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What is the impact of the U.S. export control reform act on the semiconductor industry? evidence from a quasi-experimental analysis of Taiwanese wages

Wen-Cheng Lin[1], Yi-Ying Linda Yu[1*]

[1]*School of Economics and Management, Guangdong University of Petrochemical Technology, Maoming, China.*

Corresponding author: Yi-Ying Linda Yu (*Email: yyy333@ gdupt.edu.cn*)

Abstract

This study examines the impact of the 2018 U.S. Export Control Reform Act (ECRA) on the labor market of Taiwan's semiconductor industry, aiming to assess how geopolitically driven export regulations affect wage structures in allied high-tech economies. Drawing on nationally representative data from Taiwan's Manpower Utilization Survey (2012–2023), the study employs a difference-in-differences method to estimate wage changes for workers in the electronic components manufacturing industry compared to a control group in the utility industry. The estimation is conducted using both ordinary least squares and median regression models. The results show that, after the enactment of ECRA, average wages in the treatment group rose significantly by 6–9%, with consistent findings across model specifications. A placebo test confirms that the wage effect is confined to manufacturing industries with high chip dependency and that no significant impact is observed in the service sector. Further analysis reveals that semiconductor trade flows also affect wages: imports from the United States are positively associated with wage increases, while imports from China have an adverse effect. The findings demonstrate that export controls, while designed as geopolitical instruments, yield tangible economic effects in allied labor markets. The observed wage shifts reflect evolving labor demand driven by supply chain restructuring, trade diversion, and localization incentives. ECRA has altered wage structures within high-tech manufacturing, providing new empirical insights for cross-disciplinary academic and policy debates on the consequences of security-oriented trade regulation on domestic labor.

Keywords: Difference-in-differences, Digital coalitions, Export control reform act, Semiconductor industry.

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1. Introduction

In recent years, U.S.-China trade competition has entered an era of technological barriers. Citing human rights principles and commercial fairness, the United States has restricted the export of emerging technologies to China. The primary objective is to control critical and advanced technologies to prevent China's advancement in the aerospace and military industries. Historically, U.S. efforts to curb military competition through multilateral export controls with its allies were largely non-binding [1, 2]. However, in August 2018, the U.S. government announced the Export Control Reform Act (ECRA), targeting emerging technologies. This unilateral promotion of a multilateral export control regime has introduced significant uncertainty to global economic development. Advanced technologies are not limited to military applications; they are increasingly intertwined with civilian sectors [3-6] particularly in semiconductor manufacturing, the United States has effectively broadened the scope of export controls by expanding product control lists, imposing comprehensive restrictions, and strengthening measures such as tariffs, investment review mechanisms, and digital coalitions. These actions represent a form of economic sanction extending beyond traditional non-proliferation goals [7].

In 2021, global semiconductor sales reached $556 billion, with the United States accounting for 46% of the market. However, the U.S. share of global semiconductor manufacturing capacity has declined from 37% in 1990 to only 12% today, signaling a diminishing dominance in the industry [8, 9]. Meanwhile, China currently produces approximately 25% of the world's semiconductors, with a rapid growth rate, while about 75% of global semiconductor production is concentrated in East Asia [10]. This shifting landscape was a significant factor behind the enactment of the CHIPS and Science Act in August 2022. The Act includes $52.7 billion in emergency supplemental appropriations, comprising a $39 billion incentive program over five years, $11 billion for commercial research and development and workforce development initiatives, $500 million for the CHIPS for America International Technology Security and Innovation Fund, and $200 million for semiconductor workforce growth programs. The CHIPS and Science Act aims to reduce costs, create jobs, strengthen supply chains, and counter China.

Digital coalitions are the primary tools used in the U.S. to compete with China, characterized by organized, adversarial, and collective actions targeting digital strategies, regulations, standards, industries, and products. A typical example is the CHIPS 4 alliance, led by the U.S. and comprising East Asian partners such as Japan, South Korea, and Taiwan [11]. However, the impact of the ECRA extends beyond restricting U.S. technology exports; it also affects technology firms heavily dependent on global markets. Naturally, partners within the digital coalitions are not immune to these adverse effects. Companies aligned with the coalition will likely experience losses in their current profits from the Chinese market [12]. Furthermore, trading advanced process technologies with China outside of authorized exemptions risks U.S. sanctions. On the other hand, the expanding digital coalitions also present opportunities: semiconductor and advanced technology industries may benefit from order reallocation effects. As a result, in the short term, digital partnerships such as CHIPS 4 are expected to remain relatively stable.

Within the global supply chain, Taiwanese semiconductor companies occupy a pivotal position. For decades, the industry has operated under a model of "foreign technology, Taiwanese manufacturing, and the Chinese market," establishing Taiwan as the world’s leading production base for advanced semiconductors. Consequently, Taiwan was among the first to feel the impact of U.S.-China trade tensions due to its sensitive geopolitical position [13]. Taiwan Semiconductor Manufacturing Company (TSMC) exemplifies this dynamic; before the Trump administration’s licensing restrictions on Huawei, TSMC successfully maintained business relations with China and the United States. Both powers are exerting pressure on critical players such as TSMC to align with their respective camps to constrain each other's technological progress. Meanwhile, semiconductor manufacturing in China has maintained close ties with Taiwan. Firms like TSMC, which established fabrication plants in Nanjing and other locations, alongside major Taiwanese integrated circuit design companies such as MediaTek, VIA Technologies, and Realtek, have all invested in factories or joint ventures in China. These cross-strait linkages have facilitated the mobility of Taiwanese semiconductor talent, expanding career development opportunities. Notably, many technological laborers at Semiconductor Manufacturing International Corporation (SMIC) were originally trained in Taiwan. This context highlights the broader geopolitical environment in which Taiwan’s semiconductor labor market operates, forming the background for this study.

This study argues that technological labor will become the next major battleground in U.S.-China competition. The first reason is the shortage of skilled technological labor. In recent years, the rapid development of artificial intelligence has been a primary driver of the global semiconductor talent shortage [14]. The second reason concerns the strategic pursuit of technological leadership. The CHIPS and Science Act underscores the importance of expanding the domestic semiconductor workforce by providing budgetary support for STEM education and labor development initiatives [8]. Moreover, actions such as TSMC’s construction of a new fabrication plant in Arizona and efforts to prevent managerial talent from being recruited by Chinese firms further demonstrate that technological labor is a critical factor shaping the competition for technological dominance [15]. These dynamics underscore the urgency of understanding how recent policy interventions, particularly ECRA, are influencing the labor conditions of semiconductor workers in Taiwan.

