Widening the Gap: Gendered Impacts of Capital Deepening in Vietnam, a Lower Middle-Income Country

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Abstract

Since the mid-2010s, Vietnam has experienced a concerning reversal of the gender wage gap. This study uses diverse datasets to analyze this trend at the firm, district, and individual levels. We emphasize the critical role of capital deepening in manufacturing as a key driver. Our findings indicate that the decline in female wages relative to males stems from reduced female labor demand rather than supply-side factors. We demonstrate that capital deepening differently affects the gender wage gap across districts. In high-income districts, capital deepening primarily impacts the gender wage gap through hourly wage rates. Conversely, in low-income districts, where labor mobility is limited, capital deepening influences the gender wage gap through both working hours and hourly wage rates. Younger females with lower educational attainment are particularly vulnerable to the effects of capital deepening.

Keywords: Gender wage gap, capital deepening, industrial upgrade, labor displacement, Vietnam

J.E.L. classification codes: J16, J31, O15, J23, O33

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1 Introduction

The gender dimension of automation and capital intensity in developing economies remains largely underexplored. In advanced economies, one widely observed phenomenon is job polarization, where technological change displaces labor primarily in routine, codifiable tasks while leaving those performed by high-skilled and low-skilled workers relatively unaffected (see, e.g., Acemoglu and Restrepo, 2022; Autor *et al.*, 2006, 2008; Autor and Dorn, 2013; Dustmann *et al.*, 2009; Goos and Manning, 2007; Goos *et al.*, 2014; Ikenaga and Kambayashi, 2016; Spitz-Oener, 2006). Given women's concentration in routine tasks, this shift puts them at greater risk of being replaced by automation.

Nevertheless, empirical evidence on the gender-biased effects of automation and capital intensity in advanced countries remains mixed. While some studies find that these advancements widen the gender wage gap(Aksoy *et al.*, 2021; Black and Spitz-Oener, 2010; Brussevich *et al.*, 2018; Genz and Schnabel, 2023) , others report contrasting or neutral findings (Deng *et al.*, 2023; Domini *et al.*, 2022; Ge and Zhou, 2020).

The dominant narrative suggests that jobs in developing economies are less vulnerable to automation than those in developed economies. This is attributed to their less capital-intensive production processes, which are centered around manual, in-person, and low-skilled tasks—tasks that are naturally resistant to automation at present. For example, Maloney and Molina (2016) and Das and Hilgenstock (2022) suggest that there may be no polarization in developing countries or that polarization is occurring but is offset by stronger forces.

ILO (2018) provides estimates of gender wage gaps across countries, revealing substantial heterogeneity within developing economies. The gap ranges from 34% in Pakistan to a surprising -10.3% in the Philippines, highlighting the diversity in gender pay dynamics. Similarly, the trends in gender wage gaps show divergent patterns. While higher-middle-income countries like Malaysia, the Philippines, and Thailand demonstrate a narrowing gap, some lower-middle-income countries in the region, such as Sri Lanka, Cambodia, and Vietnam, experienced a concerning reversal in the second half of the 2010s (see Figure A.1). Interestingly, these countries witnessed the reversed trend coinciding with a significant rise in their imports of automation-related capital goods during this period (see Figure A.2).

"This paper focuses on the case of Vietnam to examine how capital intensity contributes to the rising gender wage gap in the country during the second half of the 2010s. Notably, Vietnam presents a unique case study within developing economies, showcasing a comparatively equitable gender landscape in terms of labor market participation. Women in Vietnam have made significant contributions to the workforce, with a participation rate of 71.4%, only slightly lower than the 81.2% rate for men (see Figure A.1). This places female labor force participation among the highest in Southeast Asia (see Figure A.3). Various factors contribute to this, including the country's socialist legacy, excess male mortality during the Vietnam War, and particularly high labor demand due to Vietnam's export-based economic growth in recent decades (McCaig and Pavcnik, 2015, 2018; Klasen *et al.*, 2021; Kreibaum and Klasen, 2015). The relatively low barriers to female workforce participation contribute to a more moderate gender wage gap in Vietnam compared to its neighboring countries (see Table A.2)."

The gender wage gap in Vietnam has been on a dynamic journey since Doi Moi. In the initial phases of the economic transition during the 1990s and early 2000s, the gap tended to decrease and was smaller compared to most transitional economies. Identifying the factors responsible for this reduction is challenging, but one potential source is the selective withdrawal from wage employment by poorly qualified Vietnamese women (Liu, 2004; Pham and Reilly, 2007). The period from the early 2000s to the mid-2010s witnessed a further narrowing of the gender wage gap. This era experienced several key developments: the US-Vietnam Bilateral Trade Agreement (BTA) in December 2001 and Vietnam's accession to the World Trade Organization (WTO) in 2007. The observed progress in gender equality can be attributed to factors such as the rise in educational attainment among employed women and the expansion of employment opportunities for women in manufacturing, processing, as well as wholesale and retail industries (Vu and Yamada, 2018).

The gap has surprisingly expanded since the mid-2010s. This period coincided with a surge of capital inflows into Vietnam, attributed partly to the combined effects of the US-China trade war (Ha and Phuc, 2019; Ngoc and Wie) and an extensive Free Trade Agreement (FTA) network (Dhar *et al.*, 2023). This sudden divergence in the gender wage gap trajectory necessitates further investigation to unravel the underlying mechanisms at play. In this paper, we focuses on the role of capital intensity in the manufacturing sector of Vietnam, which could potentially worsen gender employment equality through several channels. Firstly, automation is likely to replace routine assembly work, which has been a major driver of female labor force participation in the past. Secondly, automation is expected to increase the demand for medium- and high-skilled occupations where female representation is lower than that of men.

We utilize various datasets and empirical model specifications to comprehensively examine the impact of capital intensity on the gender wage gap. Our key identification strategy relies on a novel measure of exposure to capital intensity constructed at the district and province levels, where we leverage the natural variation in exposure across locations. This measure captures the interaction between the nationwide trend of capital intensity of Vietnam's manufacturing sub-industries and the base-year employment structure of each location. We hypothesize that higher exposure to capital intensity would increase gender wage gap.

A potential threat to our identification strategy is the confounding effect of the base-year employment structure on the observed relationship between changes in exposure and the gender wage gap in a location. To address this concern, we choose 2008 as our base year, as it significantly precedes our analysis period of 2013-2019 and is therefore unlikely to directly affect the movement of the gender wage gap in the analysis period. We further mitigate this concern by conducting a series of placebo tests.

In addition, we conduct regression with province-level grouped employee data obtained from Vietnam labor surveys. For robustness checks, we turn to individual-level data and estimate models using wage growth data from the Vietnam Household Living Standards Surveys to examine how gender and exposure to capital intensity interact in influencing wage growth.

This study is pertinent to the growing literature on the labor market impacts of automation and industrial upgrading. Specifically, it could contribute to the literature in several ways. Firstly, it represents one of the first investigations into the role of industrial upgrading and

capital deepening in widening the gender wage gap in developing countries. Our findings challenge the prevailing notion that capital deepening and automation have a minimal impact on gender employment equality in developing economies (e.g., Maloney and Molina (2016); Das and Hilgenstock (2022)). In rare examinations within developing economies, Özge Özay (2015) and Egana-delSol *et al.* (2022) also find evidences of gender-biased effects of capital intensity in the Turkish manufacturing sector and in developing countries across Latin America.

Secondly, our findings contribute to the literature on the determinants of the gender wage gap. While an extensive body of research has explored factors explaining gender pay differences, the majority has focused on supply-side explanations, with less attention given to demand-side factors (for a recent review see, e.g., Blau and Kahn (2017); Ngai and Petrongolo (2017); Petrongolo and Ronchi (2020)). We enhance this literature by providing evidence on the role of demand-side factors. In our examination of the channels through which capital intensity influences the gender wage gap, we rule out the possibility of supply-side effects contributing to the recent increase in the gender wage gap in Vietnam.

Thirdly, the study contributes to understanding regional differences in how capital deepening affects labor markets, emphasizing the significant role of labor migration. In regions experiencing in-migration, often high-income areas, capital deepening does not affect the gender gap in working hours. The decline in the female monthly wage relative to males largely attributes to a decline in hourly wage. Conversely, however, regions with out-migration, typically low-income districts, see both the effect of capital deepening on hourly wage and working hours. These findings contribute to the research strand on the heterogeneity of wage responses to productivity changes, where labor mobility plays a critical role (Jayachandran, 2006).

Finally, our paper reveals the heterogeneous effect of capital deepening on demographic groups. We identify the specific vulnerability of younger females with lower educational attainment and who work in the manufacturing sector to the impacts of industrial upgrading. Our finding differs from previous research in advanced countries, which shows that less well-educated, older female workers (aged 40 and older), and those in low-skill clerical, service, and sales positions are disproportionately exposed to automation (Brussevich *et al.*, 2018). This discussion also holds significant policy implications for social programs aimed at mitigating the adverse effects of automated manufacturing development."

The remainder of this paper includes the following sections: Section 2 describes the data sources used in this research; Sections 3, 4, and 5 present empirical estimations at the firm-level, district-level, and individual-level, respectively; and Section 6 concludes.

2 Data Sources

To understand the effect of capital intensity on gender gap, this paper utilizes data from four major micro surveys in Vietnam, which cover all aspects of the labor market. The four surveys include Vietnam Enterprise Survey (VES), Labor Force Survey (LFS), Vietnam Household Living Standard Survey (VHLSS), and the Population Census. All data are conducted by the General Statistics Offices (GSO).[1]

The VES is a large-scale establishment data, which has been conducted annually since the early 2000s.[2] The VES covers all registered firms with employment size above a certain threshold and a sample of 10–20% of small-sized firms.[3] For firms not in the sample, the GSO creates a list and collects basic characteristics such as legal type, industry, and total employment. The VES comprises of a main module for all firms and specific modules for firms in different industries. In this study, we focus on the *Main* module which provides information on legal type, industry, employment by gender, labor income, balance sheet, and business results.

