Factory Automation, Labor Demand, and Local Labor Market

Daiji Kawaguchi, Tetsuji Okazaki, and Xuanli Zhu

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Abstract

This study examines the effects of automation on labor demand, focusing on the power loom adoption in Japan's early 20th century silk-weaving industry. Exploiting plant-level panel data, we find that, compared to non-adopted plants, power loom adaption increased the employment and wages for adult male workers likely engaged in engineering tasks. Female adults, the main manual workforce, experienced stable employment with wage increases despite displacement and task transitions. However, equilibrium spillover effects from imperfect labor market competition led to a decrease in overall female adult employment in highly mechanized areas, primarily driven by the exit of low-wage plants.

1 Introduction

The rapid advancement of automation technologies, such as artificial intelligence (AI) and robotics, has surged the debate on how new technologies affect labor demand. Despite the fact that automation has penetrated the entire process of modern technological advance since the Industrial Revolution (Acemoglu and Restrepo, 2018a, 2019; Johnson and Acemoglu, 2023), the most detailed evidence so far has come from the studies focused on recent decades where abundant micro-level data is available (Acemoglu et al., 2020, 2022, 2023; Aghion et al., 2023; Bessen et al., 2023; Dauth et al., 2021; Koch et al., 2021). However, these recent efforts often face challenges from the subtlety of technological changes, which have become more incremental and continuous (Gordon, 2017; Bloom et al., 2020). Studying the early stages of economic development thus provides a unique vantage point due to its prevalence of distinct and discontinuous technological shifts.

Factory automation led by electrification was a pivotal epoch among the past technological changes. Goldin and Katz (1998) argue that electrification initiated the modern technology-skill complementarity (and technology-unskill substitution) by enabling shifts to continuous mass production, increasing the demand for skilled workers such as engineers and managers while reducing the demand for unskilled manual workers. Their suggestive evidence in the U.S. is a positive correlation between the capital-labor ratio in 1909-1919 and the fraction (and pay) of more educated and nonproduction workers in 1940 at the industry level. Subsequent studies by Katz and Margo (2014), Lafortune et al. (2019), and Atack et al. (2023b) provide further supporting evidence using occupation-, county-, and industry-level variations, respectively, with Atack et al. (2023b) also directly exploiting variations of electrification intensity.[1] However, analyses relying on aggregate tabulations from decennial census over extended periods may mask diverse and intricate economic forces at play, such as multiple technological advances, changes in labor supply, and non-technological labor demand shifts. Consequently, there is a lack of direct and concrete casual micro-evidence on the labor market impacts of firms' automation and mechanization induced by electrification. Such evidence is also helpful in identifying how various channels of technological impact on labor demand operate at firm level, namely machine displacement, productivity improvement, and reinstatement via new task creation, as posited by the theoretical frameworks in Acemoglu

[1] The view of Goldin and Katz (1998) is, however, not without challenge. Gray (2013) and Fiszbein et al. (2020) also utilize aggregated statistics in early twenty century and find a more nuanced picture of "hallowing out"—electrification increased both high-skill and low-skill jobs but reduced middle-skill jobs. This observation echos the findings of "deskilling" during the rise of steam-powered factories at nineteenth century (Atack et al., 2004; Chin et al., 2006; Katz and Margo, 2014; Atack et al., 2023a) and the findings of labor market polarization in recent decades (Autor et al., 2006; Acemoglu and Autor, 2011; Autor and Dorn, 2013), indicating a task-based view of technological change.

and Restrepo (2018b, 2019).[2] Moreover, aggregate-level analysis often obscures the direct effect of technological adoption with spillover and market dynamics effects due to imperfect product or labor market competition (Acemoglu et al., 2020, 2023; Aghion et al., 2022, 2023), an issue that could be particularly pronounced in early modern times with highly segmented markets and limited competition among firms.

To overcome the limitation of extant studies, this paper leverages granular data within a specific historical context to conduct an in-depth examination on the intertwined effects of electrification-induced automation on labor demand. In particular, we examine the impact of factory electrification and mechanization on labor demand using plant-level panel data of the silk-weaving industry from the early 20th century in Fukui Prefecture of Japan. Fukui Prefecture was one of Japan's major centers of silk fabric industry and witnessed a rapid transition from hand looms to power looms in the early 1900s, largely due to the diffusion of electricity. The primary workforce in these plants consisted of female adult workers engaged in manual and dexterous weaving tasks, alongside a small amount of adult male workers in engineering and managerial roles and child workers as inexperienced trainees. Historical studies demonstrate that the adoption of the power looms replaced old manual tasks with more non-routine ones, remarkably increasing the labor productivity by 2.6-2.7 fold (Sanbe, 1961; Okazaki, 2021). We study how this drastic transition of production technology affected labor demand of different worker groups.

Our data set is unbalanced plant-level panel data of over 1,300 plants from 1904 to 1914 that record the number of employees and average daily wages by gender $\times$ adult/child, along with the plant's power source. We exploit the staggered adoption of power looms to estimate the dynamic effects based on an event study design. The plant-level analysis indicates that, employment for male adult workers doubled after power loom adoption compared with the non-adopting plants in the same area (village or town). In contrast, the increases in employment for female adult workers were statistically insignificant following power loom adoption, and child workers also saw no changes. Furthermore, power loom adoption led to around 10% increases in average wages for both adult males and females, with no impact on children's wages. We interpret our results to suggest that at plant level, electricity-driven automation substantially raised the demand for more-skilled workers without destroying the demand for relatively low-skilled manual labor. These plant-level outcomes are thus consistent with the claim of technological upskilling by Goldin and Katz (1998) and subsequent studies based on aggregate tabulations, yet provide more nuance into the unskill side: despite being displaced from incumbent routine manual tasks by new technology, relatively low-skilled female workers in our case were immediately

[2] A recent study by Feigenbaum and Gross (2020) highlights the importance of distinguishing between consecutive displacement and reinstatement effects of historical automation by showing that job displacement among female telephone operators due to mechanical switching in the early 1990s was fully offset by increases in clerical and service jobs in the next cohort. However, their analysis still largely relies on decennial city-industry-occupation level data and lacks firm perspective.

reinstated into new tasks and enjoyed wage increases from productivity gains.

The impact of automation on plant-level employment and wages obtained from event study analysis does not necessarily scale to market-level outcomes because new technology adoption and diffusion can trigger potential spillover and market dynamic effects in the context of imperfect labor market competition.[3] Specifically, the adoption of power-looms by one firm can prompt wage and employment adjustments among competitors due to oligopsonistic competition. Furthermore, the exit of non-adopted plants and the entry of powered plants also influence overall employment and wage levels within the area. To identify the importance of these effects, we examine the aggregate response of local-labor-markets to the diffusion of power-looms by switching the unit of analysis from plant to area. We find that area-level results show a dampened employment impact and escalated wage effects compared to plant-level results: area-level mechanization reduced adult female employment by 19% without significantly affecting the adult male and child employment, and increased the wages of adult males and females by 31% and 13%, respectively. Moreover, the area-level mechanization intensity is associated with a statistically significant reduction in the number of plants and an insignificant increase in the area HHI, suggesting a net exit of smaller plants. Using a subsample excluding powered entrants to isolate their positive impact, we find that area-level automation is associated with a 32% decline in female employment and increases of 24% and 11% in male and female wage, suggesting the dominant role of spillover and exit effects.

Lastly, we show that our plant-level and area-level empirical results can be explained by a theoretical model that integrates a task-based framework with imperfectly competitive labor markets. Female workers, subject to a negative displacement effect, have a less positive demand impact than male workers. Low labor market competition and high monopsony power dampen employment effects while raising wages. When a firm adopts power looms, its augmented labor demand from productivity gain leads competitors to reduce employment and bid up wages, generating the spillover effects that differentiate area-level results from plant-level findings. These spillover effects also induce the exit of less efficient, low-wage plants, further decreasing area-level employment and elevating area-level wages. Therefore, our empirical and theoretical results illustrate the coexistence of upskilling from electrification-induced automation and the displacement of low-skilled manual workers due to subsequent market dynamics, paralleling findings in contemporary literature of modern automation.

[3]We focus on imperfect labor market rather than product market competition, as in Acemoglu et al. (2020) and Aghion et al. (2022), because in our case, the product is a homogeneous good while the labor markets are highly segregated and concentrated. While both types of imperfect competition can generate similar business stealing effects, assuming a perfectly competitive labor market would predict no wage impact from new technology on adopting firms relative to non-adopting ones, which contradicts our plant-level findings.

2 The Silk Weaving Industry in Fukui, Japan

The pivot of the Japanese Industrial Revolution, propelled by the Meiji Restoration in 1868 and the subsequent adoption of Western technologies and institutions, was the textile industry that accounted for over 30% of total manufacturing production until the early 1930s. Within the textile industry, the weaving industry contributed to around 40% of the production. Our analysis focuses on the silk weaving industry in Fukui Prefecture, which represented more than 8% of Japan's total weaving output and 2% of the entire manufacturing output during the 1900s and 1910s (Table A1). Over 80% of Fukui's manufacturing production in the early twentieth century was in textiles, with the majority being silk fabric, particularly *habutae*, a plain silk fabric constituting 71%–74% of its manufacturing output. In fact, Fukui was responsible for over half of Japan's *habutae* production, and maintained a relatively stable output and export in the early 20th century.

During this period, the Japanese weaving industry underwent profound organizational and technological transformations as factories with power looms became increasingly prevalent. Fukui Prefecture was leading this trend of industrialization and mechanization. From near zero in 1905, the ratio of power loom plants rose to almost 80% among Fukui's *habutae* producers by 1914 (Figure A1). Factors such as the availability of inexpensive domestic power looms and access to electricity have been argued to facilitate this transition.[4] The combination of a relatively simple product market structure and the rapid diffusion of new automation technology makes Fukui silk industry an ideal context for examining the labor market impacts of technological advancement.