Amid U.S.-China technological competition, Taiwan merits attention not only for its global leadership in semiconductors but also for the unrestricted mobility of its technological workforce. Historically, driven by comparative advantage, Taiwan’s education system has emphasized engineering disciplines, making technological human capital the core input for developing its ICT sector. This emphasis has created a continuous supply of skilled labor within science parks, critical to sustaining technological innovation and production efficiency [16-18]. However, in an increasingly competitive job market, wage inequality and disparities in compensation have accelerated labor mobility and talent outflow. Compared to other regions, Taiwan’s ICT sector is predominantly composed of private enterprises, thus limiting the extent of direct political intervention. Consequently, the Taiwanese government cannot fully restrict the movement of technological talent.

Technological labor will be a decisive factor in shaping the outcome of this technological competition. Therefore, this study aims to examine the impact of the ECRA on Taiwan's semiconductor industry by analyzing workers' wages in the electronic components manufacturing sector, thereby providing insights into the current state of Taiwan's technological labor market. The use of micro-level data differentiates this study by providing a more accurate reflection of real-world impacts on the workforce. This constitutes the study's primary contribution. This addresses a gap in existing research, which has largely focused on firm-level or trade-volume effects, with less attention paid to labor-level consequences within partner economies. The remainder of this paper is organized as follows: Section 2 presents the literature review and hypotheses; Section 3 describes the database and methodology; Section 4 reports the empirical results; Section 5 provides the discussion; and Section 6 concludes with the conclusion and policy implications.

2. Literature Review and Hypotheses

2.1. Trade Disruptions and Supply Chain Realignments

Since implementing the ECRA in 2018, the semiconductor industry's global trade structure and supply chain configuration have undergone significant shifts, with straightforward impacts on East Asia. This section reviews relevant literature, focusing on East Asian responses, supply chain shifts, and implications for labor markets. In Japan, stricter export controls have led to a notable decline in exports to China, forcing firms to realign their market strategies [19]. In South Korea, U.S. restrictions on China have slowed the growth of semiconductor exports, prompting firms to pursue market diversification to mitigate risks [20]. Southeast Asia has benefited from increased China's demand for imports from countries such as Singapore and Malaysia; however, the technological capabilities of these suppliers remain insufficient to fully replace the original sources [21]. Taiwanese companies have also been affected, responding to changes in the export environment by strengthening domestic manufacturing capabilities and increasing overseas production, gradually adjusting their international strategies [22]. Furthermore, amid global supply chain restructuring, Taiwan has deepened its technological and production integration with the U.S. market [23].

2.2. Labor Market Dynamics under Export Controls

In addition to trade realignments, recent literature has also noted labor-related responses among semiconductor-producing countries. These studies highlight patterns of labor reallocation, talent shortages, and human capital development in response to shifting trade policies. Following the enactment of the CHIPS and Science Act, the global semiconductor industry has experienced even more pronounced disruptions. The Act combines financial subsidies with export restrictions to intensify pressure on China's high-end semiconductor sector, indirectly impacting major East Asian suppliers. Taiwanese firms have benefited from rising U.S. market demand while simultaneously facing increased market uncertainty and geopolitical pressures [24]. In response, Taiwanese companies have actively expanded their research, development, and investment activities in technologically advanced countries to reduce reliance on a single market [13]. Overall, U.S. export controls and the CHIPS Act have reshaped semiconductor trade patterns, accelerated supply chain regionalization, and strengthened firms' technological autonomy, contributing to a new global semiconductor order centered on security and technological control.

Since implementing these two acts, several studies adopting a macroeconomic perspective have identified profound impacts on the semiconductor labor market. In South Korea, firms have adjusted workforce allocations and increased overseas recruitment to respond to slowing exports [20]. Amid global supply chain restructuring, new semiconductor hubs such as Kaohsiung in Taiwan and Phoenix in the United States have faced significant labor shortages, intensifying the mobility of skilled technical workers [23]. In Taiwan, internal labor restructuring has emerged, with firms accelerating shifts toward advanced process technologies and technology-intensive production, thereby increasing demand for highly skilled engineers [22]. At the same time, Taiwanese companies have expanded investments in technologically advanced countries, actively recruiting talent with international R&D experience to strengthen their human capital structures [13]. Compared to the employment market fragmentation observed in South Korea and Southeast Asia, Taiwan's technological upgrading and international expansion approach have enhanced its high-end labor market's competitiveness and value-added capabilities, resulting in an overall increase in labor demand.

2.3. Research Gap and Hypothesis

As discussed in the preceding sections, existing studies have acknowledged the labor implications of geopolitical export controls and supply chain realignments, though primarily from macroeconomic or strategic perspectives. However, few of these works have empirically examined wage structures or labor market outcomes within U.S. partner economies. Addressing this gap, the present study provides micro-level evidence from Taiwan's semiconductor labor market, where the effects of U.S. export control policies remain largely unquantified. Based on the reviewed literature, this study hypothesizes that the implementation of the U.S. ECRA has led to higher labor wages in Taiwan's semiconductor manufacturing sector.

3. Database and Methodology

3.1. Research Database

This study utilizes the raw data of the Taiwan Manpower Utilization Survey (MUS) for empirical analysis, covering 2012 to 2013. The MUS has been conducted annually since May 1978, focusing on workers' wages, conditions, and environment. The sampling method employed a two-stage stratified random sampling approach. Approximately 520 sample villages were selected in the first stage, followed by around 20,000 sample households in the second stage. The sampling rate for the survey was approximately 2.5%. The survey targets individuals aged 15 and above residing in ordinary households and collective enterprises in Taiwan, with an annual observation of 50,000 individuals [25].

Next is the collection of data on semiconductor trade and macroeconomic variables. The former is sourced from Taiwan's customs statistics, which involve searching for relevant product Harmonized System codes using "semiconductor" as a keyword, then aggregating the trade values for exports and imports to present variables for the six trade routes between Taiwan and Mainland China, the United States, and the rest of the world. The latter macroeconomic variables are selected to control Taiwan's economic and trade conditions, including economic growth, exchange rate, and monthly minimum wage. Finally, the mentioned variables are merged into the MUS based on the same year. The database for this study constitutes pooled data across multiple years.