The LFS is a repeated cross sectional data that contain approximately 750–830 thousand observations each round. The data has been available since 2007 and provided sufficient information on individual's labor market outcomes, such as employment status, wages, and working hours. In this study, we aggregate the LFS data and estimate the effect of capital intensity on gender gap at the district level.[4]

The VHLSS is a biannual survey which is representative at national, regional, urban, rural and provincial levels. The VHLSS covers a wide range of socio-economic aspects at the household and individual levels, including demographic characteristics, education, labor and employment, income, and expenditures, etc. In each round, the GSO remains half of the enumeration areas surveyed in the previous rounds. This allows us to track a certain number of individuals over time.

The 2019 Population and Housing Census collects primary information on population and housing of over 96 million people in 26.9 million households. Beside the Population Census, the GSO also conducted a sample survey of around 9% of households. This sample collected different aspects such as internal migration, marital status, employment status, etc., and is claimed to be sufficiently representative to estimate district-level indicators.[5] Based on data from this sample, we construct net migration flow data at the district level for our robustness check.

[1] In addition to these surveys, this study uses the The Global Administrative Areas (GADM) version 3.6 for the boundary consistency of district-level analysis. The data can be download from GADM's website: https://gadm.org/download_country36.html.

[2] The rounds in 2006, 2011, 2016, and 2020 are census and cover the universe of registered firms in Vietnam.

[3] Table XXX in the Appendix provides sampling criteria and size thresholds over time.

[4] According to the sampling stratification, the data is representative at the provincial level. However, aggregated data at the district level can be used for estimation without causing representative issues (see, Nguyen, 2023, p. 68).

[5] See details at the Final Report, which is available at: http://tongdieutradanso.vn/uploads/data/6/files/files/Population%20and%20Housing%20Census%202019_final%20report.pdf

3 Firm-level Analysis

3.1 Employment Structure

This section examines the correlation between capital intensity and employment structure by gender at the firm level. Using data from the VES between 2013 and 2019, we estimate the following model specification:

$$Fshare_{jt} = \alpha + \beta \cdot Log(Cap_ratio_{jt}) + \delta \cdot X_{jt} + \varepsilon_{jt} \tag{1}$$

where $Fshare_{jt}$ is the share of female employment in firm j in year t. Cap_ratio_{jt} is the ratio of fixed assets to total employment of this firm. X_{jt} is a vector of control variables, including the firm's characteristics and time dummies. Two-way fixed effects, firm and time, are included.

We estimate Equation 1 separately for four industry groups: manufacturing, agriculture and mining, utilities and construction, and services. The estimation results are presented in Table 1. Within each group, the first columns are utilized without any covariates other than firm and time fixed effects. In the second columns, we include the first lag of the dependent variable to account for potential issues of autocorrelation. However, we acknowledge the possibility that the first lag of the dependent variable may influence the coefficient of *Cap_ratio* through its interaction with error terms. In the third columns, we incorporate firm characteristics as control variables, including firm size (total assets, revenue), profit-to-sales ratio, average wage and firm age.

We consistently observe a significant negative effect of capital intensity on female employment shares in manufacturing firms. The coefficients of *Cap_ratio* remain consistently negative across different specifications in columns 1-3. Regarding the magnitude of the impact of capital intensity on female employment, a 10% rise in the capital ratio would result in a 0.12% decrease in the share of female employees within the manufacturing sector. Our results are aligned with the literature on the relationship between industrial upgrading and defeminization (see, e.g., Kucera and Tejani, 2014; Tejani and Milberg, 2016)

A similarly negative, albeit less significant, effect of capital intensity is also present in agriculture and mining firms (columns 4-6). Conversely, capital intensity appears to positively influence female employment in the utilities, construction (columns 7-9), and service industries (columns 10-12).

Figure \ref{fig:firm-byyear} in the Appendix confirms a negative association between manufacturing firms' capital ratio and the proportion of female employees, indicating that firms with higher capital ratios tend to have lower female employment.

<Insert Table 1>

3.2 Gender Wage Gap

Moving forward, we aim to quantify the impact of capital intensity on the gender wage gap within a firm. We estimate the interactive effect of capital intensity and the share of female

employment on a firm's average employee wage ($Awage_{jt}$) using Equation 2 as below:

$$\begin{aligned} Awage_{jt} = \alpha + \beta 1 * Fshare_{jt} * Log(Cap_ratio_{jt}) + \beta 2 * Log(Cap_ratio_{jt}) \\ + \beta 3 * Fshare_{jt} + \gamma * Awage_{j,t-1} + \phi * X_{jt} + \varepsilon_{jt} \end{aligned} \tag{2}$$

in which, $\frac{d(Awage)}{d(fshare)} = \beta_1 * \log(Cap_ratio_{jt}) + \beta_3$, represents for the difference between the female and male wages. Consequently, β_1 represents the marginal impact of an increase in the capital ratio on the wage difference between females and males. Table 2 presents the estimation results of Equation 2 using different estimators, with varying sets of control variables, and sub-samples from manufacturing firms.

The fixed-effects estimator is applied in columns 1-6 in Table 2. In columns 1 and 2, we apply weights by utilizing firms' total employment in 2013. We observe a consistent negative value of β_1 in both column 1 (without control variables) and column 2 (which includes control variables). To investigate the influence of firm size, we run the regression without weighting in column 3. The coefficient β_1 remains negative but decreases in magnitude, implying a stronger effect of capital intensity in larger firms.

Further analysis confirms this hypothesis. Columns 4, 5, and 6 present the results for groups segmented by firm size (small, medium, and large). β_1 is negative across all groups, but its magnitude is greatest for large firms. This aligns with the expectation that large firms are more likely to invest in automation, affecting the gender employment outcomes. Our findings indicate that, on average, a 10% increase in a firm's capital ratio leads to a widening of the monthly wage gap between female and male employees by nearly 31,470 VND (approximately 1.5 USD or 0.43% of the average manufacturing monthly wage).

We also want to account for the indirect effect of *Cap_ratio* on *Awage* through *Fshare* as demonstrated in Equation 1. We employ a structural equation model (SEM) specified in Equation \ref{firm_awage2} to capture both direct and indirect effects simultaneously.

$$\begin{aligned} Fshare_{jt} &= \alpha + \theta * \log(Cap_ratio_{jt}) + \varepsilon_{jt} \\ Awage_{jt} &= \alpha + \beta_1 * Fshare_{jt} * \log(Cap_ratio_{jt}) + \beta_2 * log(Cap_ratio_{jt}) \\ &\quad + \beta_3 * Fshare_{jt} + \gamma * Awage_{j,t-1} + \phi * X_{jt} + \varepsilon_{jt} \end{aligned} \tag{3}$$

Table \ref{tab:lcap_awage}, columns 7-8, presents the SEM estimation results. Notably, β_1 exhibits a larger magnitude and stronger statistical significance in column 7 compared to the single-equation models. This implies that considering both direct and indirect effects, a 10% increase in *Cap_ratio* leads to a wider monthly wage gap between female and male employees by nearly 49,595 VND (approximately 2.4 USD or 0.68% of the average manufacturing monthly wage). Adding control variables in column 8 slightly reduces the magnitude of β_1, but it remains negative and statistically significant.

Table 2 should be inserted here

4 District-level Analysis

4.1 Baseline Estimation

To investigate the influence of capital intensity on the gender wage gap across districts, we construct a measure reflecting the districts' exposure to the economy-wide trend of capital intensity . Similar to Acemoglu and Restrepo (2020), we leverage the variation in the trend of capital intensity across industries and the industrial employment structure in districts. The employment distribution in districts is predetermined at the base year 2008, which precedes the examined period from 2013 to 2019. This approach is taken to mitigate the risk of potential reverse causality between the gender wage gap and employment outcomes. Another reason for selecting the base year 2008 is that the formation of automation capital in Vietnam mostly occurred after 2010 (see Figure A.2). We also perform a robustness analysis to assess the sensitivity of our results to different base year selections

By utilizing capital and labor data at the district-industry level from enterprise surveys in Vietnam, we can assess a district's exposure to capital intensity, denoted as R_d, as follows:

$$W_{k,-p} = \frac{FA_{k,-p,2019} / L_{k,-p,2019}}{FA_{k,-p,2013} / L_{k,-p,2013}} \tag{4}$$

$$R_d = \sum_{k \in K} \ell_{kd,2006} \times W_{k,-p} \tag{5}$$

where k, d, t represent the 2-digit SIC manufacturing industry, district, and year, respectively. $\mathrm{FA}_{k,-p,t}$ and $\mathrm{L}_{k,-p,t}$ are the total of fix assets and labor of registered firms in industry k in all provinces except for the province p where district d is located. $\ell_{kd,2008}$ is the employment share of industry k in district d in 2008. We are interested in the effect of R_d on the gender gap in monthly wage in the following equation:

$$Fmwage_{d,2013-19} = \alpha + \beta * R_d + \phi * X_d + \varepsilon_d \tag{6}$$

where $Fmwage_{d,2013-19}$ denotes the change in the ratio of female-to-male monthly wages over the 2013-2019 period. X_d is the vector of control variables at district d. The descriptive statistics of covariates are presented in Table A.3 in the Appendix. Results from estimations presented in the panel A in Table 3.

A concern with our empirical analysis is the potential confounding effect of other district-level trends on the estimated impact of capital deepening on the gender wage gap. Firstly, the development level of a district may impact the gender wage gap. In more affluent families, women might opt for less strenuous, lower-paying jobs to prioritize family time. Although district-level income per capita data is unavailable, we utilize official minimum wage categories as a proxy for district development.