The introduction of power looms led to a significant surge in labor productivity. As detailed by Okazaki (2021), an analysis of plant-level data for the *habutae* industry in Fukui Prefecture indicates a 2.62-fold increase in labor productivity in power loom factories compared to their nonpowered counterparts in 1913–1914, after controlling for plant scale and working hours.[5] This productivity gain was achieved through the automation of existing manual tasks performed by (mostly adult female) workers and the creation of new tasks. Weaving, as a process, involves three basic tasks: shuttle manipulation, warp thread regulation, and the beating of weft threads (Bythell, 1969). The transition to power looms mechanized these tasks, freeing workers from the physical constraints of handloom operation and allowing them to manage multiple machines. The remaining tasks for an operative worker involved halting the loom for thread resupply or thread repair (Uchida, 1960; Sanbe,

[4]See Kandachi (1974); Minami et al. (1982, 1983); Makino (1984); Saito and Abe (1987); Kiyokawa (1995); Hashino (2012); Hashino and Otsuka (2013) and Okazaki (2021).

[5]This increase aligns with the narratives for this period. Sanbe (1961) notes that while a foot-operated handloom could yield 1.5 tan of silk fabric daily, a power loom could produce 2 tan. Furthermore, a worker who previously could only operate one hand-and-foot-operated handloom could now manage two to three power looms. These two changes resulted in a total increase of labor productivity by more than 2.67-fold—a figure closely matching Okazaki's estimation.

1961; Tsunoyama, 1983; Hunter, 2003). Another set of newly created tasks were the installation and maintenance of powered machines, which could be only conducted by male adults.[6] As such, adopting power looms mechanizes existing tasks and generates new tasks, entailing a reallocation of workers with distinct skills into different tasks.

Lastly, despite producing one homogeneous good, the local labor markets where silk-weaving plants were located were largely not integrated. Kandachi (1974) investigates in detail the source of workers in Harue Village of Sakai County, which was one of the centers of the silk fabric industry in Fukui Prefecture, to find that most workers were from within the village and neighboring villages in the same county (pp.260-261).

3 Data and Summary Statistics

The annual Statistical Yearbook published by Fukui Prefectural Government provides annual data on factories with ten or more workers from 1904 to 1917. It includes specifics such as plant name, location (city, town, or village), owner name, foundation year, major product, power source, total horsepower used, daily working hours, and the number and daily wage of workers categorized by gender and age. We restrict our analysis to the data before 1915 as a revision in the age category that year complicates comparability with earlier data. By doing so, we also avoid the potential distortions caused by the economic boom and inflation during World War I.

We use all plants listed with products recorded as silk fabric or *habutae*. While the dataset does not explicitly outline details on silk weaving technologies, we infer the use of power looms by exploiting the documented information on power source. That is, we regard those plants using inanimate power, water, steam, gas, or electricity, as power loom plants, and the other plants as handloom plants. Electricity accounts for 88% of all power uses, followed by gas at 7% and steam at 4%.

We constructed our plant-level panel data by linking individual plants across different years based on plant name, owner's name, plant address, and foundation year.[7] Our data compilation process yielded a dataset of 1,362 distinct plants, constituting 4,470 plant-year observations and spreading across 10 counties (including Fukui city) and 135 distinct areas (towns or villages). To tailor our dataset for the

[6] Inoue (1913) reports that in the *habutae* industry in Fukui, Ishikawa and Toyama Prefectures, there were three types of workers, namely workers for preparation, weavers and mechanics, and that mechanics were "those who took charge of all the maintenance works of weaving machines including lubrication and repair, and this type of workers newly emerged after the adoption of power looms" (pp.84-85, authors' translation).

[7] Given the age of the data and the potential for documenting inaccuracies, we adopt a fuzzy-matching strategy. Specifically, we regarded plants in different years as identical if they shared the same plant addresses and at least two of the other three pieces of information—plant name, plant owner's name, and foundation year.

event study analysis, we made a series of exclusions, leading to a focused dataset of 697 plants and 3,231 plant-year observations distributed across 7 counties and 82 areas.[8] Given the dynamic nature of the industry during this period, there were numerous entries and exits over time, and our resulting panel data is thus unbalanced, with the average observation years of a plant being around 4.6 years. We will utilize entries into and exits from the panel dataset to measure plant entry and exit dynamics.

Table 1 presents the basic statistics derived from our data. A direct comparison of the observation means reveals that powered plants employed around 50 percent more workers and paid 0.22 log points higher wages. Our data further delineate three distinct worker groups within each plant: female adults constitute the majority of the workforce in silk weaving plants, especially in non-powered ones, while adult male and child workers play relatively marginal roles. Our historical narratives earlier suggest that demographic information can serve as a proxy for worker skills and tasks, a method also employed in previous studies (Atack et al., 2004; Katz and Margo, 2014). Consistently, Table 1 reveals that the average daily wages (in sen= 1/100 yen) for adult workers significantly outstrip those for child workers. Perhaps more intriguingly, we observe a mean wage reversal between adult males and females when comparing powered and non-powered plants; male adults earn less than their female counterparts in non-powered plants, while the opposite is true in powered plants. This reversal hints at the potential for adult males to possess skills more complementary to the tasks associated with power loom operation, such as installation and maintenance of power looms.[9]

4 Plant-level Analysis

This section examines the impact of power loom adoption on labor demand and wage structure at the plant level, utilizing both event study and difference-in-differences (DiD) designs. Specifically, we scrutinize how adopting power loom affects a plant's employment and wages by worker categories comparing to non-adopting counterparts in the same local market.

[8] The exclusions were carried out in several steps. Firstly, 98 observations from three counties (Nanjo, Onyu, Oi), where the habutae industry was underdeveloped, were removed. Secondly, we excluded 195 observations from plants that exhibited records of power discontinuation after initial adoption and 279 observations from plants that initially appeared in the dataset already using power looms, thereby lacking pre-treatment data. Thirdly, plants with single year observation and others not meeting our econometric specifications for the event study analysis in Section 4 were dropped. Our exclusion criteria also aids in addressing potential measurement errors from historical sources. For the area-level analysis in Section 5, we reincorporated the plants excluded in the last two steps for area-level aggregation.

[9] Given that our wage data is recorded daily wages, concerns might arise regarding variations in working hours with the adoption of power looms potentially affecting our results. However, this concern appears to be less warranted as Table 1 shows only a minor average discrepancy in working hours—about 13 minutes—between non-powered and powered plants, with small standard deviations in both categories.

Let Y_{iat} represent our dependent variable for plant i in area a at time t, which can be various plant-level outcomes of interest such as employment or the natural logarithm of the average wages. The specification of our event study analysis is as follows

$$Y_{iat} = \sum_{k=-10}^{-2} \gamma_k 1\{t - G_i = k\} + \sum_{k=0}^{5} \gamma_k 1\{t - G_i = k\} + \alpha_i + \delta_{at} + \epsilon_{it}. \quad (1)$$

where G_i is the first year of adopting the motor power by the plant i, α_i represents plant fixed effects, and δ_{at} signifies area-by-year fixed effects. The coefficients of interest, γ_k, capture the dynamic effects pre- and post-event, with γ_{-1} normalized to zero to serve as the baseline. We validate the causality of this specification through a standard pre-trend falsification test, indicated by statistically insignificant lead coefficients, and complement it with a sensitivity analysis as proposed by Rambachan and Roth (2023), which tests the severity of potential violations of the parallel trends assumption. Given the now well-known problem that two-way fixed effects (TWFE) regression potentially introducing unwanted comparisons between treatment groups, we employ the estimation method proposed by Sun and Abraham (2021) that solves this issue by using never-treated and last-treated cohorts as comparison groups.[10] In complement to the event study analysis, we also estimate a DiD model using a single post-treatment indicator, which collapses all post-event dynamic effects into a single, permanent effect. For both the event study and DiD analyses, we cluster our standard errors at the plant level.

We start by exploring the impact of power loom adoption on employment. Figure 1 illustrates the event study outcomes, highlighting heterogeneous effects across different worker categories and overall employment changes. We find a significant rise in the demand for male adult workers following the power loom introduction, starting with an initial addition of about 1.5 workers at event time ($k = 0$), and extending to around 3 workers in subsequent periods. Given the average of fewer than 2 male adult workers in nonpowered plants, this indicates a marked upsurge in high-skilled labor demand. In contrast, for female adult workers, we observe no statistically significant changes immediately after adoption. Although the coefficients showing an upward trend, culminating in an average addition of 9 female adult workers by period $k = 4$, we aware the potential for sample attrition across different post-treatment periods and the level rather than growth (log) comparison driving these dynamic effects.[11] We thus cautiously posit that the power loom im-

[10] In the Appendix A.2, we further confirm the robustness of our findings using alternative methods proposed by Callaway and Sant'Anna (2021); De Chaisemartin and d'Haultfoeuille (2020); Borusyak et al. (2021). Notably, in the specification of Callaway and Sant'Anna (2021), we include both never-adopted plants and not-yet-adopted plants as control groups. These alternative estimators yield similar results to our baseline findings.

[11] Our area-level analysis in Section 5 reveals the exit of small non-adopted firms alongside power-loom diffusion, potentially reducing the statistical power in later post-treatment periods. Also, our

plementation did not generate an immediate and significant increase in adult female employment compared with non-powered plant in the same area. For child workers, the analysis yields no statistically significant power adoption impact across all post-treatment periods. Lastly, our overall labor demand findings closely mirror the patterns observed for female adult workers, which is expected given their dominant role in the workforce. Our DiD analysis, presented in Table 2, corroborates the event study findings. For male adults, there is a statistically significant increase of 2.20 workers post adoption, more than doubling the control group's mean of 1.77. However, the changes for female adults and children are statistically insignificant, with coefficients of 1.06 and -1.26 (with control mean 16.55 and 4.10), respectively.