3.2. Quasi-Experimental Method Design

This study employs a quasi-experimental design using the difference-in-differences (DID) method. The DID is constructed from the "difference" over time and between groups, and it has become widely adopted for policy effect analysis [26-28]. The difference in time is set in 2018, comparing the difference before and after the enactment of ECRA in the United States. The difference in the group is set by considering the subjects affected by ECRA. In MUS, the electronic components manufacturing industry (abbreviated as ECM) employees are considered the treatment group[1]. The control group is selected from the electricity, water, and gas supply industry (abbreviated as EWG), primarily because of its fixed wage system, which is less susceptible to business fluctuations and other external factors, similar to the public sector [28, 29].

3.3. Regression Models and Estimation Methods

This study pertains to wage research within the field of labor economics. The empirical analysis refers to the wage functions proposed by Mincer [30] and Heckman, et al. [31]. The primary determinants of wages include DID variables, individual characteristics of workers, employment environment, trade, and macroeconomic variables. The equation is as in Equation 1:

$$Y_{it} = \beta_0 + \beta_1\, ECRA_t + \beta_2\, treatment_i + \beta_3\, ECRA_t * treatment_i + \gamma X_{it} + \delta Z_t + v_{it} \tag{1}$$

In Equation (1), Y represents the dependent variable, wages; the independent variables include $ECRA$, $Treatment$ and $ECRA * Treatment$ which represent the post-event, treatment group, and policy effect, respectively. X denotes other control variables, while υ stands for the random error. The subscripts i and t represent sample observations and time dimensions, respectively.

Besides being estimated using ordinary least squares (OLS), the regression model of this study also employs the method of least absolute deviations for median regression (MR). This dual-estimation strategy provides a more comprehensive understanding of policy effects across wage distribution. While OLS captures the average treatment effect, median regression is more robust to outliers and better suited for skewed wage distributions both characteristics common in labor market data. In contrast to most existing studies that rely solely on mean-based estimates, our approach allows us to assess distributional heterogeneity in policy impact, which remains underexplored in prior ECRA-related labor research. Compared to OLS, the least absolute deviations method tends to yield more robust estimates in the presence of outliers, and quantile regression imposes fewer assumptions on the error terms. For non-normal distributions, quantile regression estimates are more robust [32] as expressed in Equation 2:

$$\min Q = -\sum_{i\,:\,y_i < X_i'\hat{\beta}_{(\tau)}}^{N} (1-\tau)\left(y_i - X_i'\hat{\beta}_{(\tau)}\right) + \sum_{i\,:\,y_i \geq X_i'\hat{\beta}_{(\tau)}}^{N} \tau\left(y_i - X_i'\hat{\beta}_{(\tau)}\right) \tag{2}$$

In the equation, $\hat{u}_{(\tau)i}$ represents the residual at the τ quantile, corresponding to the regression estimate $\hat{y}_{(\tau)i} = X_i'\hat{\beta}_{(\tau)}$. Therefore, our main objective is to derive the estimator ($\hat{\beta}_{(\tau)}$)underweight residuals at the 50th quantile and examine whether the significance of the estimator remains consistent across both median and mean wage distributions.

3.4. Variables and Descriptive Statistics

The variable design is presented in Table 1. In this study, the dependent variable is the natural logarithm of real monthly wages. Several factors are considered to influence wages. First, we include three dummy variables for the DID estimation. Second, we account for working hours and work experience. Third, individual characteristics of workers, such as gender, marital status, education level, number of children, and academic major, are incorporated. Fourth, the employment environment of workers, including business size and work location, is also taken into consideration. In addition to these micro-level factors, we incorporate trade variables related to the semiconductor industry in Taiwan, as well as relevant macroeconomic variables, to control for external economic conditions that may affect wage outcomes.

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[1] The electronic components manufacturing industry includes “semiconductor manufacturing,” “passive electronic component manufacturing,” “printed circuit board manufacturing,” “optoelectronic materials and component manufacturing,” and “other electronic component manufacturing” sectors.

Table 1.
Variables Design.

Variable	Description
Wages	Dependent variable for this study. The wage is the real monthly wage and is denoted "*lnrwage*". The formula is as follows: ln(rwage) = ln [monthly wage*(1-inflation rate/100)]. The unit is Taiwan dollars.
Quasi-natural experiments	1. Dummy variables during the policy. ECRA is recorded as "*ECRA*=1" from 2018 to 2023 and "*ECRA*=0" from 2012 to 2017. 2. Dummy variables of the treatment group. The electronic components manufacturing industries are the treatment group, recorded as "*Treatment*=1;" the electricity, water, and gas industries are the control groups, recorded as " *Treatment* =0." 3. The policy effect is multiplied by the treatment group and denoted as *ECRA***ECM*.
Working hours	The work hours per week are denoted as "*lnhour*". The unit is hours.
Experience	The potential work experience is denoted as "*lnexp*". The formula is as follows: ln(exp) = ln [age-year of schooling-6]. The unit is the year.
Individual characteristics	1. Dummy variable of gender denoted as "*male*." 1 for males and 0 for females. 2. Dummy variable of marriage denoted as "*married*." 1 is married, 0 is other status. 3. Education is represented by four dummy variables: doctoral degree (*phd*), master's degree (*master*), bachelor's degree (*college*), and high school or below (*senior*). The *college* and *senior* are used as reference groups. 4. Majors are represented by six dummy variables: humanities and law (*ll*), business and management (*bm*), science and engineering (*es*), agriculture and medicine (*am*), other majors (*other*), and not applicable (*not*). The *ES* are used as reference groups. 5. The number of children in the household is represented by three continuous variables based on their ages: the number of children under the age of 3 (*child3*), the number of children aged 3 to 18 (*child3_18*), and the number of adult children (*child18*).
Employment environment	1. The workplace is represented by a dummy variable for small and medium-sized enterprises, denoted as "*sme*." 1 indicates a small or medium-sized enterprise, while 0 indicates a large enterprise. 2. Work location is represented by 20 dummy variables based on administrative regions in Taiwan. Hsinchu County and Hsinchu City are used as reference groups.
Macroeconomic	The macroeconomic indicators are based on annual observations and control three variables: the economic growth rate (*GDP*), the exchange rate (*exchange*), and the monthly minimum wage (*mw_m*).
Semiconductor trade	Taiwan's semiconductor-related product trade variables are measured in millions of US dollars. These include exports to the United States (*lnex_usa*), imports from the United States (*lnim_usa*), exports to China (*lnex_chn*), imports from China (*lnim_chn*), exports to the rest of the world (*lnex_row*), and imports from the rest of the world (*lnim_row*).