Secondly, the education attainment of female labor in a district could also act as a confounding factor. A lower level of education among female workers may widen the gender wage gap. We employ two measures of the gender gap in education: the gender-skilled labor ratio, calculated as the ratio of skilled male labor to total male labor divided by the ratio of skilled female labor to total female labor; and the gender-tertiary educated labor ratio, deter-

mined as the ratio of tertiary-educated male labor to total male labor divided by the ratio of tertiary-educated female labor to total female labor. We assess the gender education gap both at the beginning of our analysis period in 2013 and as the change during the 2013-2019 period.

Thirdly, cultural factors may also serve as confounding factors. In districts with strong gender discrimination, female wage growth could be hindered. Using data from the 2019 population and housing census, we proxy gender discrimination by the male-to-female ratio of children aged 0-5 years old and aged 0-10 years old within each district. Districts with higher ratios would be expected to exhibit more severe gender discrimination.

Figure 2 depicts the geographic distribution of exposure to capital intensity, minimum wage, the gender education gap in 2013, the change in gender education during 2013-2019, and the male-to-female ratio of children. We observe a weak correlation between exposure to capital intensity and minimum wages (with a correlation of 0.0972), the 2013 gender-skilled labor ratio (0.1385) and the change in this ratio from 2013 to 2019 (-0.1163). Other potential confounding factors showed almost no correlation. To further address concerns regarding confounding effects, we incorporate the aforementioned potential confounding factors as covariates in our regressions. Additionally, we include economic conditions and demographic factors as control variables.

The estimation results in Panel A in Table 3 consistently indicate that exposure to capital intensity increases the gender monthly wage gap. In column 1, we run a regression with province fixed-effects and use district working population as a weight. We find a robust effect of capital intensity exposure on the gender wage gap, with a coefficient of -0.034 (standard error is 0.017). Exposure to capital intensity alone accounts for approximately 17% of the change in the gender monthly wage gap within a province.

In columns 2, we control for economic conditions, including the district share of manufacturing workers, the share of manufacturing in other districts within the same province, the ratio of public servants to total employment, the unemployment rate, the enrollment rate in first-grade school, and the urbanization ratio. In column 3, we further control for demographics, mostly consisting of age structure and educational attainment. In column 4, we add the minimum wage and measures of the gender education gap and gender discrimination. Adding these covariates slightly increases the magnitude of the coefficient of exposure to capital intensity. In column 5, we run a regression with all covariates but do not use a weight. This specification has a lower magnitude but still a statistically significant coefficient of exposure to capital intensity. This rules out the possibility that estimation results are seriously distorted by an outlier district with a large population.

In columns 6-9, we partitioned the sample into two subgroups: one comprised of the highest-income districts, determined by the highest minimum wage level in Vietnam's four-tier minimum wage categories, and another comprised of the remaining districts. Our analysis reveals a consistent impact of capital intensity exposure on the monthly gender wage gap within both groups of districts.

Table 3 should be inserted here

Demand vs. supply side effects

It is noteworthy that the common practice in Vietnam is to compensate workers with a base salary for official working hours, while additional hours are worked for extra income. The monthly wage gap for workers is not fixed but largely depends on the number of additional working hours. Both reductions in the number of working hours and decreases in the hourly wage rate can contribute to a decline in the female monthly wage.

The impact of capital intensity on the gender monthly wage gap can result from both supply and demand sides. On the demand side, employers might opt to replace female labor with automation. On the supply side, increased productivity and income due to capital intensity might reduce the motivation for female workers to work extra hours, potentially leading to a decline in their monthly wages. While both supply and demand side effects could negatively impact female working hours, they may affect hourly wages differently. Supply side effects, for instance, would likely result in an increase in the female hourly wage rate rather than a decrease.

To examine the channel through which capital deepening affects the labor market, we estimate the effect of R_d on the hourly wage gap using Equation 7 as follows:

$$Fhwage_{d,2013-19} = \alpha + \beta * R_d + \phi * X_d + \varepsilon_d \tag{7}$$

in which $Fhwage_{d,2013-19}$ represent the change in the ratio of female-to-male hourly wage over the 2013-2019 period. The estimation results displayed in Panel B of Table 3 consistently reveal negative coefficients of R_d across all specifications. This implies that the influence of capital intensity is more likely occurring through the demand side of the female labor market. Moreover, it is particularly noteworthy that the negative coefficients of R_d have a substantially larger magnitude in regressions involving the higher-income districts (columns 8-9) compared to those concerning the lower-income districts (columns 6-7). This serves as counterfactual evidence because if the influence of R_d were through the supply channel, it would most likely happen in higher-income districts, and we would be more likely to observe a decrease in the gender hourly wage gap in those districts.

Migration and margin effects

To examine the margin effects of capital deepening, we estimate Equation 8, where $Fhwage_{d,2013-19}$ represents the change ratio of female-to-male weekly working hours over the period 2013-2019:

$$Fhrw_{d,2013-19} = \alpha + \beta * R_d + \phi * X_d + \varepsilon_d \tag{8}$$

The estimation results are presented in panel C of Table 3. Generally, we find evidence for intensive margin effects in all regressions except those for high-income districts. Specifically, we observe a statistically significant and negative effect of R_d in specifications from columns 1-5. In columns 6-7, when excluding high-income districts, we observe a slightly larger magnitude of coefficients of R_d compared to regressions with the whole sample.

Interestingly, the coefficients of R_d are almost zero in columns 8-9, indicating that intensive margin effects do not exist in high-income districts. One explanation is that, by contrast to low-income district, the extensive margin margins play a important role in high-income districts due to labor migration mechanism. Migrant female workers in high-income districts

could return to their hometowns when wages decrease. This repatriation could, on the other hand, amplify the effects of capital intensity on the intensive margin in lower-income districts, leading to larger gaps in both monthly wages and working hours.

To verify this explanation, we leverage migrant data from the Vietnam Population and Housing Census 2019 and the Intercensal Survey 2014. Both surveys categorize migration purposes, including those related to job-seeking. This allows us to calculate the number of female and male job-related migrants to each districts during the 2014-2019 periods. We want to investigate the effect of R_d on relative size of female job-related migration by estimate the equation as below:

$$MigrationRatio_{FM,2014-19} = \alpha + \beta_1 * R_d + +\beta_2 * H_d + +\beta_3 * R_d * H_d + \varepsilon_d \tag{9}$$

in which, $MigrationRatio_{FM,2014-19}$ is the ratio of female-to-male job-related net migration during 2014-2019. H_d is a dummy variable representing for high-income districts. Our primary focus lies on examining the interactive effects between exposure to capital intensity and the high-income district dummy. In Table 4, we observe contrasting effects of R_d on the ratio of female-to-male job-related net migration in high-income versus low-income districts. While R_d exhibits negative coefficients in columns 1-2, suggesting that exposure to capital intensity reduces female job-related migration relative to male in high-income districts, it shows positive coefficients in columns 3-4, indicating that exposure to capital intensity increases female job-related migration relative to male in low-income districts. In the specifications in columns 5-6, we observe that the interaction terms between exposure to capital intensity and high-income districts are negative.

Table 4 should be inserted here

4.2 Robustness Estimations

We conduct several robustness estimations to verify the relationship between the exposure to capital intensity and gender wage gap. Firstly, we employ an intra-provincial rank regression to examine the potential impact of outliers and validate our exclusion of the top and bottom 2% outliers,. This involves ranking districts within a province based on their gender gap in monthly wages and working hours and subsequently estimating the effect of exposure to capital intensity on the change in rank over the period 2013-2019. The estimation results presented in Table A.4 in the Appendix consistently show the negative effects of capital intensity on gender employment gaps.

Secondly, we conduct a sensitivity check for the base year to construct R_d. Years 2006 is used instead of the year 2008 as the base year, and we re-estimate equations 6. The estimation results are presented in panels A and B in Table A.5. The coefficients of R_d are consistently negative across regression specifications.

Thirdly, we take the average of gender wage gaps in 2013 and 2014 rather than the year 2013 alone in estimate the long-difference gender wage gap. We find similar negative coefficients of

R_d in panel C of Table A.6.

Fourthly, since predetermined employment can be potentially correlated with future disturbances, we perform a robustness check by constructing a balanced panel of district-level exposure to capital intensity running from 2013 to 2019 (see equation 10) .

$$\overline{R}_{dt} = \sum_{k \in K} \ell_{kdt} \times W_{k,-p} \tag{10}$$

where ℓ_{kdt} is the employment share of industry k in district d at time t. To further address the threat of endogeneity, we employ the system GMM estimator developed by Arellano and Bover (1995) and Blundell and Bond (1998) to estimate the equation 11 below:

$$Fmwage_{dt} = \alpha + \beta \cdot \overline{R}_{dt} + X'_{dt} \cdot \gamma + \varepsilon_{dt} \tag{11}$$

where $Fmwage_{dt}$ is the gender monthly wage gap at district d in year t. X' is the vector of control variables , and ε_{dt} is the idiosyncratic term. Table 5 presents the results of panel estimations. Columns 1-2 show results from the random effects estimator, while columns 3-4 display results from the fixed effects estimator. Notably, a consistent negative coefficient of R_{dt} is observed across all specifications. Our primary focus lies in column 6, which presents the estimates from the system GMM estimator. Here, we find a negative and statistically significant coefficient for R_{dt}.