We next examine the impact on wages. Figure 2 displays the corresponding event study results. Log wages for both adult male and female workers increase by around 0.1 log points following the adoption of power looms, and this increase remains stable throughout the post-treatment periods. In contrast, log wages for child workers do not exhibit statistically significant changes, if anything, they show a slight decreasing trend in the first and second post-treatment periods, accompanied by larger standard deviations. Overall, plant-level mean wage increases by about 0.1 log points and is statistically significant. Our DiD outcomes in Table 2 Panel B again corroborate these findings. Estimated treatment coefficients for the log wages of male adults, female adults, and overall workers are 0.08, 0.10, and 0.09, respectively, while the coefficient for child log wages is -0.16 and statistically insignificant. Therefore, power loom adoption resulted in an average wage increase of 10 percent for most workers, with the exception of inexperienced child workers.

While our event study plots show minimal evidence of pre-trends, particularly in cases where significant post-treatment effects are observed, we do note small but significant coefficients in several pre-treatment periods. To assess the robustness of our findings, we apply the methods proposed by Rambachan and Roth (2023) to evaluate how our results withstand potential violations of the parallel trends assumption. Specifically, we explore the extent to which our significant results could be overturned under varying magnitudes of post-treatment trend violations. The robustness analyses presented in Figures A4 and A5 demonstrate that the post-treatment parallel trend violations would need to be substantially more severe than the worst or the linear violation observed in the pre-treatment periods to invalidate the significant treatment effects, thereby lending credibility to the causality of our results.[12]

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robustness test using a log employment specification shows less an ascending trend in treatment effects, suggesting that the result is partially due to a level-based parallel trends assumption.

[12] In this empirical context, our confidence in the causality lies on the rapid technology diffusion within a short span, suggesting the exogeneity of new technology availability, and on the area-year fixed effects controlling for other confounding determinants of labor demand. However, it's important to note that the lack of pre-trend violations does not necessarily imply that technological adoption at each plant is exogenous and free from selection. Instead, our theoretical framework in Appendix B. shows that in an oligopsonistic labor market, more efficient firms—those with larger

To summarize, our plant-level event study and DiD analysis show an upskilling of the workforce following power-loom adoption, with no discernible destruction of incumbent jobs—at least not within the annual span of our data. Both male and female adult workers, engaged in distinct tasks, experienced moderate wage increases, likely due to productivity gains. The rise in the portion of adult males, presumably tasked with machine installation and maintenance, is consistent with the technology-skill complementarity documented in the literature. The sustained employment levels among female workers, despite being displaced from previous routine tasks by power looms and relocated into new tasks involving more advanced machines, suggest that displacement effects were offset by productivity and reinstatement effects.[13] A note of caution, however, is that the effects we've estimated are relative changes compared to the never-treated and last-treated cohorts within an area. Therefore, the observed changes in labor demand may not reflect similar aggregate-level outcomes if power loom adoption triggers equilibrium spillover effects on non-adopters or if other important market dynamics are at play.[14] Consequently, we will explore aggregate effects and these additional dynamics in our area-level analyses in the next section.

5 Area-level Analysis

To investigate the impact of power looms at the area level, we aggregate plant-level employment and calculate an employment-weighted average of plant wages (i.e. $W_{at} \equiv \sum_{i \in a} s_{it} W_{it}$, where s_{it} is the employment share of plant i in area a in year t). We do this for all worker categories and by using the full sample, including power switchers, powered entrants, and other observations excluded from the plant-level analysis. We similarly define an employment-weighted intensity of power adoption in an area, E_{at}. We then estimate the following area-level TWFE model,

$$Y_{at} = \mu E_{at} + \alpha_a + \delta_t + \epsilon_{at}, \tag{2}$$

where Y_{at} represents the area-level aggregate employment or the natural logarithm of area-level average wages. We control for area fixed effects, α_a, and year fixed effects, δ_t. The coefficient of interest is μ, which captures all potential effects from changes

employment and higher wages—are more likely to adopt automation technologies, a prediction that we also observe in our data.

[13]The data limitation prevents us from identifying individual workers and their job switches, making it difficult to distinguish selection with aforementioned effects. However, the low wage variance across nonadopted and adopted plants suggests that selection is less likely an issue for adult female workers.

[14]In other words, with equilibrium spillover effects from imperfect market competition, the stable unit treatment value assumption (SUTVA) condition will be violated for our event study and DiD analysis (Roth et al., 2023).

in power intensity (Table B1).[15] We cluster our standard errors at the area-level.

Table 3 Panel A displays the regression results of employment. The results show that a shift in area power intensity from 0 (no adoption) to 1 (full adoption) did not significantly affect male adults and children. However it led to a statistically significant reduction in employment for female adults and overall employment by 19% and 13%, respectively, compared to the control mean. Since the area power intensity increased from 0 to 80% between 1904 and 1914, female adult employment and total employment in the Fukui silk weaving industry were reduced by 15% and 10%, respectively. Table 3 Panel B further shows the impacts of area mechanization on average wages. A unit increase in power intensity lifted log wage by 0.27 log points for male adults, 0.12 log points for female adults, and 0.14 log points for overall workers. No statistically significant effects are observed for child workers.

Therefore, the area-level results reveal more dampened employment effects and stronger wage effects compared to plant-level outcomes. The equilibrium spillover effects from strategic responses under imperfect market competition, and from the resulting exit of low-productivity, low-wage plants due to intensified mechanization, can generate these results, as we will elaborate in Section 6 and Appendix B.. Conversely, the entry of power-loom adopted plants should mechanically increase employment and raise wages due to the productivity effects discovered in our plant-level analysis. To show this, we isolate the entry effect by redoing the area-level analysis described in Equation (2) with a sample that excludes powered entrants. The results, shown in Table A2, reveal that now one unit increase in power intensity was associated with a 32% and 25% decline in female and overall employment, respectively, and increases of 0.22 and 0.1 log points in male and female log wages, indicating the dominant role of spillover and exit effects. We further verify the net exit and changes in market structure resulting from area power penetration by directly incorporating the number of plants and the employment concentration as the area-level outcomes (Y_{at}) in our estimation of Equation (2). The results reported in Table 3 Panel C confirms our hypothesis: the transition from no power to full power reduced the number of plants in the area by about 1.05 plants, where the average is 4.49 in a non-electrified area. Meanwhile, the employment Herfindahl-Hirschman Index (HHI) increased insignificantly by 0.046 points from a control mean of 0.5, suggesting the exit of firms with relatively lower employment than new entrants. Without powered entrants, as shown in Table A2 Panel C, area mechanization led to a reduction of 1.5 plants and an increase of 0.08 points in HHI, both statistically significant.

Lastly, we characterize the selection of the plants induced by power loom pene-

[15]The reason we are rather confident in using a simple TWFE regression here is that our event study analysis reveals minimal dynamic effects from power loom adoption, and that exit and entry effects are inherently instantaneous. It also facilitates direct comparison to the existing studies using aggregate data.

tration. To this end, we estimate the following equation to assess the determinants of plant exits:

$$Exit_{it+1} = \beta_1 \Delta E_{at+1} + \beta_2 1(W < Med)_{at} + \beta_3 \ddot{E}_{at+1} \cdot 1(W \ddot{<} Med_{at}) + u_{it}, \qquad (3)$$

where $Exit_{it+1}$ indicates whether a plant exits between t and $t+1$, ΔE_{at+1} is the change in the power penetration between t and $t+1$, and $1(Wage < Med)_{at}$ is an indicator for plants with wage below the median in area a at time t, serving as a proxy for less efficient plants. The interaction term is defined using deviations from the sample mean, denoted by $\ddot{X}$. The results reported in the first column of Panel D shows that the penetration of power loom inducd the exit of plants and that lower wage plants were more likely to exit. The impact of power loom adoption on plant exit is about two times larger for low-wage plants than for high-wage plants. To avoid the mechanical link between plant exit and area-level power-loom intensity, we try an alternative specification that uses the lagged variable of ΔE_{at} as an explanatory variable. The results reported in the second column indicate that the results are robust in this alternative specification. Overall, our results show that the penetration of new technology accelerates the exit of less efficient plants, depressing area-level employment but raising average wages.

6 Theoretical Explanations for the Plant-level and Area-level Results

To facilitate the interpretation of our estimation results, we build a theoretical model in Appendix B. that integrates the task-based framework developed by Acemoglu and Restrepo (2018a,b) with the oligopsony framework proposed by Berger et al. (2022). Our model assumes that local labor markets are oligopsonistic, but product and machine markets are perfectly competitive. These assumptions are realistic given high commuting/immigration costs comparing to integrated product and machine markets at that era. The model can fully account for plant-level and area-level empirical results outlined as follows:

(i) The model shows that workers directly displaced by new automation technologies are subject to a negative displacement effect on labor demand, offsetting the positive productivity effect from enhanced efficiency (see Equation (B16)). In our case, this explains why male adults, whose tasks are not replaced but possibly extended, exhibit stronger labor demand compared to female adults and children, whose tasks are directly susceptible to machine replacement. The retained adult female workers, reinstated to new tasks, benefit from the productivity effect, thereby experiencing wage increases.

(ii) The model suggests that whether the increased labor demand from power machines and productivity gains manifests in increased employment or raised wages hinges on the elasticity of labor supply (see Equations (B14) and (B15)). The subdued employment response among adult females at the plant-level, alongside a wage increase, can be thus ascribed to an inelastic intra-market labor supply for this group. In contrast, the notable employment rise and moderate wage escalation for adult males are likely to be a joint result of their more elastic intra-market labor supply, which is reasonable given their lesser utilization in the industry, and the spillover effects described next.