Note:
1. Labor-related variables are sourced from the Manpower Utilization Survey (https://srda.sinica.edu.tw).
2. Macroeconomic variables are obtained from Taiwan's Directorate-General of Budget, Accounting, and Statistics (https://www.stat.gov.tw).
3. Semiconductor-related trade data are sourced from Taiwan's customs statistics (https://portal.sw.nat.gov.tw).

This study's sample selection excluded observations with zero work hours, negative wages, workers located outside Taiwan, and negative potential experience. Subsequently, statistical computations for variables within the groups were conducted using STATA 17 software. Table 2 shows that the number of observations for the treatment and control groups is 19,171 and 1,420, respectively. The control group exhibits higher averages in wages and work experience, whereas the treatment group shows higher average working hours. The proportion of males and married observations is higher in the control group. Both groups' professional fields and educational backgrounds primarily concentrate on science and engineering disciplines and bachelor's degrees. Additionally, most employers for both groups are small and medium-sized enterprises. Furthermore, as illustrated in Figure 1, trade of Taiwan's semiconductor-related products steadily increased until a sharp decline began in 2022. Taiwan's exports of semiconductor-related products to China exceed those to the United States, whereas its imports exhibit the opposite pattern.

Table 2.
Descriptive Statistics.

	Treatment group: ECM (N=19,171)				Control group: EWG (N=1,420)			
Variable	**Mean**	**Std. D.**	**Min.**	**Max.**	**Mean**	**Std. D.**	**Min.**	**Max.**
lnrwage	10.55	0.38	8.49	13.82	10.82	0.36	9.12	12.94
lnhour	3.74	0.13	2.08	4.28	3.69	0.10	3.00	4.28
lnexp	2.55	0.75	0.00	4.23	3.06	0.72	0.00	4.14
male	0.59	0.49	0.00	1.00	0.81	0.40	0.00	1.00
married	0.48	0.50	0.00	1.00	0.69	0.46	0.00	1.00
senior	0.31	0.46	0.00	1.00	0.29	0.45	0.00	1.00
college	0.53	0.50	0.00	1.00	0.58	0.49	0.00	1.00
master	0.15	0.36	0.00	1.00	0.12	0.33	0.00	1.00
phd	0.01	0.09	0.00	1.00	0.00	0.07	0.00	1.00
ll	0.02	0.15	0.00	1.00	0.03	0.16	0.00	1.00
bm	0.26	0.44	0.00	1.00	0.21	0.40	0.00	1.00
es	0.51	0.50	0.00	1.00	0.60	0.49	0.00	1.00
am	0.01	0.11	0.00	1.00	0.02	0.13	0.00	1.00
other	0.09	0.28	0.00	1.00	0.07	0.25	0.00	1.00
not	0.10	0.30	0.00	1.00	0.08	0.28	0.00	1.00
child3	0.08	0.29	0.00	3.00	0.05	0.25	0.00	2.00
child3_18	0.42	0.77	0.00	6.00	0.29	0.67	0.00	3.00
child18	0.23	0.68	0.00	8.00	0.77	1.13	0.00	5.00
sme	0.36	0.48	0.00	1.00	0.17	0.37	0.00	1.00
gdp	2.99	1.40	1.28	6.62	2.98	1.39	1.28	6.62
exchange	30.33	1.10	28.02	32.32	30.36	1.10	28.02	32.32
mw_m	9.99	0.11	9.84	10.18	9.99	0.11	9.84	10.18
lnex_usa	5.97	0.38	5.47	6.55	5.96	0.38	5.47	6.55
lnim_usa	8.24	0.22	7.81	8.66	8.24	0.22	7.81	8.66
lnex_chn	6.59	0.69	5.48	7.50	6.57	0.69	5.48	7.50
lnim_chn	6.52	0.37	5.90	7.10	6.53	0.38	5.90	7.10
lnex_row	7.07	0.59	6.17	7.92	7.06	0.60	6.17	7.92
lnim_row	9.39	0.42	8.90	10.17	9.38	0.42	8.90	10.17

Note: "Std. D." means a standard deviation.

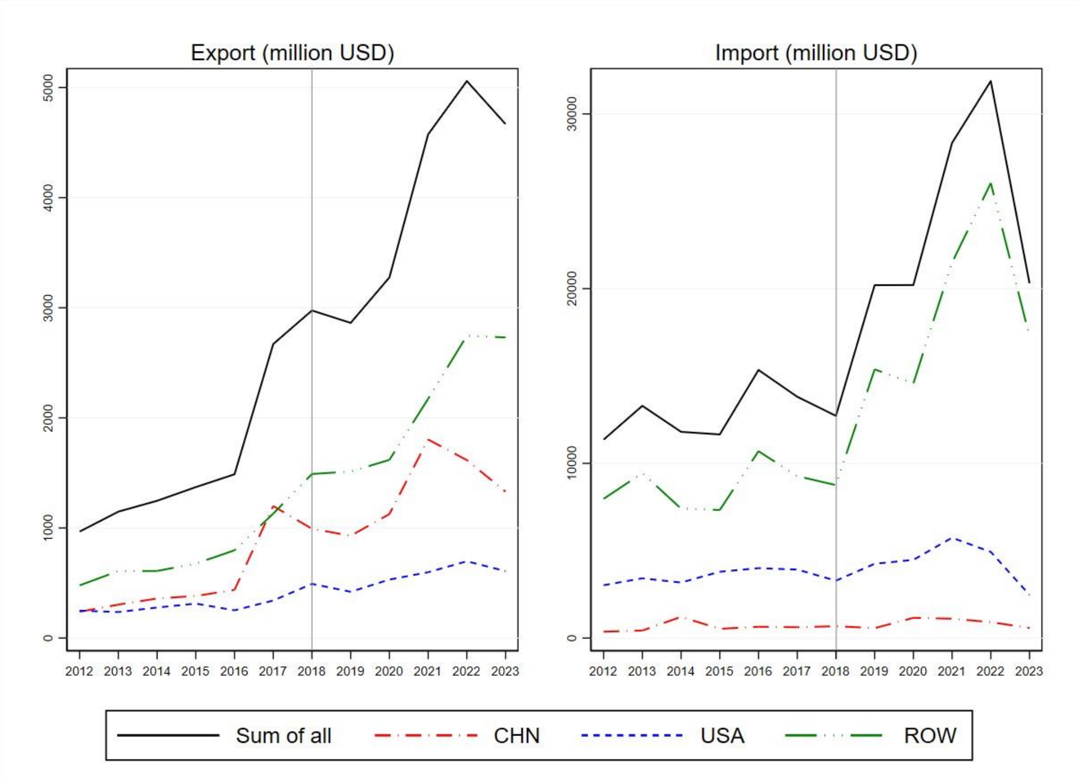

Figure 1.
Trade of Taiwan's semiconductor-related products.