Table 5 should be inserted here

4.3 Placebo Analysis

We address the potential threat of pre-existing gendered trends in wages or employment by conducting placebo checks. These checks involve re-estimating the regressions in Table 3 with differences over the 2007-2013 period, a period before the observed reversal in the gender wage gap trend . The results of these placebo checks are presented in Table A.7. Panel A investigates whether historical trends in the gender wage gap (2007-2013) are linked to subsequent differences in district capital intensity. After accounting for all controlling variables, the coefficient of exposure to capital intensity is essentially zero (column 6). No significant influence is found across all specifications. Similarly, Panel B shows no effect of pre-existing trends in the gender hourly wage gap on capital intensity. While a moderate positive association between past trends in the female-to-male working hour ratio and capital deepening appears in Panel C (column 1), this effect vanishes once control variables are considered (columns 2 onwards).

Figure 1 illustrates the relationship between exposure to capital intensity and changes in the gender monthly wage gap during the periods of 2007-2013 and 2013-2019. The figure clearly demonstrates no correlation between exposure to capital intensity and the gender monthly wage gap change during 2007-2013, while indicating a negative correlation during 2013-2019.

Figure 1 should be inserted here.

5 Individual-level Analysis

5.1 Household-level Data

The Vietnam Household Living Standards Surveys (VHLSS) ask participants to break down their income into wages and other sources. As the VHLSS rotates around half of its sample from one survey round to the next round, which occurs every two years, we can trace individuals through multiple survey rounds. The maximum number of rounds that an individual could participate in is three, covering a four-year period, enabling us to track changes over time for the same individuals. We identified 1,794 individual observations participating in three consecutive survey rounds, encompassing the cycles of 2012-2014-2016 or 2014-2016-2018, and estimate the equation 12 below:

$$Dwage_i = \alpha + \beta_0 \cdot R_d \cdot D + \beta_1 \cdot R_d + \beta_1 \cdot D + \gamma X_i + \varepsilon_i \tag{12}$$

where $Dwage_i = wage_{it}/wage_{i,t-4}$. D is dummy for gender, taking value 1 if worker i is female and 0 otherwise; vector X_i contains characteristics of worker i. The parameter of interest, denoted as β_0, represents the effect of capital intensity on the gender wage gap. The estimation results of equation 12 are provided in Table 6.

Given that the VHLSS does not specifically focus on wage data collection and instead instructs respondents to categorize their income, we conduct a sensitivity analysis by adjusting outlier cut-offs. We vary the cut-offs at 10% (columns 1-2), 20% (columns 3-4), 25% (columns 5-6), and 30% (columns 7-8) for both upper and lower bounds. Additionally, we employ quantile regressions to mitigate the influence of outliers on the regression outcomes.

In Table 6, we consistently observe negative estimates for the parameter of interest, β_0, across all regressions except for column 1.

Table 6 should be inserted here

5.2 Grouped Data Regression

This study utilizes a grouped data regression approach to examine the impact of capital intensity on individual labor, utilizing data from the Vietnam Labor Force Survey. Due to the absence of sample rotation in the annual surveys conducted by the Vietnam Labor Force Survey, direct observation of the long-term differences in the gender wage gap at the individual labor level is not feasible. Within each province, we categorize surveyed workers according to three dimensions: industry (manufacturing vs. non-manufacturing), age group (under 25, 25-34, 35-44, and 45+ years old), and educational attainment (unskilled, without a tertiary degree, and with a tertiary degree). This creates 24 distinct subgroups per province, for which we calculate the female-to-male monthly wage gap in each year. The primary advantage of this approach is its ability to investigate how the impact of capital intensity interacts with specific female labor attributes. We calculate the capital intensity exposure at the provincial level,

denoted as R_p, using a methodology similar to that employed for estimating R_d.

$$R_p = \sum_{k \in K} \ell_{kp,2008} \times W_{k,-p} \tag{13}$$

in which, $W_{k,-p}$ is estimated above in Equation 4. $\ell_{kp,2008}$ is the employment share of industry k in province p in 2008.

$$Fmwage_{g,2013-19} = \alpha + \beta * R_p + \phi * X_g + \varepsilon_g \tag{14}$$

where $Fmwage_{g,2013-19}$ is the change the gender monthly wage gap over each group over the 2013-2019 period in group g. X_g is the vector of control variables for group g, including the characteristics of groups (i.e., industry, age, and education) and provinces.

We start with an all-group estimation of equation 14 . The highly statistical significance of R_p in column 1 in Table 7 affirms the impact of capital intensity on the gender wage gap. We then separate the groups working in manufacturing sectors from other sectors. As expected, estimation results in Panel A indicates that capital intensity has stronger effects on manufacturing female labor.

Moving forward, we split groups by age and education and present estimation results in panel B and panel C, respectively. We observe that female groups with lower levels of education attainment and those in younger age brackets are most affected by capital intensity. The negative effects of R_p decrease significantly in older labor groups, possibly attributable to the majority of manufacturing labor being below the age of 35 [6]. Interestingly, capital intensity shows no statistically significant effect on the gender wage gap for workers with a tertiary degree, while exhibiting moderate, albeit statistically insignificant, negative effects in unskilled groups and demonstrating the strongest negative effects in groups with middle education attainment. This implies the potential polarization effect of industrial upgrades in developing countries. Overall, our findings indicate that younger females with lower educational attainment who work in the manufacturing sector are susceptible to the impacts of industrial upgrading. This differs from the trend observed in advanced countries where older female workers (aged 40 and older) and those in low-skill clerical, service, and sales positions are disproportionately exposed to automation (Brussevich *et al.*, 2018). Moreover, there are potentially differences in the effect of industrial upgrading in different emerging countries. For example, in contrast to our paper, Egana-delSol *et al.* (2022) find that the gendered effects of automation are present across all age and education groups in Latin American countries.

Table 7 should be inserted here

[6]Companies in certain labor-intensive manufacturing industries, such as the garment and footwear sectors, have been known to employ strategies to terminate the employment of older workers, typically referring to those aged 35 and above (Nguyen, 2023).

6 Conclusion

The gender-biased impact of industrial upgrading and automation carries significant policy implications for achieving gender equality in the labor markets of developing countries. This concern is heightened, as it may impede existing efforts and progress towards equal participation. The magnitude of these effects is likely influenced by various factors, including the relative importance of manufacturing within the labor market and the economy's ability to transition to the service sector. Vietnam may be one of the lower-middle income countries where these conditions coincide.

In this study, we present compelling evidence suggesting a strong link between increasing capital intensity in manufacturing and the widening gender wage gap observed in recent years. Our findings, based on diverse data sources ranging from firm-level and district-level data to individual-level information, remain robust and consistent across different approaches. This robustness is further strengthened by rigorous placebo testing and robustness analyses.

Investigating the channels through which capital intensity impacts the gender wage gap, we emphasize the dominant roles of demand-side effects on female labor. Notably, our analysis reveals a crucial district-level heterogeneity in this relationship. In low-income districts, the "intensive margin effect" dominates, meaning female workers are hired for fewer hours compared to their male counterparts. Conversely, in high-income districts, the "extensive margin effect" takes precedence, indicating that capital deepening reduces the relative demand for female labor, leading to a higher ratio of female repatriation. Finally, our findings highlight the particular vulnerability of young females with lower educational attainment to the effects of industrial upgrading.

We identify several promising avenues for future research. The decreasing cost of automation technology, fueling the worldwide trend of industrial upgrading and more capital-intensive manufacturing, is a noteworthy observation. The existing literature provides limited insight into the heterogeneity in the impact of industrial upgrading and capital intensity on the gender gap in developing countries. We hypothesize that capital intensity would have a stronger effect in lower-middle-income countries with limited ability to quickly transition to the service sector to absorb displaced female labor. This underscores the need for comprehensive cross-country studies.

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TABLE 1.—Firm-level capital intensity and female employment

	Fixed-effect estimation of female employee shares											
	Manufacturing			Agri & mining			Utilities & con			Services		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Log of capital ratio	-0.012***	-0.012**	-0.010*	-0.003	-0.004	-0.007	0.012***	0.013***	0.011***	0.008*	0.005	0.004
	(0.004)	(0.005)	(0.006)	(0.004)	(0.005)	(0.005)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
	40669	32098	32098	3215	2303	2303	12281	9258	9258	23389	17344	17344
Number of obs	0.006	0.009	0.017	0.001	0.010	0.030	0.016	0.020	0.036	0.004	0.003	0.014
R-squared	0.006	0.009	0.021	0.001	0.010	0.030	0.016	0.020	0.039	0.004	0.003	0.019
Covariates												
Firm and time fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weight	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lag of female shares	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Firm characteristics	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Firm fixed effects are included in all regressions. Robust standard errors are in parentheses. The sample excludes firms with wages falling within the bottom 5% and top 95%. Weights using firms' total employment in 2013 are applied in all regressions. Firm characteristics include time dummies, firm size (total assets, revenue), average wage, profit-to-sales ratio, and firm age.

TABLE 2.—Effect of capital intensity on wage gap in manufacturing firms

Sample	Fixed-effect estimator: Direct effects of capital intensity						SEM: Direct and indirect effects	
	All firms	All firms	All firms	Small firms: less than 50 employees	Medium firms: 50-199 employees	Large firms with 200 employees and	All firms	All firms
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female shares * Log of capital ratio	-314.369	-310.004	-16.896	162.314	-67.925	-359.084	-495.951*	-202.995***
	(202.916)	(202.033)	(75.804)	(193.817)	(185.503)	(260.727)	(302.452)	(65.005)
Log of capital ratio	231.396*	258.435**	200.817***	-60.381	211.494**	243.522	786.067***	390.561***
	(121.419)	(126.017)	(45.625)	(121.926)	(92.084)	(171.575)	(89.948)	(83.478)
Female employee shares	1542.741**	1572.100**	212.103	-1020.701	801.674	1744.776*	261.745	-1460.587
	(783.322)	(781.992)	(375.172)	(1003.819)	(866.031)	(963.671)	(3160.917)	(581.354)
Number of observations	40669	40669	40876	7931	15335	17403	40876	40876
R-squared	0.383	0.392	0.334	0.216	0.328	0.404		
Covariates								
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weight	Yes	Yes	No	Yes	Yes	Yes	Yes	No
Firm characteristics	No	Yes	Yes	Yes	Yes	Yes	No	Yes

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors are in parentheses in columns 1-6. Standard errors are clustered by individual firms in column 7. The sample excludes firms with wages falling within the bottom 5% and top 95%. Weights using firms' total employment in 2013. Firm characteristics include firm size (total assets, revenue), profit-to-sales ratio, and firm age.