(iii) Under the assumption of greater intra-market labor supply elasticity compared to inter-market elasticity (Assumption (B11)), the model predicts that increased labor demand from an adopting plant will trigger both a decline in competitors' employment and an elevation in their wages (see Equation (B17)). The intuition behind is that in a Cournot competition labor market, firms act as strategic substitutes in employment and strategic complements in wage setting. Hence, at the market level, we would expect to see a more subdued employment impact and a more pronounced wage effect from power loom diffusion compared to plant-level results. This is exactly what we find in our area-level analysis.

(iv) Additionally, the model exposes an extensive margin of business stealing. Less efficient firms that forgo new technology adoption face increased labor costs due to competitors' automation and labor market competition, leading to continual profit declines and eventual market exit (see Equation (B18)). This exit effect thus aggravates the intensive spillover effects at the market level: overall market labor demand diminishes and market wages rise as inefficient, low-wage firms are phased out. Our area-level analysis confirms this market dynamic: with the proliferation of power looms, low-wage firms are edged out. This dynamic explains the significant decrease in female adult employment observed at the area level.

The consistency between the model's predictions and the empirical findings demonstrates that the local labor markets of our study can be effectively characterized by the task-based framework's representation of technological evolution and the oligopsony model's depiction of labor market dynamics.

7 Conclusion

This study examined the impact of automation of silk-weaving plants brought by electrification on employment and wages across demographic groups using early 20th-century plant-level panel data from Japan. The plant- and area-level evidence picture a remarkable dynamism brought to the local labor market by automation. The technological change was skill-biased, as shown by the substantial increase in employment and wages for adult male workers skilled in engineering jobs. The automation technology was also displacing and destructive at least in the shortrun—the area-level employment for adult female workers engaged in manual tasks decreased by 19 percent despite their productivity in new tasks being doubled. This negative aggregate employment effect mainly stemmed from the the exit of less efficient plants under rapid diffusion of new technologies, and was only partially mitigated by new powered entrants. Perhaps interestingly, our empirical findings about the relatively rudimentary technologies during the period of factory electrification—that labor demand was retained at adopted plants but destroyed due to market dynamics—largely resonate with evidence newly discovered by the emerging literature on more recent automation technologies (Acemoglu et al., 2020; Aghion et al., 2022). Unlike the modern literature, which focuses on business stealing effects from product market competition, our study highlights a similar effect arising from imperfect labor market competition, which was presumably pervasive during the early modern periods. These findings suggest that technological displacement may be more a consequence of market competition dynamics than of the technologies themselves. Further research into how the combination of new technologies and evolving market competition dynamics affects labor market demand is promising.

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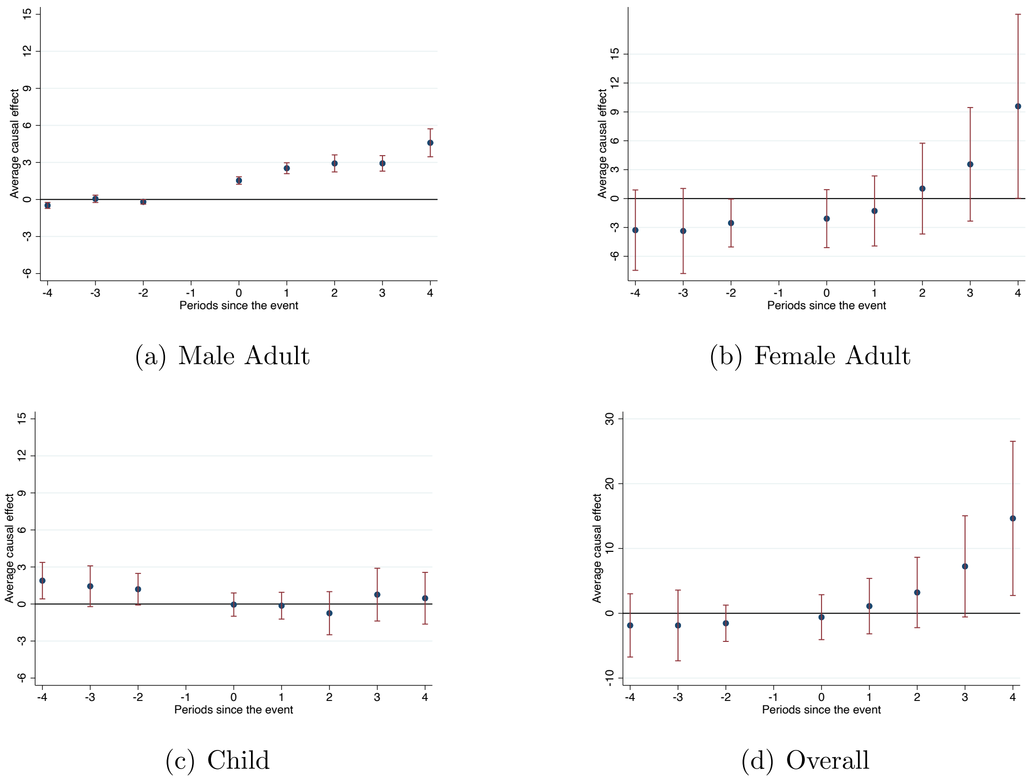
Figure 1: The Plant-Level Impacts of Power Adoption on Employment



(a) Male Adult

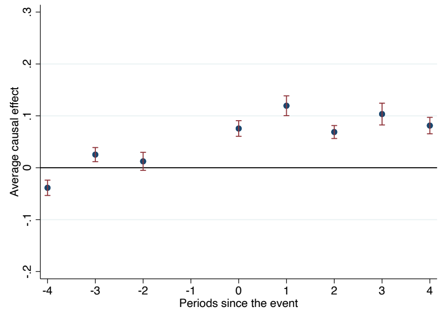
(b) Female Adult

(c) Child

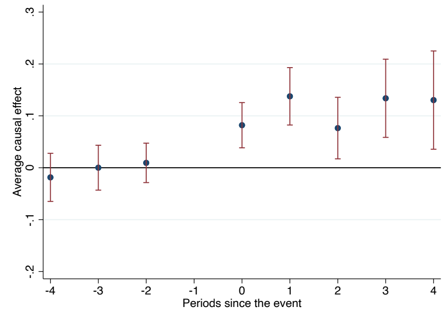
(d) Overall

Note: This figure reports the results of plant-level event studies on employment across different worker categories and overall. In particular, the dot plots are the estimated γ_k in Equation (1), i.e. the coefficients for the lead and lag event-time dummies, and the error bar indicates the 95% confidence intervals based on the standard errors clustered at the plant level. Both plant fixed effects and area-by-year fixed effects are controlled. The estimation follows the method proposed by Sun and Abraham (2021) and uses never-treated and last-treated cohorts as control groups.

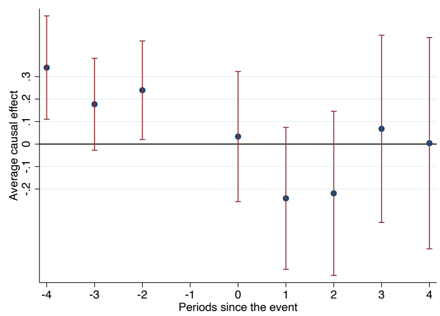
Figure 2: The Plant-Level Impacts of Power Adoption on ln(Wage)



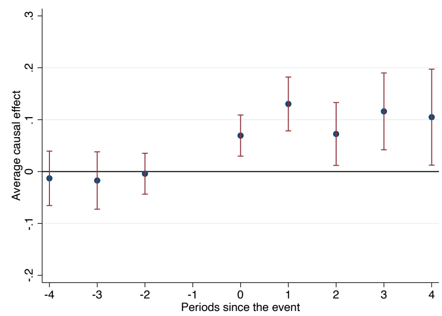
(a) Male Adult



(b) Female Adult



(c) Child



(d) Overall

Note: This figure reports the results of plant-level event studies on employment across different worker categories and overall. In particular, the dot plots are the estimated γ_k in Equation (1), i.e. the coefficients for the lead and lag event-time dummies, and the error bar indicates the 95% confidence intervals based on the standard errors clustered at the plant level. Both plant fixed effects and area-by-year fixed effects are controlled. The estimation follows the method proposed by Sun and Abraham (2021) and uses never-treated and last-treated cohorts as control groups.

Table 1: Summary Statistics

	NonPowered Plants (Mean)	Powered Plants (Mean)	Powered - NonPowered
Total Worker Per Plant	22.42	34.14	11.71
	[17.69]	[31.92]	(1.01)
- Male Adult Worker	1.77	4.69	2.93
	[2.55]	[5.77]	(0.16)
- Female Adult Worker	16.55	26.91	10.36
	[13.56]	[25.38]	(0.78)
- Child Worker	4.10	2.53	-1.57
	[6.41]	[5.35]	(0.31)
Work Hour Per Day	11.46	11.68	0.22
	[1.35]	[1.17]	(0.07)
Average Daily Wage Per Plant	16.87	23.60	6.73
	[4.14]	[4.20]	(0.20)
- Male Adult Worker	14.31	26.51	12.20
	[11.47]	[11.17]	(0.56)
- Female Adult Worker	17.60	23.71	6.11
	[4.03]	[4.22]	(0.20)
- Child Worker	1.85	0.91	-0.94
	[2.14]	[1.34]	(0.10)
Observations	2743	488	3231

Note: Means are reported. Standard deviations are reported in square brackets; Standard errors are reported in parentheses

Table 2: The Plant-Level Effect of Power Introduction on Employment and Wages

	(1) Male Adult	(2) Female Adult	(3) Child	(4) Overall
Panel A: Effect on employment				
Power	2.202	1.059	-1.264	1.997
	(0.697)	(1.954)	(0.757)	(2.365)
Control Means	1.77	16.55	4.10	22.42
N	3,231	3,231	3,231	3,231
Panel B: Effect on Ln(Wages)				
Power	0.084	0.096	-0.163	0.092
	(0.021)	(0.017)	(0.123)	(0.018)
Control Means	3.15	2.94	0.85	2.89
N	2,001	3,220	1,882	3,231

Notes: This table reports the regression coefficients of plant-level employment (Panel A) or the natural logarithm of average wages (Panel B) on the indicator variable for adopting power. The unit of observation is plant. Clustering robust standard errors against the plant-level correlations are reported in parentheses. All specifications include firm and area $\times$ year fixed effects.