A more intuitive approach is to examine the wage trends of the treatment and control groups. As shown in Figure 2, the wages of the treatment group have exhibited a steady upward trend since 2012. In contrast, the wages of the control group fluctuated around 10.80 with no apparent growth trend. However, the absolute wages of the control group remain higher, further highlighting the rationale for employing DID estimation.

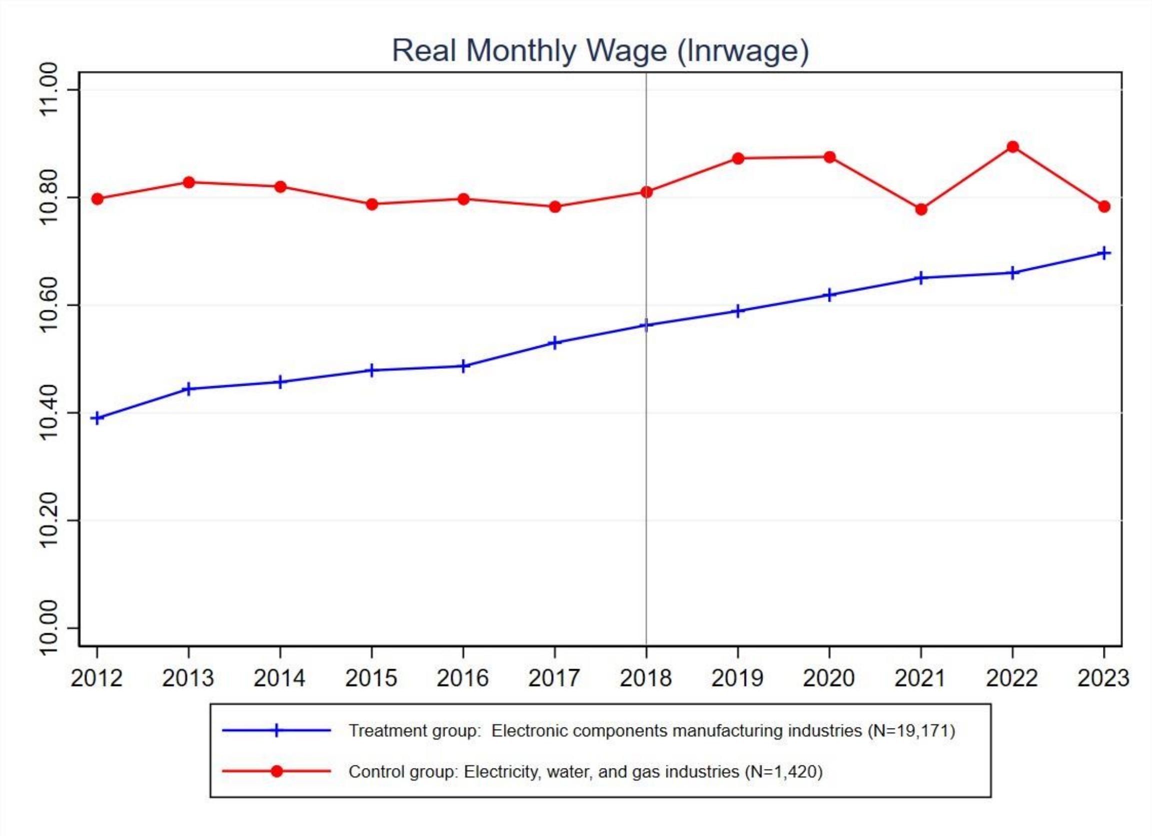

Figure 2.
Wage Trends in Quasi-Experimental Design.

4. Empirical Results

4.1. Baseline Regression Results

Table 3 presents the results of the baseline regression model[2]. From the OLS estimation coefficients, we find that the estimates in models (1) to (4) are all statistically significant. This indicates that, after the implementation of the ECRA in the United States, the wages of ECM workers in Taiwan increased by 0.06% relative to those of EWG workers. Table 4 presents the estimation coefficients of MR, showing results similar to those obtained from OLS, with the estimated value being approximately 0.09%. Although the wage estimates are more representative in MR, the results from OLS are comparable, indicating that the wages in our sample do not exhibit significant quantile bias.

Next, we examine the variables in the labor supply function. An increase in working hours is found to significantly raise wages. According to the OLS results, a 1% increase in working hours corresponds to a 0.20% to 0.21% increase in wages, indicating a labor supply elasticity of approximately 4.76 to 5. In comparison, the estimates derived from the method of MR suggest a higher labor supply elasticity, ranging from approximately 6.25 to 7.14. In addition, potential experience also shows a significant positive relationship with wages. The OLS estimation indicates that a 1% increase in potential experience leads to a 0.11% wage increase, while the MR estimation shows a slightly lower effect, with a 0.09% increase in wages.

Finally, we examine the impact of trade in semiconductor-related goods on wages. Tables 3 and 4 show that an increase in export value does not significantly affect wages. When Taiwan increases imports of semiconductor-related products from the United States, wages rise, while imports from China lead to a decrease in wages. When both import and export variables are jointly estimated, in addition to confirming the previous results, we also find that an increase in Taiwan's semiconductor-related exports to the rest of the world leads to higher wages for local ECM workers, while the opposite occurs for imports.

[2] The results of the homoscedasticity tests show that the estimates from both the White and Breusch–Pagan tests are statistically significant. Therefore, this study employs robust standard errors for the OLS estimation.

Table 3.
Empirical results of baseline regression using OLS.

Dependent Variable: *lnrwage*	**(1)**	**(2)**	**(3)**	**(4)**
ECRA	-0.05*	-0.04*	-0.06**	-0.08***
	(0.02)	(0.02)	(0.02)	(0.02)
Treatment	-0.21***	-0.21***	-0.21***	-0.21***
	(0.01)	(0.01)	(0.01)	(0.01)
*ECRA*Treatment*	0.06***	0.06***	0.06***	0.06***
	(0.02)	(0.02)	(0.02)	(0.02)
lnhour	0.20***	0.20***	0.21***	0.21***
	(0.02)	(0.02)	(0.02)	(0.02)
lnexp	0.11***	0.11***	0.11***	0.11***
	(0.00)	(0.00)	(0.00)	(0.00)
lnex_usa		-0.00		-0.09*
		(0.02)		(0.04)
lnim_usa			0.05***	0.13***
			(0.01)	(0.03)
lnex_chn		0.03*		-0.09**
		(0.01)		(0.03)
lnim_chn			-0.02**	-0.02*
			(0.01)	(0.01)
lnex_row		0.00		0.20**
		(0.03)		(0.06)
lnim_row			-0.05***	-0.14***
			(0.01)	(0.04)
Other control variables	control	control	control	control
constant	3.74***	5.43***	2.00***	1.31
	(0.43)	(0.98)	(0.60)	(1.43)
N	20,591	20,591	20,591	20,591
adj. R^2	0.50	0.50	0.50	0.50

Note:
1. "*," "**," and "***" indicate that the coefficient is significant at the 5%, 1%, and 0.1% levels, respectively.
2. The numbers in parentheses represent robust standard errors.
3. The other control variables include individual characteristics, employment environment, and macroeconomic factors.