TABLE 3.—Long-Difference Estimation: 2013-2019

	All districts					Low-income districts		High-income districts	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Change in female-to-male monthly wage ratio									
Exposure to capital intensity	-0.034**	-0.035**	-0.037**	-0.047***	-0.038**	-0.033**	-0.035**	-0.041	-0.032
	(0.017)	(0.017)	(0.016)	(0.017)	(0.015)	(0.016)	(0.017)	(0.066)	(0.073)
Number of observations	469	469	469	439	439	382	382	57	57
R-squared	0.168	0.185	0.206	0.281	0.285	0.327	0.355	0.496	0.455
Panel B: Change in female-to-male hourly wage ratio									
Exposure to capital intensity	-0.013	-0.013	-0.020	-0.030	-0.017	-0.010	-0.016	-0.036	-0.031
	(0.019)	(0.019)	(0.018)	(0.019)	(0.017)	(0.018)	(0.019)	(0.069)	(0.078)
Number of observations	469	469	469	439	439	382	382	57	57
R-squared	0.166	0.190	0.214	0.290	0.294	0.330	0.353	0.491	0.463
Panel C: Change in female-to-male working hour ratio									
Exposure to capital intensity	-0.023***	-0.023***	-0.018**	-0.019**	-0.023***	-0.024***	-0.021**	-0.004	-0.000
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)	(0.010)	(0.030)	(0.031)
Number of observations	469	469	469	439	439	382	382	57	57
R-squared	0.175	0.187	0.242	0.258	0.259	0.261	0.254	0.521	0.559
Covariates									
Weight	Yes	Yes	Yes	Yes	No	No	Yes	No	Yes
Province	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Economic conditions	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Demographics	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Minimum wage	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Gender Education gap	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Gender discrimination	No	No	No	Yes	Yes	Yes	Yes	No	Yes

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors are in parentheses. The sample excludes districts with R_d falling within the bottom 2% and top 98%. High-income districts are those characterized by the highest minimum wage levels among Vietnam's four minimum wage categories. Weights using firms' total employment in 2013. The descriptive statistics of covariates are presented in Table A.3 in the Appendix.

TABLE 4.—Effects of capital intensity of migration

	Female-to-male Net Job-Related Migration Ratio					
	High-income districts		Low-income districts		All districts	
	(1)	(2)	(3)	(4)	(5)	(6)
Exp. capital intensity*High-income					-0.848	-1.173*
					(0.532)	(0.664)
Exposure to capital intensity	-0.672	-1.013	0.177	0.160	0.177	0.160
	(0.513)	(0.665)	(0.164)	(0.103)	(0.164)	(0.103)
High-income district					1.362	2.039*
					(0.895)	(1.153)
Number of observations	57	57	403	403	460	460
R-squared	0.032	0.056	0.003	0.005	0.005	0.016
Weight	No	Yes	No	Yes	No	Yes

Notes: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Robust standard errors are in parentheses. High-income districts are those with the highest minimum wage level in Vietnam's four-tier category. Weights are based on districts' working-age population.

TABLE 5.—Robustness analysis with district panel of gender monthly wage gap

	Random-effects estimator		fixed-effects estimator		Two-step system GMM
	(1)	(2)	(3)	(4)	(5)
Exposure to capital intensity	-0.013	-0.006	-0.014	-0.009	-0.019**
	(0.008)	(0.007)	(0.012)	(0.012)	(0.010)
Lag of dependent variable					0.140***
					(0.038)
Number of groups	483	460	483	460	480
Number of observations	3275	3106	3275	3106	2800
Covariates					
Province	Yes	Yes	-	-	Yes
Time	Yes	Yes	Yes	Yes	Yes
Economic development	No	Yes	No	Yes	Yes
Demographics	No	Yes	No	Yes	Yes
Potential confounding	No	Yes	No	Yes	Yes
Specification test (p-value)					
a) Sargan test					*0.179*
b) Serial correlation second-order					*0.578*

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors are in parentheses. Standard errors in estimation from (1)–(4) are robust. The descriptive statistics of covariates are presented in Table A.3 in Appendix.

TABLE 6.—Wage growth from household surveys

Sample	10th - 90th		20th - 80th		25th - 75th		30th - 70th	
Estimator	OLS	Quantile Regression	OLS	Quantile Regression	OLS	Quantile Regression	OLS	Quantile Regression
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female*Exposure to capital intensity	0.017	-0.083	-0.064	-0.148*	-0.128**	-0.148*	-0.080	-0.126*
	(0.093)	(0.113)	(0.073)	(0.088)	(0.058)	(0.082)	(0.051)	(0.066)
Exposure to capital intensity	0.023	0.100	0.091**	0.153**	0.096**	0.116**	0.093**	0.106**
	(0.065)	(0.078)	(0.046)	(0.061)	(0.041)	(0.055)	(0.037)	(0.047)
Female	0.046	0.207	0.150	0.301*	0.270**	0.315**	0.155	0.245**
	(0.172)	(0.208)	(0.135)	(0.165)	(0.107)	(0.153)	(0.095)	(0.123)
Number of observations	1394	1394	1052	1052	880	880	701	701
R-squared	0.061		0.076		0.092		0.143	
Covariates								
Year fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Job characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors are in parentheses. Individual characteristics include: age, general education level, vocational training, marital status, and relation to the household head. Job characteristics include: 1-digit level industrial classification, 1-digit level occupational classification. The estimates are computed using various outlier cut-off values and analyzed with both OLS and Quantile Regression estimators.

TABLE 7.—Group analysis

(a) Panel A: Across industry groups

	Group working hours long-difference: 2013-2019		
	All groups	Manufacturing	Non-manufacturing
	(1)	(2)	(3)
Exposure to capital intensity	-0.049***	-0.123**	-0.028
	(0.019)	(0.049)	(0.018)
Number of observations	1295	547	748
R-squared	0.034	0.062	0.081
Covariates:			
Age groups	Yes	Yes	Yes
Education groups	Yes	Yes	Yes
Provincial control variables	Yes	Yes	Yes

(b) Panel B: Across age groups

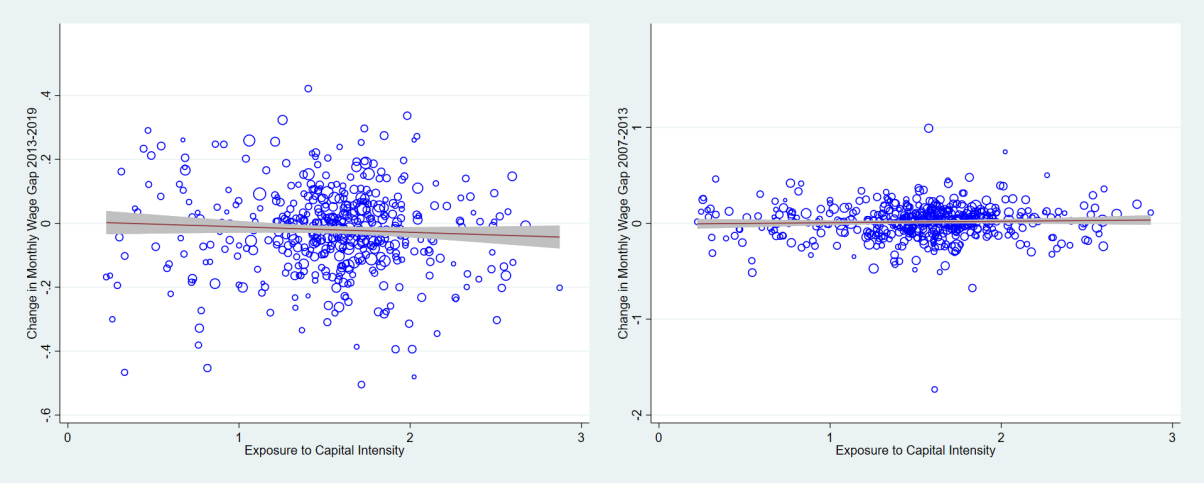
	Age groups				
	All groups	Under 25 years old	25-34 years old	35-44 years old	45+ years old
	(1)	(2)	(3)	(4)	(5)
Exposure to capital intensity	-0.049***	-0.128***	-0.046	-0.007	-0.029
	(0.019)	(0.038)	(0.032)	(0.039)	(0.036)
Number of observations	1295	311	354	326	304
R-squared	0.034	0.076	0.085	0.066	0.088
Covariates:					
Industry groups	Yes	Yes	Yes	Yes	Yes
Education groups	Yes	Yes	Yes	Yes	Yes
Provincial control variables	Yes	Yes	Yes	Yes	Yes

(c) Panel C: Across education groups

	Education groups			
	All groups	Unskilled	Without a tertiary degree	With a tertiary degree
	(1)	(2)	(3)	(4)
Exposure to capital intensity	-0.049***	-0.048	-0.083***	0.005
	(0.019)	(0.030)	(0.028)	(0.041)
Number of observations	1295	492	469	334
R-squared	0.034	0.085	0.050	0.068
Covariates:				
Industry groups	Yes	Yes	Yes	Yes
Age groups	Yes	Yes	Yes	Yes
Provincial control variables	Yes	Yes	Yes	Yes