Table 3: The Area-Level Effect of Power Introduction on Employment and Wages

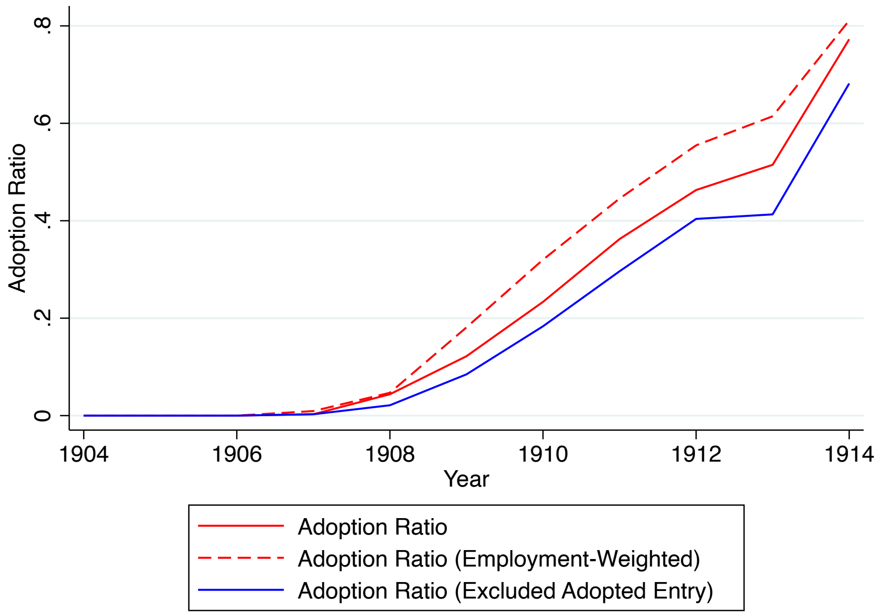
	(1) Male Adult	(2) Female Adult	(3) Child	(4) Overall
Panel A: Effect on Employment				
Area Power Intensity	2.484	-14.679	-1.090	-13.303
	(2.198)	(6.332)	(3.665)	(7.017)
Control Means	7.73	76.81	20.10	104.64
N	898	898	898	898
Panel B: Effect on ln(Wage)				
Area Power Intensity	0.269	0.120	0.045	0.141
	(0.067)	(0.029)	(0.156)	(0.033)
Control Means	3.13	2.94	0.86	2.88
N	736	898	647	898
Panel C: Effect on Market Structure				
	# of Plants	HHI		
Area Power Intensity	-1.048	0.046		
	(0.362)	(0.039)		
Control Means	4.49	0.50		
N	898	898		
Panel D: Effect on Plant Exit between t and $t+1$				
Δ Area Power Intensity	0.140	0.140		
	(0.051)	(0.061)		
Wage < Median	0.026	0.031		
	(0.013)	(0.015)		
$\ddot{\Delta}$ Area Power Intensity	0.276	0.229		
$\times$Wage $\ddot{<}$ Median	(0.094)	(0.110)		
Δ Area Power Intensity	$t, t+1$	$t-1, t$		
N	2,826	2,582		

Notes: This table reports the regression coefficients of area aggregate employment (Panel A), employment weighted average of the natural logarithm of average wages (Panel B), or area-level market structure (Panel C) on the employment weight averaged indicator variable for adopting power. The unit of observations is area $\times$ year. Clustering robust standard errors robust against the area-level correlations are reported in parentheses. All specifications include area and year fixed effects. Panel D reports the results of regressing an plant-level exit dummy at period t+1 (where exit is defined by the first year a plant disappeared in our data set) on the first difference of area power intensity, the dummy variable indicating that the plant wage is below the area-level median wage, the interaction between the mean deviations of two variables. The second column reports the results of the specification with the lagged first difference of area power intensity. All the observations in the first and the last year of panel data and belonging to power entrants and power changers are dropped in this analysis.

Appendix A. Additional Figures and Tables

A.1 Historical Background and Dataset

Figure A1: Trend of Power Adoption



Source: The panel dataset used in the main text.

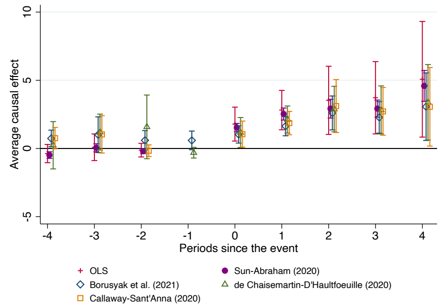
Table A1: Composition of Sector Production in Early 20th Century Japan

	A. Japan total		B. Fukui Prefecture	
Year	1909	1914	1909	1914
Agriculture	1,314,000	1,549,000	13,543	15,672
Manufacturing total	1,970,203	2,552,945	28,800	32,181
Textile	619,617	830,482	23,976	26,514
Weaving	265,331	326,467	22,399	26,514
Silk	100,234	102,482	21,116	24,821
Habutae	38,599	39,636	20,412	23,777
Mixture of silk & cotton	26,233	25,543	317	547
Cotton	116,412	150,386	303	333

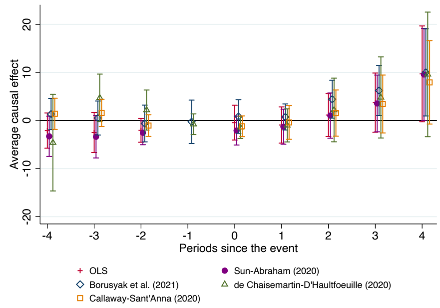
Source: The data on Japan total are from Umemura et al. (1966), and Shinohara (1972), pp.142-143. The data on Fukui Prefecture are from Statistical Yearbook of Fukui Prefecture, 1909 and 1914 issues.

A.2 Robustness on Event Study Estimation

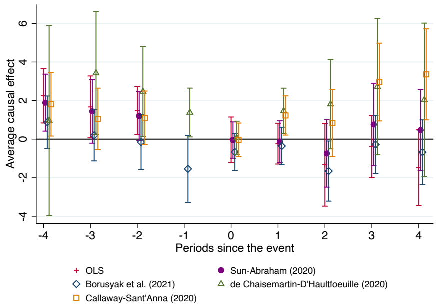
Figure A2: Comparison of estimators for plant-level event-study estimation (employment)



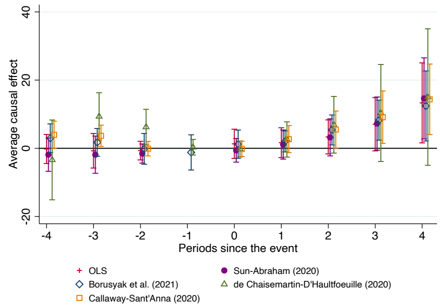
(a) Male adult



(b) Female adult



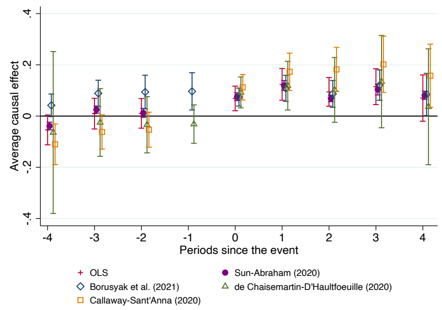
(c) Child



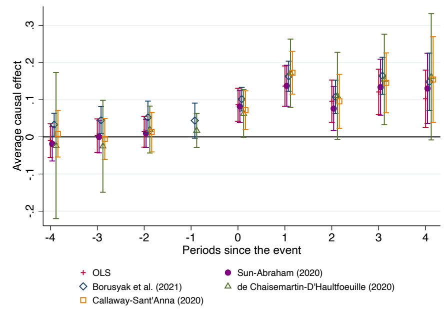
(d) Overall

Note: This figure reports a robustness check of the plant-level event studies on employment in Figure 1 under different estimators. In particular, we test with five estimators that has been used in the literature: the OLS estimator, the Sun and Abraham (2021) estimator (the baseline one used in the main text), the Callaway and Sant'Anna (2021) estimator, the De Chaisemartin and d'Haultfoeuille (2020) estimator, and the estimator in Borusyak et al. (2021). In the case using Callaway and Sant'Anna (2021) estimator, we include also the not-yet-adopted firms in the control group, in addition to the never-treated or last-treated plants used in our baseline estimation. Since the estimators of Callaway and Sant'Anna (2021) and Borusyak et al. (2021) require more data for statistical power, we replace the area-by-year fixed effects used in our main text with simply year effect and county-by-year effect, respectively. We follow the suggestions in Roth (2024) to ensure that the plots produced by the methods of Callaway and Sant'Anna (2021) and De Chaisemartin and d'Haultfoeuille (2020) are comparable to conventional event-study plots.

