037	−0.152*
	(0.148)	(0.183)	(0.156)	(0.203)	(0.053)	(0.058)	(0.072)	(0.090)
Panel B. Wage outcomes								
B.1. Average wage (log)								
Exposure to robots	0.015	0.030	0.022	0.043	0.014*	0.030***	0.012	0.033**
	(0.014)	(0.022)	(0.018)	(0.026)	(0.008)	(0.010)	(0.014)	(0.015)
B.1a. Average formal wage (log)								
Exposure to robots	0.027**	0.049**	0.022	0.045**	0.020**	0.045***	0.011	0.038**
	(0.014)	(0.020)	(0.018)	(0.022)	(0.010)	(0.015)	(0.015)	(0.015)
B.1b. Average informal wage (log)								
Exposure to robots	0.003	0.019	−0.003	0.016	0.014	0.019**	0.002	0.007
	(0.022)	(0.028)	(0.024)	(0.034)	(0.012)	(0.009)	(0.013)	(0.017)
Panel C. Population								
C.1. Working-age population (15-65; log)								
Exposure to robots	0.083	0.112	0.099	0.141	0.027*	0.041*	0.028**	0.042**
	(0.070)	(0.074)	(0.086)	(0.097)	(0.016)	(0.022)	(0.013)	(0.019)
C.2. Labor force participants (log)								
Exposure to robots	0.084	0.112	0.100	0.139	0.034**	0.047**	0.035***	0.046**
	(0.066)	(0.069)	(0.083)	(0.091)	(0.016)	(0.021)	(0.013)	(0.021)
C.3. Total in-migration (log)								
Exposure to robots	0.134	−0.015	0.193	0.194*	0.109**	0.118	0.155	0.265*
	(0.097)	(0.196)	(0.169)	(0.110)	(0.051)	(0.085)	(0.108)	(0.136)
C.4. Total out-migration (log)								
Exposure to robots	0.229	0.423	0.029	0.494	0.801	0.503	0.794	0.832
	(0.788)	(0.823)	(0.596)	(0.974)	(0.565)	(0.656)	(0.492)	(0.876)
KP F-stat	123.3	122.3	124.1	130.5	110.8	112.9	107.5	115.5
Number of districts								
Observations	637	630	641	634	667	660	672	665
Specification details:								
Full controls	✓	✓	✓	✓	✓	✓	✓	✓
Excludes top 1%		✓		✓		✓		✓

Notes. The table presents 2SLS estimates of the effects of exposure to robots on labor market outcomes and population dynamics in Viet Nam for different subperiods. All specifications include full controls (as in columns 4 and 5 of Tables 1 and 2). Columns 1-2, 3-4, 5-6, and 7-8, correspond to the periods 2014 vs 2020, 2014 vs 2019, 2015 vs 2020, and 2015 vs 2019, respectively. Even columns exclude the 1 percent districts with the highest exposure to robots.

Table B17: Robustness to alternative inference–BHJ

	(1)	(2)	(3)	(4)	(5)
		Panel A. Employment outcomes			
A.1. Total Employment (log)					
Exposure to robots	0.082***	0.064***	0.055***	0.062***	0.095**
	(0.022)	(0.016)	(0.016)	(0.018)	(0.042)
A.1a. Salaried jobs - formal (log)					
Exposure to robots	0.070**	0.026	0.017	0.031*	0.070
	(0.032)	(0.021)	(0.017)	(0.018)	(0.049)
A.1b. Salaried jobs - informal (log)					
Exposure to robots	0.039**	0.043**	0.042**	0.060***	0.095*
	(0.019)	(0.019)	(0.020)	(0.022)	(0.051)
A.1c. Non-salaried jobs (log)					
Exposure to robots	0.055**	0.064***	0.053***	0.055**	0.067
	(0.025)	(0.019)	(0.019)	(0.023)	(0.041)
A.2. Unemployment (log)					
Exposure to robots	0.103***	0.034	0.036	0.029	0.063
	(0.032)	(0.033)	(0.029)	(0.038)	(0.086)
		Panel B. Wage outcomes			
B.1. Average wage (log)					
Exposure to robots	0.001	0.016***	0.015**	0.017***	0.033***
	(0.007)	(0.006)	(0.006)	(0.006)	(0.008)
B.1a. Average formal wage (log)					
Exposure to robots	0.012**	0.024***	0.020***	0.025***	0.047***
	(0.005)	(0.006)	(0.007)	(0.008)	(0.010)
B.1b. Average informal wage (log)					
Exposure to robots	−0.004	0.005	0.004	0.002	0.011
	(0.009)	(0.005)	(0.006)	(0.007)	(0.008)
		Panel C. Population			
C.1. Working-age population (15-65; log)					
Exposure to robots	0.081***	0.064***	0.052***	0.057***	0.091**
	(0.021)	(0.018)	(0.016)	(0.019)	(0.045)
C.2. Labor force participants (log)					
Exposure to robots	0.083***	0.064***	0.054***	0.061***	0.094**
	(0.022)	(0.016)	(0.016)	(0.018)	(0.043)
C.3. Total in-migration (log)					
Exposure to robots	0.166***	0.141***	0.134***	0.129***	0.141**
	(0.035)	(0.034)	(0.039)	(0.042)	(0.062)
C.4. Total out-migration (log)					
Exposure to robots	0.009	0.590***	0.571**	0.453*	0.498
	(0.261)	(0.215)	(0.232)	(0.254)	(0.404)
KP F-stat	29.8	34.3	37.4	32.6	19.5
Observations	154	154	154	154	154
Specification details:					
District FE	✓	✓	✓	✓	✓
Subregion × year FE	✓	✓	✓	✓	✓
Demographics		✓	✓	✓	✓
Industry shares		✓	✓	✓	✓
Labor market conditions			✓	✓	✓
Trade with China				✓	✓

Notes. The table presents 2SLS estimates of the effects of exposure to robots on labor market outcomes and population dynamics in Viet Nam during 2014–2020; following the SSIV econometric framework developed by Borusyak, Hull, and Jaravel (2022). Specifications are analogous to Table 1 and Table 2.

Table B18: Rotemberg weights

Panel A: Negative and positive weights

	Sum	Mean	Share
Negative	-0.000	-0.000	0.000
Positive	1.000	0.053	1.000

Panel B: Industries with the highest Rotemberg weights

	$\hat{\alpha}_k$	g_k	$\hat{\beta}_k$	Ind Share
Computers and electronics	0.493	11.21	0.059	0.34
Electrical equipment	0.364	15.45	0.078	0.19
Automotive	0.079	5.65	0.071	0.11
Rubber and plastics	0.059	3.46	0.070	0.31
Metal products	0.002	0.12	0.101	0.99
Toys and misc. manufacturing	0.001	0.10	0.183	0.44
Food and beverages	0.001	0.06	0.316	2.35

Notes. This table reports statistics about the Rotemberg weights. Panel A reports the share and sum of negative and positive Rotemberg weights separately. Panel B reports the industries with highest positive Rotemberg weights. The g_k is the average industry growth in robot adoption between 2014 and 2020, $\hat{\beta}_k$ is the coefficient from the just-identified regression, and Ind Share is the industry share (multiplied by 100 for legibility).