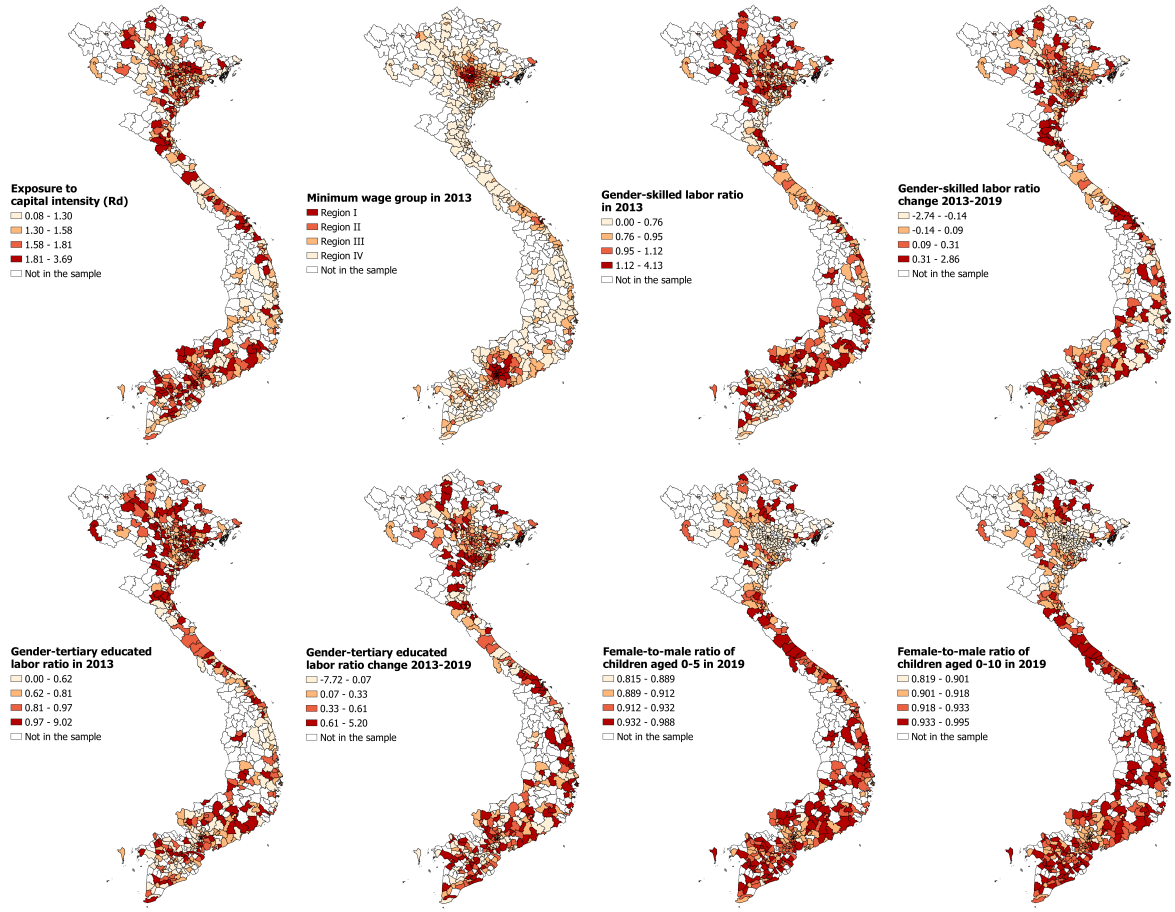
Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors are in parentheses.

FIGURE 1.—Gender wage gap: difference between 2007-2013 and 2013-2019



Notes: This graph represents the placebo test to ascertain whether there is any correlation between districts' exposure to capital intensity and changes in the gender wage gap, both in monthly and hourly wages, over the period 2007-2013. The bubble size represents the working-age population in each district, and the shaded areas indicate the 5% confidence interval.

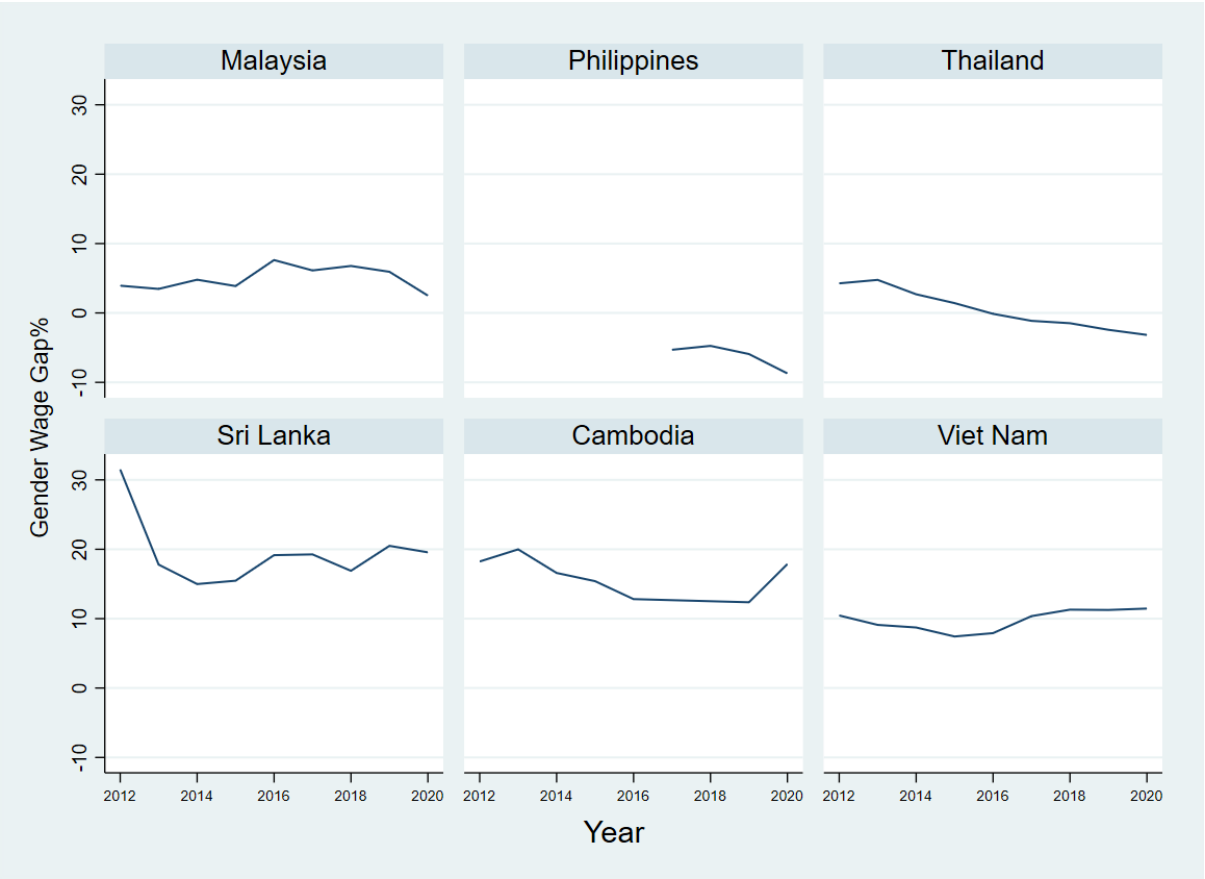
FIGURE 2.—Spatial distribution of potential confounding factors



Notes: Maps demonstrate districts' exposure to capital intensity and some potential confounding factors. The working population-weighted correlation between exposure to capital intensity and minimum wages is 0.092, the gender-skilled labor ratio in 2013 is 0.1385, the change in gender-skilled labor ratio from 2013 to 2019 is -0.1163, the gender-tertiary educated labor ratio in 2013 is 0.0377, the change in gender-tertiary educated labor ratio from 2013 to 2019 is 0.0187, the male-to-female ratio of children aged 0-5 years old in 2019 is 0.0035, and the male-to-female ratio of children aged 0-10 years old is -0.0013.