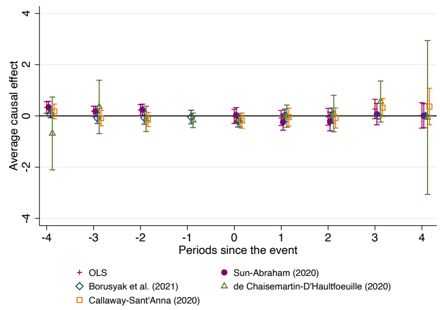
Figure A3: Comparison of estimators for plant-level event-study estimation (log wage)



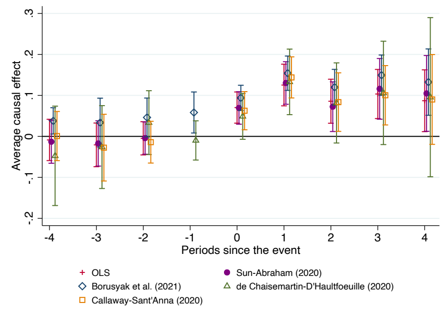
(a) Male adult



(b) Female adult



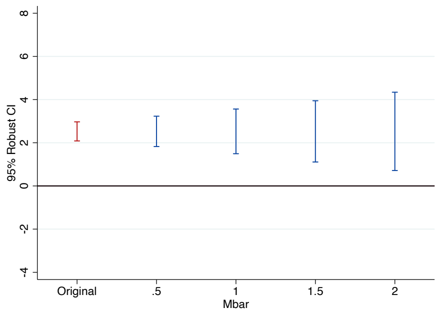
(c) Child



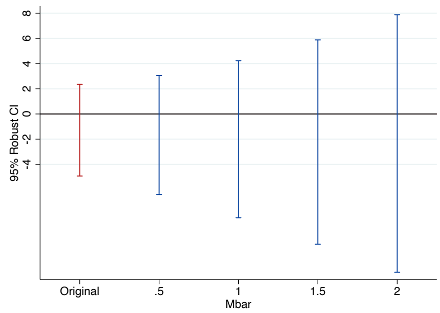
(d) Overall

Note: This figure reports a robustness check of the plant-level event studies on log wage in Figure 2 under different estimators. In particular, we test with five estimators that has been used in the literature: the OLS estimator, the Sun and Abraham (2021) estimator (the baseline one used in the main text), the Callaway and Sant'Anna (2021) estimator, the De Chaisemartin and d'Haultfoeuille (2020) estimator, and the estimator in Borusyak et al. (2021). In the case using Callaway and Sant'Anna (2021) estimator, we include also the not-yet-adopted firms in the control group, in addition to the never-treated or last-treated plants used in our baseline estimation. Since the estimators of Callaway and Sant'Anna (2021) and Borusyak et al. (2021) require more data for statistical power, we replace the area-by-year fixed effects used in our main text with simply year effect and county-by-year effect, respectively. We follow the suggestions in Roth (2024) to ensure that the plots produced by the methods of Callaway and Sant'Anna (2021) and De Chaisemartin and d'Haultfoeuille (2020) are comparable to conventional event-study plots.

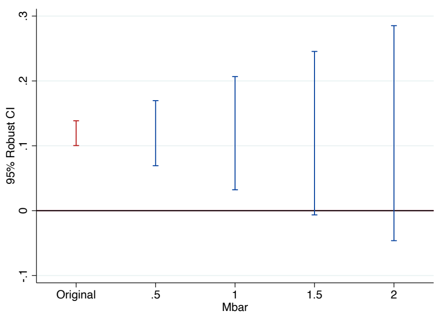
Figure A4: Sensitivity analysis on parallel trends using relative magnitudes restrictions



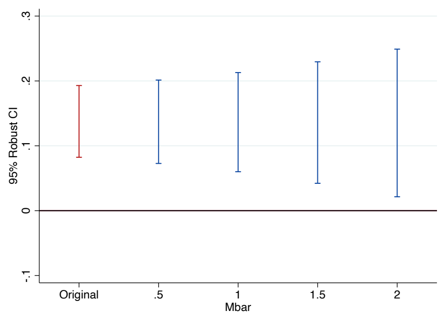
(a) Male adult: Employment



(b) Female adult: Employment



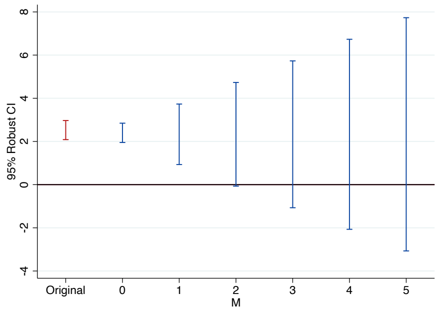
(c) Male adult: Log wage



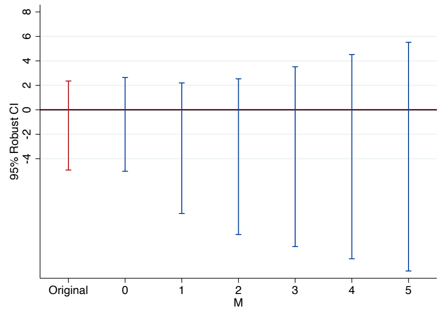
(d) Female adult: Log wage

Note: This figure reports a robustness check of the parallel trend assumption required for the plant-level event study analysis, employing the methods proposed by Rambachan and Roth (2023). Specifically, it displays robust confidence intervals (95% including the true parameter) under the restrictions that the maximum deviation from parallel trends in the post-treatment period does not exceed an $\bar{M}$-fold of the worst pre-treatment trend deviation. For the pre-treatment periods, we use periods from $k = -4$ to $k = -2$, same as the ones we use in event study plots. For the assessed post-treatment effects, we average the effects over periods $k = 1$ to $k = 3$. The analysis reveals that substantial post-treatment violations of parallel trends would be necessary to nullify the observed significant treatment effects on male adult employment, and male and female adult log wages.

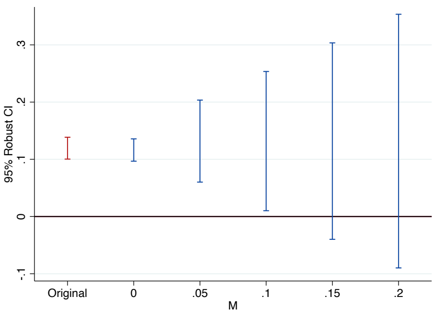
Figure A5: Sensitivity analysis on parallel trends using smoothness restrictions



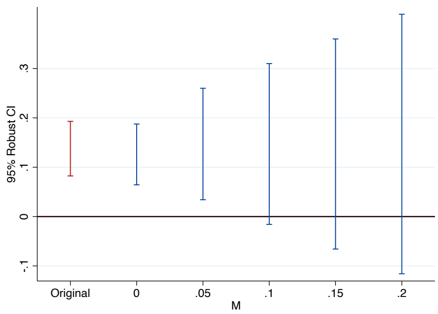
(a) Male adult: Employment



(b) Female adult: Employment



(c) Male adult: Log wage



(d) Female adult: Log wage

Note: This figure reports a robustness check of the parallel trend assumption required for the plant-level event study analysis, employing the methods proposed by Rambachan and Roth (2023). Specifically, it displays robust confidence intervals (95% including the true parameter) under the restrictions that the maximum deviation from parallel trends in the post-treatment period does not exceed a symmetric slope range $[-M, M]$ centered on the linear extrapolation of pre-treatment trends. In conducting this robustness check, we use pre-treatment periods from $k = -4$ to $k = -2$, mirroring the time frames in our event study plots. The post-treatment effects are averaged over the post-treatment periods $k = 1$ to $k = 3$. The analysis reveals that only a considerable departure from the linearly extrapolated pre-treatment trend approximating the magnitude of the original effect would overturn the significant treatment effects observed on male adult employment, and on the log wages for both male and female adults.

A.3 Additional Results on Area-level Impact

Table A2: The Effect of Area Power Intensity on Area Level Outcomes (Powered Entrants Excluded)

	(1) Male Adult	(2) Female Adult	(3) Child	(4) Overall
Panel A: Effect on Employment				
Area Power Intensity	-0.871	-24.206	-0.959	-26.036
	(1.778)	(6.479)	(3.585)	(7.689)
Control Means	7.74	76.63	19.45	103.82
N	882	882	882	882
Panel B: Effect on ln(Wage)				
Area Power Intensity	0.223	0.100	0.050	0.106
	(0.067)	(0.029)	(0.151)	(0.032)
N	711	882	632	882
Panel C: Effect on Market Structure				
	# of Plants	HHI		
Area Power Intensity	-1.505	0.081		
	(0.446)	(0.039)		
Control Means	4.47	0.50		
N	882	882		

Notes: This table reports the area-level regression results similar to the analysis in the main text but using a subsample for aggregation. In particular, the area-level data is now aggregated from a sample that excludes plants with power loom adopted at entry, with discontinuation in power use, and with only single observation year. This sample is thus more restrictive and contain less measurement errors. It helps to distinguish the dynamic effects of power loom diffusion in the local labor market especially separated from the channel of power-equipped new entrants. For other information see the note in Table 3.

Table A3: The Effect of Area Power Intensity on Never Adopted Plants

	(1) Male Adult	(2) Female Adult	(3) Child	(4) Overall
Panel A: Effect on Employment				
Area Power Intensity	-0.171	0.993	-1.398	-0.575
	(0.474)	(1.597)	(1.148)	(2.014)
N	2,168	2,168	2,168	2,168
Panel B: Effect on ln(Wage)				
Area Power Intensity	0.160	0.122	-0.299	0.133
	(0.069)	(0.038)	(0.242)	(0.047)
N	1,260	2,158	1,306	2,164

Notes: This table reports the results of the regression of area-level power intensity on the employment and wages of never adopted plants. The measure of area-level power intensity is same as the one in Table 3.