Table 4.
Empirical results of baseline regression using MR.

Dependent Variable: *lnrwage*	**(1)**	**(2)**	**(3)**	**(4)**
ECRA	-0.06**	-0.07**	-0.07***	-0.10***
	(0.02)	(0.02)	(0.02)	(0.02)
Treatment	-0.26***	-0.26***	-0.26***	-0.26***
	(0.01)	(0.01)	(0.01)	(0.01)
*ECRA*Treatment*	0.09***	0.09***	0.09***	0.10***
	(0.02)	(0.02)	(0.02)	(0.02)
lnhour	0.14***	0.15***	0.15***	0.16***
	(0.02)	(0.02)	(0.02)	(0.02)
lnexp	0.09***	0.09***	0.09***	0.09***
	(0.00)	(0.00)	(0.00)	(0.00)
lnex_usa		-0.01		-0.05
		(0.03)		(0.05)
lnim_usa			0.05**	0.10*
			(0.02)	(0.04)
lnex_chn		0.01		-0.07
		(0.02)		(0.04)
lnim_chn			-0.03**	-0.03*
			(0.01)	(0.01)
lnex_row		0.04		0.16*
		(0.03)		(0.07)
lnim_row			-0.02	-0.09*
			(0.02)	(0.05)
Other control variables	control	control	control	control
constant	4.29***	6.55***	3.09***	3.45*

	(0.48)	(1.11)	(0.70)	(1.63)
N	20,591	20,591	20,591	20,591
pseudo R^2	0.32	0.32	0.32	0.32

Note:
1. "*," "**," and "***" indicate that the coefficient is significant at the 5%, 1%, and 0.1% levels, respectively.
2. The other control variables include individual characteristics, employment environment, and macroeconomic factors.

4.2. Heterogeneity Analysis

The heterogeneity analysis considers individual characteristics as factors leading to wage differences, focusing on policy effects categorized by gender, marital status, majors, and education level. As shown in Table 5, when categorized by gender, there is no difference in policy effects between males and females, with consistent results under both OLS and MR estimation methods. There are differences in the OLS estimates for marital status, where the policy effect influences married workers, while MR indicates that both married and other status workers are affected. Policy effects show differences in education level and majors under both estimation methods. Overall, the results for education level are concentrated and significant in the college group. Regarding majors, the OLS estimation shows significance only for workers in economics and management, whereas the MR estimation reveals significant effects not only in economics and management but also in engineering, science, and medical/agricultural fields. Based on the above analysis, MR estimation shows less pronounced heterogeneity overall.

Table 5.
Heterogeneity analysis of policy effects

Variable	**OLS**			**MR**		
	coefficient	**N**	**adj. R^2**	**coefficient**	**N**	**pseudo R^2**
Male (*male*=1)	0.04*	12,363	0.45	0.05*	12,363	0.28
Female (*male*=0)	0.16***	8,228	0.4	0.21***	82,28	0.23
Married (*married*=1)	0.05*	10,214	0.53	0.07**	10,214	0.36
Other status (*married*=0)	0.03	10,377	0.44	0.07*	10,377	0.27
High school or below (*senior*=1)	0.06	6,321	0.39	0.13***	6,321	0.23
Bachelor's degree (*college*=1)	0.04*	10,986	0.39	0.07**	10,986	0.23
Master's degree(*master*=1)	0.07	3,113	0.39	0.1	3,113	0.24
Doctoral degree (*phd*=1)	0.22	171	0.31	0.24	171	0.27
Humanities and law (*ll*=1)	0.16	505	0.42	0.24	505	0.27
Business and management (*bm*=1)	0.13***	5,347	0.4	0.17***	5,347	0.23
Science and engineering (*es*=1)	0.03	10,698	0.45	0.05*	10,698	0.28
Agriculture and medicine (*am*=1)	0.31	265	0.53	0.65***	265	0.37
Other majors (*other*=1)	0.17*	1,764	0.36	0.11	1,764	0.22
Not applicable (*not*=1)	0.08	2,012	0.34	0.05	2,012	0.18

Note: "*," "**," and "***" indicate that the coefficient is significant at the 5%, 1%, and 0.1% levels, respectively.

The parallel trends test examines whether there are no differences between the treatment and control groups before the policy implementation. In this study, we decompose the policy effect in Equation 1 by year, as represented by P in Equation 3. We obtained 12 dummy variables representing the policy effects, with other control variables held constant, and performed the regression analysis using 2018 as the reference year.

$$Y_{it} = \beta_0 + \beta_1\ ECRA_t + \beta_2\ Treatment_i + \sum_{p=-6}^{p=6} \beta_p\ T(Event = p) * Treatment_i$$
$$+\gamma X_{it} + \delta Z_t + v_{it} \tag{3}$$

Figure 3 presents the estimated results of the parallel trends test. In the OLS graph, we observe that, relative to the policy implementation in 2018, the only year with a significant deviation from zero before the policy occurred was 2012. Overall, before the implementation of the ECRA, the differences between the treatment and control groups were not substantial. However, the MR estimation graph shows that 2014 also exhibits a significant deviation from zero. Furthermore, the fluctuations in the confidence intervals are more pronounced. Therefore, the parallel trends estimated using MR appear to be relatively unstable.