A Appendix

FIGURE A.1.—Regional Gender Wage Gap



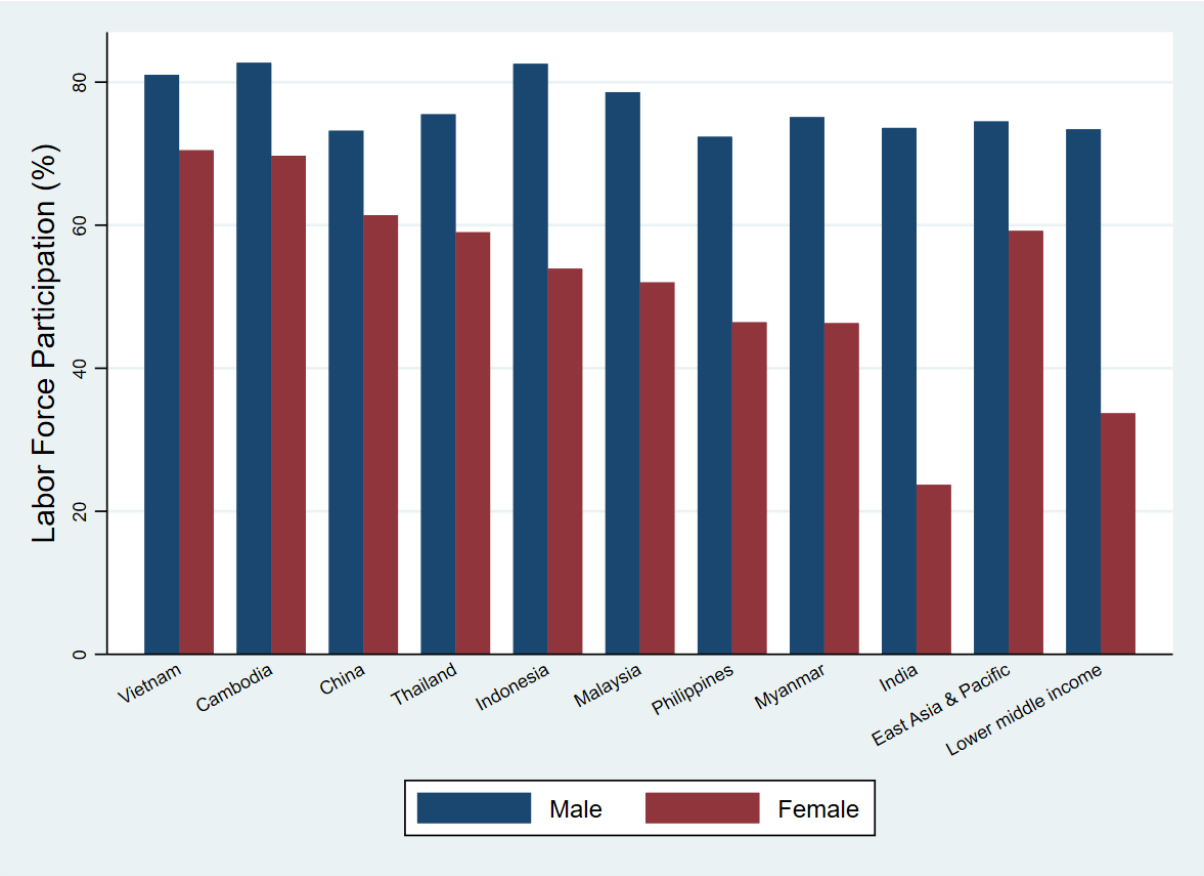
NOTE: Data are compiled from ILOSTAT data. The wage gap is measured as the difference between the monthly income of women and men divided by men's income.

FIGURE A.2.—Imports of automation machines



NOTE: Data is compiled from Trade Map (International Trade Center). The Harmonized System (HS) codes used to define importing products related to automation follow those proposed by Acemoglu and Restrepo (2022) and Domini *et al.* (2022). The import volume is normalized by dividing by the 2010 volume.

FIGURE A.3.—Labor force particiaption rates in regional countries



Source: The World bank database

FIGURE A.4.—Female employee shares and capital ratio by year

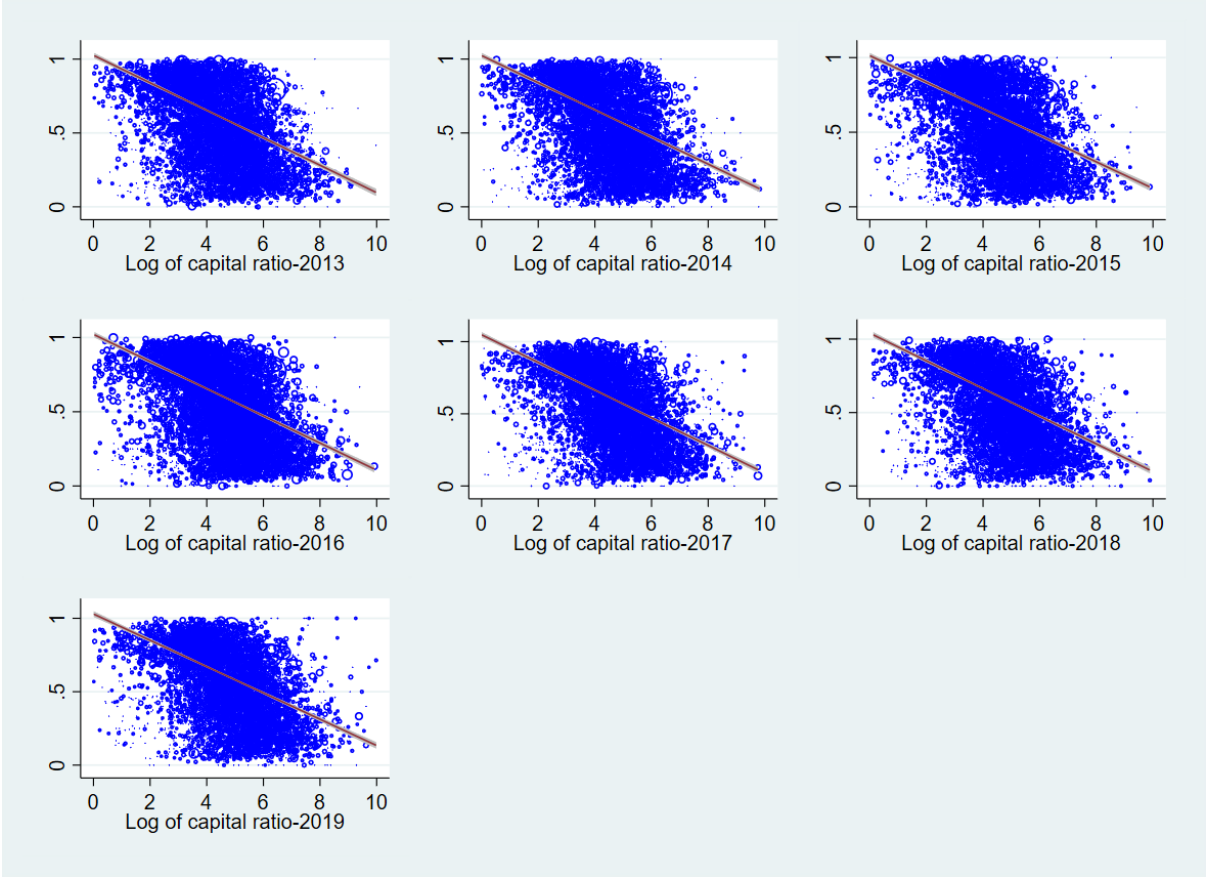


TABLE A.1.—Labor force participation rate (%)

	Whole country			Urban			Rural		
	Male	Female	Diff	Male	Female	Diff	Male	Female	Diff
Average	81.2	71.4	9.8	75.2	63.6	11.6	84.3	75.6	8.7
2021	74.2	61.5	12.7	71.0	59.5	11.5	76.2	62.9	13.3
2020	79.9	69.0	10.9	71.4	59.2	12.2	84.9	75.3	9.6
2019	81.9	71.8	10.1	75.9	63.9	12.0	85.2	76.3	8.9
2018	82.3	71.6	10.7	74.8	62.6	12.2	86.5	77.0	9.5
2017	81.9	71.9	10.0	74.8	62.8	12.0	85.7	77.2	8.5
2016	82.4	72.5	9.9	76.7	65.0	11.7	85.4	76.5	8.9
2015	83.0	72.9	10.1	77.3	65.5	11.8	85.9	76.9	9.0
2014	82.5	73.3	9.2	76.5	64.7	11.8	85.4	77.9	7.5
2013	82.1	73.2	8.9	76.3	64.8	11.5	84.8	77.5	7.3
2012	81.2	72.5	8.7	75.7	64.8	10.9	84.0	76.5	7.5
2011	81.7	72.6	9.1	75.7	64.2	11.5	84.5	76.8	7.7
2010	82.0	73.0	9.0	75.7	63.8	11.9	84.7	77.2	7.5
2009	81.0	72.3	8.7	76.1	65.7	10.4	83.1	75.3	7.8

SOURCE.—General Statistics Office of Vietnam.

TABLE A.2.—Gender wage gaps by country

	Hourly wages	Monthly earnings
Viet Nam - 2016	7.7	10.5
China - 2013	17.2	19
India - 2012	34.5	NA
Indonesia - 2016	7.8	17.8
Philippines - 2016	-10.3	-6.6
Thailand - 2015	-2.7	0
Lower middle income (average)	16.2	15.8

Note: Data are from ILO (2018)