Appendix B. Theoretical Framework

In this section, we construct a theoretical framework to better interpret our empirical findings in the main text, by integrating the task-based framework of Acemoglu and Restrepo (2018a,b) with the oligopsony framework proposed by Berger et al. (2022). We assume local labor markets are imperfectly competitive but the product and machine markets are perfectly competitive. Our focus on an oligopsony setting in the local labor market instead of a monopoly or oligopoly one (see, e.g., Acemoglu et al. (2020); Koch et al. (2021)) is motivated by the fact that the silk-weaving plants under our study predominantly produced one homogenous raw good, *habutae*, and that wage dispersed significantly for different plants in our data. With a perfectly competitive labor market, which is likely to be infeasible especially in our historical context, plants would react to any technological or demand shocks exclusively by adjusting employment levels, leaving wages unaffected. Nevertheless, our model retains the business stealing effect highlighted in Acemoglu et al. (2020) and Aghion et al. (2022), manifested through the competition in the local labor market.

Production. Consider a firm i located in a local labor market j populated with number of firms n_j. All firms in this market produce one homogeneous good with its price normalized to one. As suggested by the task-based literature, the production is achieved by completing a set of different tasks ranging from $N-1$ to N:

$$\ln Y_i = \ln z_i \int_{N-1}^{N} \ln y_i(x) dx, \tag{B1}$$

where Y_i represents total production of the good, $y(i)$ denotes task-level production, and z_i stands for firm specific productivity. Each task is produced according to the following technological regime:

$$y_i(x) = \begin{cases} \gamma_l(x) l_i(x) + \gamma_m(x) m_i(x) & \text{if } x \in [N-1, I] \\ \gamma_l(x) l_i(x) & \text{if } x \in (I, I') \\ \gamma_h(x) h_i(x) & \text{if } x \in [I', N], \end{cases} \tag{B2}$$

where I and I' represent technological and skill thresholds, and γ are continuous functions indicating the productivity of three inputs: machine m, low-skilled labor l, and high-skilled labor h, across different tasks. Tasks lying between $N-1$ and I can be carried out either by low-skilled labor l or machinery m in a perfectly substitutive manner. Beyond I, a task can be only produced by human labor, and thus I implies a technological constraint on current automation technologies. An additional constraint in Equation (B2) is that low-skilled worker and high-skilled worker conduct separate tasks with the boundary defined by I'. In our case, this constraint could arise from either distinct comparative advantages between men and women or social and cultural norms that dictated the roles of men and women during that historical era. As a result, new automation technologies modeled as an increase in I would directly replace low-skilled labor l but not high-skilled labor h.[16]

To simplify, we assume that machinery m is competitively supplied by external producers at a fixed rate R. In contrast, both types of labor, l and h, are supplied elastically in the local labor market.

Household and local labor market. We assume that the representative household in the local labor market j faces the following problem,

$$\max_{C_i, L_i, H_i} U_j \left(\mathbf{C} - \frac{\mathbf{L}^{\frac{\phi_L+1}{\phi_L}}}{\frac{\phi_L+1}{\phi_L}} - \frac{\mathbf{H}^{\frac{\phi_H+1}{\phi_H}}}{\frac{\phi_H+1}{\phi_H}} \right)$$
$$\text{s.t.} \quad \mathbf{C} = \sum_{i\in j} W_{iL} L_i + \sum_{i\in j} W_{iH} H_i + \Pi_j, \ \mathbf{L} = \left(\sum_{i\in j} L_i^{\frac{\eta_L+1}{\eta_L}} \right)^{\frac{\eta_L}{\eta_L+1}}, \text{ and } \mathbf{H} = \left(\sum_{i\in j} H_i^{\frac{\eta_H+1}{\eta_H}} \right)^{\frac{\eta_H}{\eta_H+1}}, \tag{B3}$$

where $L_i = \int_{N-1}^{N} l_i(x)dx$ and $H_i = \int_{N-1}^{N} h_i(x)dx$ are the firm-level labor inputs, and Π_j is the aggregated firm profits in location j. The use of the aggregate indexes $\mathbf{L}$ and $\mathbf{H}$, which do not correspond to any real aggregates, is a convenient way to model the oligopolistic competition between m_j firms in the local labor market j. Berger et al. (2022) shows that this supply system can be derived from a microfundation of heterogeneous agents making discrete job choices on heterogeneous firms. The elasticity parameters $\eta_L > 0$ and $\eta_H > 0$ captures the extent of competition in the local labor market, similar to the elasticity of substitution in a monopoly or oligopoly setting. In other words, η_L and η_H capture the degree of differentiation among employers within an area. The larger the η_L and η_H are, the less the employers are differentiated, and the more competitive are the local labor markets. In the extreme case where $\eta_L \to \infty$ or $\eta_H \to \infty$, the local labor market tends to perfect competition and marginal products are equalized at a single wage in an area. In addition, parameters $\phi_L > 0$ and $\phi_H > 0$ capture the labor supply elasticities at the market level, which could potentially reflect either the household's trade-off between work and leisure or housework, or the labor market competition across different locations, or both. As we will not explicitly model the between-market competition, hereafter we omit the subscript j and focus on the analysis of a particular labor market. Solving the household problem gives us the labor supply curve that firms

[16]While we follow the convention and use the terms "low-skilled" and "high-skilled," one can equally use alternative terms to distinguish these two types of labor as "routine" and "non-routine," or more accurately, "displaceable" and "non-displaceable." The essential distinction lies in the nature that the tasks conducted by one type of labor to be supplanted by automation in the impending technological advance while the tasks of the other type remain unaffected or complemented. In fact, under certain conditions, we can have "low-skilled" labor being paid even higher wage than "high-skilled" labor before the introduction of the new automation technology.

face:
$$W_{iS} = \mathbf{S}^{\frac{1}{\phi_S}-\frac{1}{\eta_S}} S_i^{\frac{1}{\eta_S}} \text{ for } S \in \{H, L\}, \tag{B4}$$
where W_{iS} is the wage of labor S setting by firm i.

Characterization. We now solve the firm's optimization problem in two steps and then characterize the market equilibrium.

Firstly, given machine price R and the firm-level optimal choices of wages and input uses, firms optimally allocate resources into the production of different tasks. Since low-skilled labor and machine are perfect substitutes for tasks between $N-1$ and I, a firm's optimal input choices on these tasks are determined by comparing the marginal rate of substitution, $\gamma_l(x)/\gamma_m(x)$, with the ratio of marginal costs, mc_{iL}/mc_m. Given our setting, the marginal cost for machine, mc_m, is just the machine price R, while the marginal cost for low-skilled labor, mc_l, is larger than the firm wage, W_{iL}, due to the fact that firms face an upward-sloping labor supply curve under the existence of monopsony. In particular, we have $mc_{iL} = W_{iL}/\mu_{iL}$, where $\mu_{iL} \in [0, 1]$ represents the inverse of firm-specific markdown on labor l, with the expression we will derive below. If $\frac{mc_{iL}}{R} > \frac{\gamma_l(I)}{\gamma_m(I)}$, firm i's input choice is technologically bounded, i.e. although using machines for tasks beyond I can be potentially more productive or cost-saving than using human labor, such technology is currently unavailable. Otherwise, firm i is not technologically constrained and will choose an interior threshold $I_i^* < I$. In the oligopolistic case where more productive firms will employ more workers, pay higher wages, and have higher markdowns, as we will show below, our model suggests that large firms, faced with higher marginal costs on labor, is more likely to be technologically constrained. Consequently, our model can predict that larger firms are more likely to adopt new automation technologies following a technological breakthrough, which is consistent with our data. However, to ease the analysis, we abstract from any ex-ante difference in the technological thresholds among firms by assuming
$$\frac{mc_{iL}}{R} > \frac{\gamma_l(I)}{\gamma_m(I)} \ \forall i \tag{B5}$$
.[17] In other words, we assume that, prior to the coming of new power loom technology, all firms in our case had their input choices technological bounded, that is, $I_i^* = I \ \forall i$, and thus the adoption of the new automation technology (an increase in I) will induce increased use of machinery and enhanced production efficiency.

[17]While the study of endogenous technological adoption in our framework is itself interesting, it complicates our analysis by allowing additional adjustment on the endogenous technological threshold, and adds little additional insights into our primary objective—assessing the technological impact on labor demand. One interesting feature when we combine endogenous technology adoption and oligopsony framework is that the adoption by one firm could potentially increase the wages of other firms through oligopsonistic competition and thus force them to follow up in adoption, generating technological diffusion.

Given the same input prices across different tasks at firm level, a firm will equalize the marginal product for tasks that utilize identical inputs (i.e. m, l, or h). Under our Cobb-Douglas form of task aggregation, this results the same amount of inputs being used across tasks utilizing the same input type. Thus we can rewrite the firm production function in Equation (B1) as a function of firm level input uses (M_i, L_i, and H_i):

$$Y_i = B_i\left(\frac{M_i}{I-N+1}\right)^{I-N+1}\left(\frac{L_i}{I'-I}\right)^{I'-I}\left(\frac{H_i}{N-I'}\right)^{N-I'}, \tag{B6}$$

$$\text{where } B_i = z_i \exp\left(\int_{N-1}^{I} \ln \gamma_m(x) + \int_{I}^{I'} \ln \gamma_l(x) + \int_{I'}^{N} \ln \gamma_h(x) dx\right).$$

As a typical result of the task-based framework, the technological threshold I directly enters the share term of the input that can be substituted (here L), leading to a direct displacement effect under advancement in automation technology. In comparison, factor-augmenting technological changes, represented by increasing in γ terms, only affect the factor-neutral productivity, B_i, and thus always result in a positive effect on labor demand.