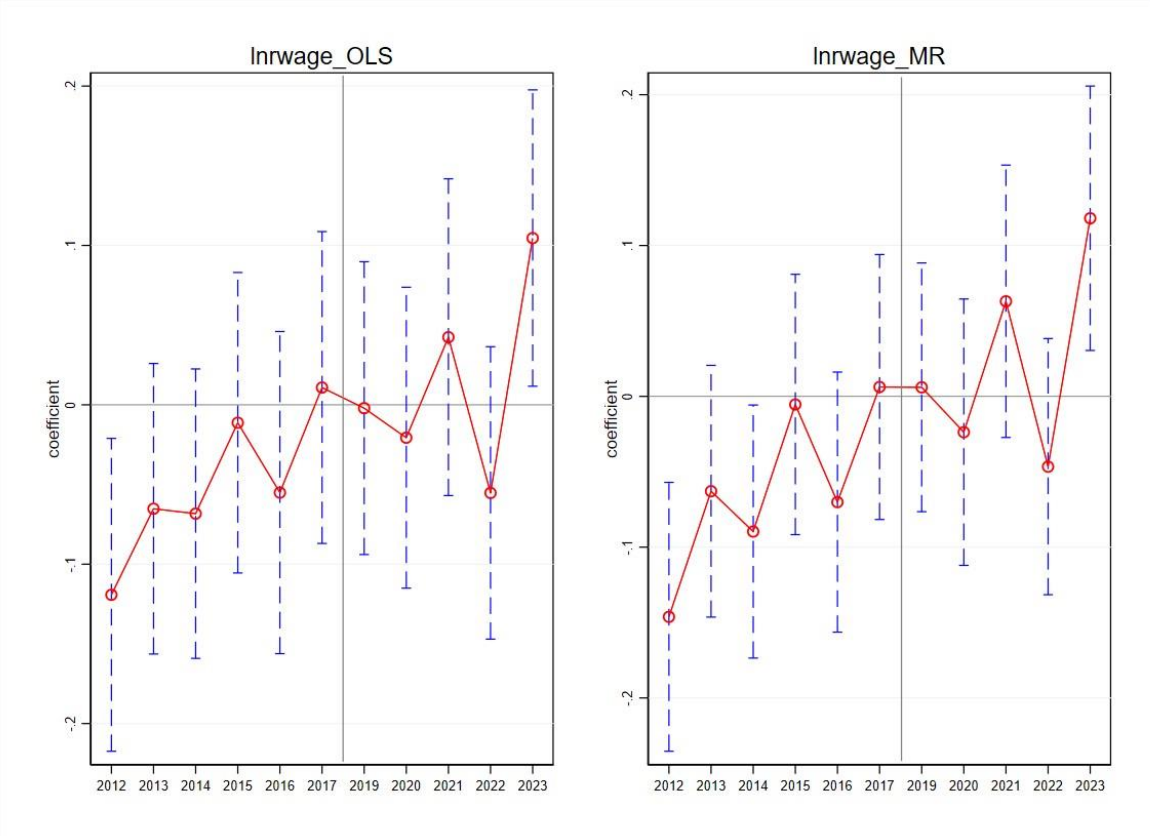

Figure 3.
Parallel Trend Test.

4.3. Robust Test

The robustness check involves adjusting the sample period by modifying the original sample length from 2012 to 2023 and conducting two tests. The first method is a sub-sample that shortens the original sample length to make it more concise. The primary approach is to remove the sample from the year of the ECRA implementation and compare the wage differences between the treatment and control groups from 2019 to 2023 with those from 2013 to 2017. As shown in Table 6, results demonstrate that the estimated effects before and after the ECRA are similar to those from the baseline regression, particularly regarding the significance of the policy effects.

The second method involves extending the sample to assess whether changes influence the policy effect within the sample. The original sample is expanded from 2012 to 2023 to include data from 2005 to 2023, thereby adding samples from 2005 to 2011 prior to the ECRA implementation. As shown in the results from Table 7, the policy effect remains significantly positive, indicating that the wage differences between the treatment and control groups are not affected by the inclusion of pre-event samples. The robustness check with sample adjustment suggests that the baseline regression results are relatively reliable.

Table 6.
Empirical results of the robust test on the sub-sample

Dependent Variable: *lnrwage*	**(1)**	**(2)**	**(3)**	**(4)**
ECRA	-0.05*	-0.04	-0.06**	-0.03
	(0.02)	(0.02)	(0.02)	(0.02)
Treatment	-0.20***	-0.20***	-0.20***	-0.20***
	(0.01)	(0.01)	(0.01)	(0.01)
*ECRA*Treatment*	0.05**	0.05**	0.05**	0.05**
	(0.02)	(0.02)	(0.02)	(0.02)
lnhour	0.18***	0.18***	0.19***	0.19***
	(0.02)	(0.02)	(0.02)	(0.02)
lnexp	0.10***	0.10***	0.10***	0.10***
	(0.00)	(0.00)	(0.00)	(0.00)
lnex_usa		-0.01		-0.18
		(0.03)		(0.09)
lnim_usa			0.03*	0.21**
			(0.01)	(0.08)
lnex_chn		0.03		-0.20*
		(0.01)		(0.08)
lnim_chn			-0.03**	-0.01
			(0.01)	(0.01)
lnex_row		-0.02		0.62**
		(0.03)		(0.21)
lnim_row			-0.03	-0.34**
			(0.02)	(0.12)
Other control variables	control	control	control	control
constant	3.94***	4.55*	2.81***	9.57***
	(0.59)	(1.79)	(0.69)	(0.30)
N	17,084	17,084	17,084	17,084
adj. R^2	0.50	0.50	0.50	0.50

Note:
1. "*," "**," and "***" indicate that the coefficient is significant at the 5%, 1%, and 0.1% levels, respectively.
2. The numbers in parentheses represent robust standard errors.
3. The other control variables include individual characteristics, employment environment, and macroeconomic factors.

Table 7.
Empirical results of the robust test about the extended sample.

Dependent Variable: *lnrwage*	**(1)**	**(2)**	**(3)**	**(4)**
ECRA	-0.05**	-0.05**	-0.06***	-0.08***
	(0.02)	(0.02)	(0.02)	(0.02)
Treatment	-0.24***	-0.24***	-0.24***	-0.24***
	(0.01)	(0.01)	(0.01)	(0.01)
*ECRA*Treatment*	0.09***	0.08***	0.08***	0.08***
	(0.01)	(0.01)	(0.01)	(0.01)
lnhour	0.21***	0.22***	0.22***	0.22***
	(0.02)	(0.02)	(0.02)	(0.02)
lnexp	0.11***	0.11***	0.11***	0.11***
	(0.00)	(0.00)	(0.00)	(0.00)
lnex_usa		0.01		-0.03
		(0.01)		(0.02)
lnim_usa			0.07***	0.08***
			(0.01)	(0.02)
lnex_chn		0.02**		-0.00
		(0.01)		(0.01)
lnim_chn			-0.02***	-0.02**
			(0.00)	(0.01)
lnex_row		0.02		0.08*
		(0.02)		(0.03)
lnim_row			-0.07***	-0.09***
			(0.01)	(0.02)
Other control variables	control	control	control	control
constant	4.57***	6.33***	2.19***	3.61***

	(0.26)	(0.41)	(0.47)	(0.61)
N	32,226	32,226	32,226	32,226
adj. R^2	0.53	0.53	0.53	0.53

Note:
1. "*," "**," and "***" indicate that the coefficient is significant at the 5%, 1%, and 0.1% levels, respectively.
2. The numbers in parentheses represent robust standard errors.
3. The other control variables include individual characteristics, employment environment, and macroeconomic factors.