TABLE A.3.—Descriptive statistics of variables

	Obs	Mean	S.D	Min	Max
Variables used in firm regressions					
Female labor share	40,876	0.463	0.247	0.000	1.000
Average monthly wage	40,876	7232	3293	1603	19038
Log of capital ratio	40,876	4.709	1.405	0.006	9.977
Log of total assets	40,876	11.372	1.564	2.944	19.325
Log of revenue	40,876	11.507	1.731	2.079	20.053
Profit to sale ratio	40,876	0.152	0.110	-0.004	0.714
Firm age	40,876	14.312	8.898	2.000	69.000
Variables used in district regressions					
Long-diff of gender monthly wage gap: 2013-2019	487	-0.024	0.135	-0.505	0.499
Long-diff of gender monthly wage gap: 2013/14-2019	487	-0.025	0.121	-0.421	0.394
Long-diff of gender hourly wage gap: 2013-2019	487	-0.033	0.152	-0.697	0.590
Long-diff of gender working hour gap: 2013-2019	487	0.008	0.076	-0.344	0.263
Exposure to capital intensity with baseyear 2008	488	1.534	0.555	0.080	3.688
Exposure to capital intensity with baseyear 2006	488	1.505	0.612	0.019	3.950
Covariates: Economic conditions					
Manufacturing employment shares: District	488	0.144	0.104	0.000	0.788
Mfg shares: other districts in the same province	488	0.138	0.073	0.008	0.383
Public servant (% of employment)	488	0.096	0.061	0.000	0.413
Unemployment rate	488	0.023	0.018	0.000	0.101
First-grade enrollment rate (% of pop.)	488	0.056	0.025	0.004	0.202
Urban population (% of pop.)	488	0.483	0.337	0.000	1.000
Covariates: Demographics					
Aged below 15 (% of pop.)	488	0.231	0.035	0.103	0.408
Aged between 15-19 (% of pop.)	488	0.077	0.020	0.033	0.135
Aged between 20-24 (% of pop.)	488	0.070	0.022	0.014	0.196
Aged between 15-24 (% of pop.)	488	0.147	0.033	0.070	0.293
Aged 60 and above (% of pop.)	488	0.119	0.039	0.023	0.268
Illiterates (% of pop.)	488	0.028	0.032	0.000	0.252
Secondary school level (% of pop.)	488	0.236	0.088	0.085	0.552
High school level (% of pop.)	488	0.103	0.053	0.012	0.326
Elementary/middle vocational school	488	0.017	0.021	0.000	0.196
Undergraduates and Graduates	488	0.053	0.053	0.000	0.416
Potential confounding factors					
Minimum wage	488	1846	248	1650	2350
Gender-skilled labor ratio	485	1.158	0.445	0.242	3.820
Gender-skilled labor ratio change 2013-2019	484	-0.125	0.514	-2.063	1.604
Gender-tertiary educated labor ratio	483	1.446	0.896	0.000	7.727
Gender-tertiary educated labor ratio change 2013-2019	483	-0.503	1.000	-7.175	5.857
Male-to-female ratio of children aged 0-5 years old	463	0.910	0.032	0.815	0.988
Male-to-female ratio of children aged 0-10 years old	463	0.914	0.030	0.819	0.995
Variables used in provincial grouped data and household regressions					
Long-diff of wage gap: 2013-2019 (province)	1,295	-0.015	0.227	-2.295	2.062
Exposure to capital intensity at province-level	1,383	1.761	0.315	0.872	3.362
Log of provincial income per capita 2012	1,383	7.427	0.324	6.631	8.203
Provincial unemployment rate	1,383	0.020	0.010	0.003	0.046
Public servant (% total employment)	1,383	0.102	0.026	0.053	0.210
Number of high-ranking officers/10,000 population	1,383	4.197	3.893	0.000	20.747
Manufacturing employment (% total employment)	1,383	0.123	0.072	0.015	0.324
Aged below 15 (% of pop.)	1,383	0.242	0.030	0.193	0.345
Aged between 15-19 (% of pop.)	1,383	0.079	0.012	0.060	0.108
Aged between 20-24 (% of pop.)	1,383	0.071	0.012	0.042	0.097
Aged 60 and above (% of pop.)	1,383	0.111	0.027	0.053	0.177
Secondary school level (% of pop.)	1,383	0.217	0.059	0.118	0.350
High school level (% of pop.)	1,383	0.093	0.035	0.024	0.182
Elementary/middle vocational school	1,383	0.016	0.013	0.003	0.061
Undergraduates and Graduates	1,383	0.052	0.020	0.022	0.141
Log of provincial population	1,383	13.997	0.566	12.623	15.876
Log of provincial total employment	1,383	13.489	0.549	12.278	15.232
Log of provincial working age population	1,383	13.549	0.573	12.250	15.508
Wage growth compiled from VHLSS	1,794	1.929	2.690	0.068	57.500

TABLE A.4.—Intra-provincial rank regression

	(1) Ordered logit	(2) Ordered logit	(3) Ordered logit	(4) Ordered logit	(5) Ordered probit
Panel A: Change in the rank of female-to-male monthly wage ratio 2013-2019					
Exposure to capital intensity	-0.396*	-0.335	-0.268	-0.333	-0.207*
	(0.213)	(0.210)	(0.209)	(0.223)	(0.114)
Observations	469	469	469	439	439
Panel B: Change in the rank of female-to-male hourly wage ratio 2013-2019					
Exposure to capital intensity	-0.188	-0.160	-0.155	-0.269	-0.157
	(0.205)	(0.199)	(0.200)	(0.221)	(0.116)
Observations	469	469	469	439	439
Panel C: Change in the rank of female-to-male working hour ratio 2013-2019					
Exposure to capital intensity	-0.546***	-0.532***	-0.447**	-0.494**	-0.234**
	(0.199)	(0.201)	(0.200)	(0.216)	(0.108)
Observations	469	469	469	439	439
Covariates:					
Province	Yes	Yes	Yes	Yes	Yes
Economic conditions	No	Yes	Yes	Yes	Yes
Demographics	No	No	Yes	Yes	Yes
Minimum wage	No	No	No	Yes	Yes
Gender education gap	No	No	No	Yes	Yes
Gender discrimination	No	No	No	Yes	Yes

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors are in parentheses. A district with the first rank is the district having the largest gap in a province. The ordered logistic estimator is used in columns (1)-(4). The ordered probit estimator is used in column (5). The descriptive statistics of covariates are presented in Table A.3 in Appendix.

TABLE A.5.—Sensitivity check with base year 2006

	(1)	(2)	(3)	(4)	(5)
Panel A: Change in female-to-male monthly wage ratio					
Exposure to capital intensity	-0.024	-0.024	-0.029*	-0.033**	-0.031
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Number of observations	468	468	468	438	438
R-squared	0.147	0.166	0.188	0.273	0.283
Panel B: Change in female-to-male hourly wage ratio					
Exposure to capital intensity	-0.022	-0.022	-0.030*	-0.033**	-0.031*
	(0.017)	(0.017)	(0.016)	(0.017)	(0.016)
Number of observations	468	468	468	438	438
R-squared	0.149	0.175	0.200	0.291	0.298
Panel C: Change in female-to-male working hour ratio					
Exposure to capital intensity	-0.004	-0.003	-0.001	-0.002	-0.002
	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)
Number of observations	468	468	468	438	438
R-squared	0.151	0.163	0.221	0.234	0.222
Covariates					
Weight	Yes	Yes	Yes	Yes	No
Province	Yes	Yes	Yes	Yes	Yes
Economic conditions	No	Yes	Yes	Yes	Yes
Demographics	No	No	Yes	Yes	Yes
Minimum wage	No	No	No	Yes	Yes
Gender Education gap	No	No	No	Yes	Yes
Gender discrimination	No	No	No	Yes	Yes

Notes: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Robust standard errors are in parentheses. The sample excludes districts with R_d falling within the bottom 2% and top 98%. Weights are based on firms' total employment in 2013. Descriptive statistics of covariates are presented in Table A.3 in the Appendix.

TABLE A.6.—Sensitivity check with average gender gap in 2013 and 2014

	(1)	(2)	(3)	(4)	(5)
Panel A: Change in female-to-male monthly wage ratio					
Exposure to capital intensity	-0.021	-0.022	-0.024	-0.034**	-0.032**
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Number of observations	469	469	469	439	439
R-squared	0.145	0.162	0.181	0.225	0.241
Panel B: Change in female-to-male hourly wage ratio					
Exposure to capital intensity	-0.002	-0.002	-0.009	-0.020	-0.012
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
Number of observations	469	469	469	439	439
R-squared	0.150	0.166	0.193	0.241	0.261
Panel C: Change in female-to-male working hour ratio					
Exposure to capital intensity	-0.018**	-0.018**	-0.013*	-0.015*	-0.019**
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Number of observations	469	469	469	439	439
R-squared	0.163	0.174	0.223	0.243	0.257
Covariates					
Weight	Yes	Yes	Yes	Yes	No
Province	Yes	Yes	Yes	Yes	Yes
Economic conditions	No	Yes	Yes	Yes	Yes
Demographics	No	No	Yes	Yes	Yes
Minimum wage	No	No	No	Yes	Yes
Gender Education gap	No	No	No	Yes	Yes
Gender discrimination	No	No	No	Yes	Yes

Notes: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Robust standard errors are in parentheses. The sample excludes districts with R_d falling within the bottom 2% and top 98%. Weights are based on firms' total employment in 2013. Descriptive statistics of covariates are presented in Table A.3 in the Appendix.

TABLE A.7.—Placebo Analysis with 2007-2013 Difference Estimation

	All districts					Low-income districts		High-income districts	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Change in female-to-male monthly wage ratio									
Exposure to capital intensity	0.015	0.018	0.019	0.017	0.008	0.009	0.020	-0.012	0.004
	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.025)	(0.024)	(0.094)	(0.099)
Number of observations	468	468	468	438	438	382	382	56	56
R-squared	0.125	0.151	0.221	0.275	0.242	0.252	0.283	0.664	0.636
Panel B: Change in female-to-male hourly wage ratio									
Exposure to capital intensity	-0.004	0.000	0.003	0.003	-0.003	-0.003	0.002	-0.012	0.015
	(0.026)	(0.026)	(0.026)	(0.026)	(0.027)	(0.028)	(0.026)	(0.095)	(0.100)
Number of observations	468	468	468	438	438	382	382	56	56
R-squared	0.125	0.157	0.207	0.271	0.247	0.258	0.284	0.657	0.637
Panel C: Change in female-to-male working hour ratio									
Exposure to capital intensity	0.018*	0.017*	0.015*	0.014	0.010	0.011	0.018*	-0.004	-0.015
	(0.009)	(0.009)	(0.009)	(0.010)	(0.010)	(0.011)	(0.011)	(0.041)	(0.039)
Number of observations	468	468	468	438	438	382	382	56	56
R-squared	0.128	0.158	0.189	0.200	0.194	0.206	0.212	0.511	0.497
Covariates									
Weight	Yes	Yes	Yes	Yes	No	No	Yes	No	Yes
Province	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Economic conditions	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Demographics	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Minimum wage	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Gender Education gap	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Gender discrimination	No	No	No	Yes	Yes	Yes	Yes	No	Yes

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors are in parentheses. The sample excludes districts with R_d falling within the bottom 2% and top 98%. High-income districts are those characterized by the highest minimum wage levels among Vietnam's four minimum wage categories. Weights are based on firms' total employment in 2013. Descriptive statistics of covariates are presented in Table A.3 in the Appendix.