4.4. Placebo Test

In a quasi-natural experiment, the event must exhibit strong exogeneity and no spillover effects. Our placebo test adopts the method of a fictional treatment group, where we verify that ECM is an appropriate treatment group through various experimental groups. Additionally, we examine whether the ECRA impacts other industries. We design three fictional treatment groups based on the degree of ECRA's impact on various industries: "Computer, electronic products, and optical product manufacturing "industries[3] (abbreviated as CEOM) and "Automotive and its parts manufacturing industries" (abbreviated as APM), both of which are related to chip demand; additionally, we select "Sports, entertainment, recreation services, and creative and performing arts" (abbreviated as SERC), which represents service-based industries.

Table 8 reports that during the original sample period (2012–2023), only CEOM exhibits a significant policy effect at the 95% confidence level, while neither APM nor SERC shows evidence of policy spillover under the baseline model. To assess whether the policy effect is sensitive to sample size, we apply a stepwise sample expansion to track the trend of policy effect estimates. As shown in Table 8, industries related to chip demand exhibit varying degrees of impact from the ECRA, whereas the pure service industry (SERC) remains unaffected as the sample expands. This further corroborates that the ECRA acts as an exogenous shock for the ECM defined in this study. Following sample adjustments, the ECRA continues to impact manufacturing industries without producing spillover effects in the service sector.

Table 8.
Policy effects of the fictional treatment group for extended samples.

sample	**Treatment group:**	**Fictional treatment group:**		
	ECM	**CEOM**	**APM**	**SERC**
2012-2023	0.0627***	0.0453*	0.0119	0.0036
2011-2023	0.0808***	0.0578**	0.0324	0.0167
2010-2023	0.0870***	0.0587***	0.0410*	0.0218
2009-2023	0.0872***	0.0563***	0.0402*	0.0268
2008-2023	0.0830***	0.0512**	0.0355*	0.0266
2007-2023	0.0857***	0.0548***	0.0358*	0.0323
2006-2023	0.0844***	0.0538***	0.0351*	0.0305
2005-2023	0.0841***	0.0523**	0.0345*	0.0292

Note: "*," "**," and "***" indicate that the coefficient is significant at the 5%, 1%, and 0.1% levels, respectively.

5. Discussion

Based on the baseline regression results, this study confirms that the ECRA has a positive impact on wages in Taiwan's semiconductor industry under both OLS and MR estimations. Second, robustness checks employing refined sub-samples and extended samples produce consistent findings with the baseline results. Third, a placebo analysis using three alternative treatment groups examines whether policy spillovers vary with sample expansion. The results reveal that manufacturing sectors related to chip demand exhibit increasingly significant positive effects as the sample broadens. However, this effect remains limited to chip-related manufacturing, with no evidence of spillovers into service industries. Overall, the empirical findings robustly validate the hypothesis that the U.S. ECRA contributed positively to labor wages in Taiwan's semiconductor sector.

These results are consistent with broader research on supply chain security and techno-geopolitics, which finds that strategic realignments often trigger workforce upskilling and labor reallocation. Such macro-level patterns support our micro-level evidence of wage shifts in Taiwan's semiconductor industry under U.S. trade regulation [33]. This study thus contributes to the emerging discussion on how security-oriented trade policies reshape high-tech labor markets.

6. Conclusion and Policy Implications

6.1. Conclusion and Findings

This study confirms that the U.S. Export Control Reform Act has reshaped Taiwan's semiconductor industry's global positioning and corporate development, resulting in wage premiums for domestic workers. Semiconductor-related trade, specifically imports from the United States, remains indispensable to Taiwan's industry. Taiwan's leadership in foundry services and research and development establishes it as a critical node in the global semiconductor supply chain, driven by the efficient allocation of labor inputs. Talent mobility hinges on market maturity, underscoring the need for robust labor systems and improved working conditions.

[3] The computer, electronic product, and optical product manufacturing industries (CEOM), encompassing the "computer and peripheral equipment manufacturing," "communication equipment manufacturing," "audio and video electronic product manufacturing," "data storage media manufacturing," "measurement, navigation, control equipment, and clock manufacturing," "radiation and electronic medical equipment manufacturing," and "optical instrument and equipment manufacturing" sectors.

The global semiconductor supply chain operates as a highly complex, interdependent, and mutually driven system of international division of labor. From silicon wafer production to wafer fabrication and final integration into end-use products, multiple stages of cross-border processing and trade are required, involving intricate competitive and cooperative dynamics across numerous countries and regions, beyond the capacity of any single economy to sustain on its own. The escalating conflict between the United States and China over Taiwan, a longstanding and unresolved issue, has further intensified tensions between the two powers, underscoring the increasing global race for critical technologies upon which the world relies [34].

6.2. Theoretical and Practical Implications

Beyond immediate wage effects, the findings resonate with broader discussions on open trade, talent circulation, and cross-border technological collaboration. In addition to superior human capital and export policies, Taiwan's semiconductor development is often attributed to its strengths in cultural diversity. This progress reflects the synergy of government initiatives, global collaboration, and multicultural integration [35, 36]. For example, the contributions of foreign workers to Taiwan's semiconductor production further exemplify this dynamic [37]. Collectively, these factors form the foundation of a resilient global technological ecosystem, underscoring the enduring principles of open trade and the free exchange of knowledge and technology to advance global society [12].

6.3. Limitations and Future Research

Despite robust findings, this study faces inherent data constraints that merit consideration and offer avenues for future empirical advancement. This study faces a primary limitation: due to Taiwan's personal data protection regulations, detailed information on workers' employing firms and finer industrial classifications within the semiconductor sector are unavailable. As a result, the analysis is confined to the mid-level classification of electronic components manufacturing. Future research that overcomes this constraint by integrating more granular customs trade data could significantly enhance the precision of studies on technology policy and labor market dynamics.

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