Equation (B6) provides us the marginal product for each type of input use at firm level, through which we can link to the labor supply side and characterize the firm optimal choices. In particular, our second step is to solve the firm problem of profit maximization:

$$\Pi_i = \max_{H_i, L_i, M_i} Y_i - W_{iH}H_i - W_{iL}L_i - RM_i \tag{B7}$$

$$\text{s.t. } W_{iS}\left(S_i, S^*_{-i}\right) = \mathbf{S}^{\frac{1}{\phi_S}-\frac{1}{\eta_S}} S_i^{\frac{1}{\eta_S}} \text{ and } \mathbf{S}\left(S_i, S^*_{-i}\right) = \left[S_i^{\frac{\eta_S+1}{\eta_S}} + \sum_{k\neq i} S_k^{*\frac{\eta_S+1}{\eta_S}}\right]^{\frac{\eta_S}{\eta_S+1}} \text{ for } S \in \{H, L\}.$$

Here the firm takes the actions of its competitors as given and a Nash equilibrium is achieved when all firms in the local labor market are making their optimal choices. The first order conditions are

$$\frac{\partial Y_i}{\partial M_i} = R \tag{B8}$$

$$\underbrace{\frac{\partial Y_i}{\partial S_i}}_{\text{Marginal product: } mp_{Si}} = \underbrace{W_{iS} + \left.\frac{\partial W_{iS}}{\partial S_i}\right|_{S^*_{-i}} S_i}_{\text{Marginal cost: } mc_{Si}} \text{ for } S \in \{H, L\}. \tag{B9}$$

Following the derivation in Berger et al. (2022), we can rewrite Equation (B9) as

$$mp_{iS} = W_{iS}/\mu_{iS}, \text{where } \mu_{iS} = \frac{\varepsilon_{iS}}{\varepsilon_{iS}+1},$$

$$\varepsilon_{iS} := \left[\left.\frac{\partial \ln W_{iS}}{\partial \ln S_i}\right|_{S_{-i}}\right]^{-1} = \left[(1-e_{iS})\frac{1}{\eta_S} + e_{iS}\frac{1}{\phi_S}\right]^{-1} \text{ and } e_{iS} = \frac{W_{iS}S_i}{\sum_i W_{iS}S_i}. \tag{B10}$$

Here, μ_{iS} denotes the inverse of the markdown of firm i on input $S \in \{H, L\}$, ε_{iS}

is the inverse of the firm's wage elasticity of labor supply on S, and e_{iS} denotes the firm's share of input S's wage bill in the local labor market. In the case where $\eta_S > \phi_S$, i.e. the substitution between firms within the market is more elastic than the market-level labor supply elasticity, firms with higher marginal products will offer higher wages, employ more workers, attain a larger share of the labor market, and end up facing a less elastic labor supply curve and experiencing a higher markdown (i.e. greater market power). Given that this is the most relevant case in the empirical literature (Berger et al., 2022), we will maintain this assumption in our analysis of technological impact, i.e.

$$\eta_S > \phi_S \text{ for } S \in \{H, L\} \tag{B11}$$

.

Our final step of characterization is to integrate the labor demand and labor supply sides by using wage rate, W_{iS}. In particular, from Equations (B4), (B6) and (B10), we have

$$\begin{aligned} W_{iL} = \mu_{iL} mp_{Li} = \mu_{iL}(I' - I)Y_i/L_i \text{ (labor demand of } L) \\ W_{iL}\left(L_i, L^*_{-i}\right) = \mathbf{L}^{\frac{1}{\phi_L} - \frac{1}{\eta_L}} L_i^{\frac{1}{\eta_L}} \text{ (labor supply of } L), \end{aligned} \tag{B12}$$

and

$$\begin{aligned} W_{iH} = \mu_{iH} mp_{Hi} = \mu_{iH}(N - I')Y_i/H_i \text{ (labor demand of } H) \\ W_{iH}\left(H_i, H^*_{-i}\right) = \mathbf{H}^{\frac{1}{\phi_H} - \frac{1}{\eta_H}} H_i^{\frac{1}{\eta_H}} \text{ (labor supply of } H). \end{aligned} \tag{B13}$$

The market equilibrium for this local economy is thus defined as a set of input uses $\{M_i, L_i, H_i\}_{i \in j}$ and firm-specific wages $\{W_{iL}, W_{iH}\}_{i \in j}$ such that, given the machine price R, the Equations (B8), (B12) and (B13) are satisfied for each firm i in the local labor market j.

Technological impact. With above framework in hand, we are now poised to examine the influence of new technology adoption on both a firm's own labor demand and that of its competitors, providing context for interpreting our empirical results. Specifically, we characterize a technology adoption event as an increase in the I for a particular firm i while keeping other competing firms' Is unchanged. We first analyze the first-round effect of a technology adoption event, i.e. how changes in I_i affect the firm i's optimal allocations, without considering any subsequent interactions and spillover effects arising from labor market competition triggered by this technological shift.[18] Combining the labor demand and labor supply equations in Equations (B12) and (B13) to obtain equilibrium employment and wages, and

[18]Alternatively, this is the case of a monopsonistic firm in the local labor market.

then taking derivatives, we have

$$
\begin{aligned}
\frac{d\ln W_{iL}}{dI} &= \frac{1}{1+\eta_L}\left(\frac{d\ln\mu_{iL}}{dI}+\frac{d\ln(I'-I)}{dI}+\frac{d\ln Y_i}{dI}\right)+\frac{\eta_L-\phi_L}{\phi_L(1+\eta_L)}\frac{d\ln\mathbf{L}}{dI}\\
\frac{d\ln L_i}{dI} &= \frac{\eta_L}{1+\eta_L}\left(\frac{d\ln\mu_{iL}}{dI}+\frac{d\ln(I'-I)}{dI}+\frac{d\ln Y_i}{dI}\right)+\frac{\phi_L-\eta_L}{\phi_L(1+\eta_L)}\frac{d\ln\mathbf{L}}{dI},
\end{aligned}
\tag{B14}
$$

and

$$
\begin{aligned}
\frac{d\ln W_{iH}}{dI} &= \frac{1}{1+\eta_H}\left(\frac{d\ln\mu_{iH}}{dI}+\frac{d\ln Y_i}{dI}\right)+\frac{\eta_H-\phi_H}{\phi_H(1+\eta_H)}\frac{d\ln\mathbf{H}}{dI}\\
\frac{d\ln H_i}{dI} &= \frac{\eta_H}{1+\eta_H}\left(\frac{d\ln\mu_{iH}}{dI}+\frac{d\ln Y_i}{dI}\right)+\frac{\phi_H-\eta_H}{\phi_H(1+\eta_H)}\frac{d\ln\mathbf{H}}{dI}
\end{aligned}
\tag{B15}
$$

.[19] Notably, equations in Equations (B14) and (B15) can be rewritten as

$$
\begin{aligned}
\frac{d\ln(W_{iL}L_i)}{dI} &= \underbrace{\frac{d\ln\mu_{iL}}{dI}}_{\text{Markdown effect }<0}+\underbrace{\frac{d\ln(I'-I)}{dI}}_{\text{Displacement effect }<0}+\underbrace{\frac{d\ln(Y_i/L_i)}{dI}}_{\text{Productivity effect }>0}\\
\frac{d\ln(W_{iH}H_i)}{dI} &= \underbrace{\frac{d\ln\mu_{iH}}{dI}}_{\text{Markdown effect }<0}+\underbrace{\frac{d\ln(Y_i/H_i)}{dI}}_{\text{Productivity effect }>0}
\end{aligned}
\tag{B16}
$$

.[20] It is thus clear from Equation (B16) that an increase in I would generate a more positive impact on high-skilled labor demand ($W_H H$) compared to low-skilled labor demand ($W_L L$) ceteris paribus since the latter faces an additional, negative direct displacement effect. This could explain why we observe a stronger overall demand impact on male adults compared to female adults post power-looms adoption in our estimation results, indicate the task-biased nature of the automation technologies during the historical time.[21]

Given that elastic labor is inherent in our oligopsony setting (i.e. even if the labor supply is perfectly inelastic at market level firms can still adjust workers as long as $\eta > 0$), the extent of technological impact on labor employment versus wages depends on the wage elasticity of labor supply from within-market competition, i.e. the level of imperfect labor market competition. By comparing the equations inEquations (B14) and (B15), it is clear that the impact of technological change would be larger on employment than wage when η is large, i.e. when the labor market is more

[19]In particular, the formulas for the equilibrium employment and wages are $W_{iL} = (\mu_{iL}(I'-I)Y_i)^{\frac{1}{1+\eta_L}}\mathbf{L}^{\frac{\eta_L-\phi_L}{\phi_L(1+\eta_L)}}, L_i = (\mu_{iL}(I'-I)Y_i)^{\frac{\eta_L}{1+\eta_L}}\mathbf{L}^{\frac{\phi_L-\eta_L}{\phi_L(1+\eta_L)}}$, and $W_{iH} = (\mu_{iH}(N-I')Y_i)^{\frac{1}{1+\eta_H}}\mathbf{H}^{\frac{\eta_H-\phi_H}{\phi_H(1+\eta_H)}}, H_i = (\mu_{iH}(N-I')Y_i)^{\frac{\eta_H}{1+\eta_H}}\mathbf{H}^{\frac{\phi_H-\eta_H}{\phi_H(1+\eta_H)}}$.

[20]Acemoglu and Restrepo (2019) derive a decomposition equation of technological impact similar to Equation (B16). In their setting, labor inputs are perfectly inelastic, and thus demand shocks would entirely manifest as changes in wages. Moreover, our oligopolistic framework brings an additional markdown effect, which will be negative under Assumption (B11), reflecting the labor demand depression effect from increased labor market power.

[21]When the machine supply is perfect elastic, the net of the displacement effect and productivity effect is always positive. While the markdown effect is negative under Assumption (B11), it is an indirect and second order effect following the direct demand changes, thus will not alter the signs.

competitive.This is intuitive: in a more competitive labor market, a productive firm can more easily poach workers from its competitors without significantly increasing wages. Conversely, in a highly oligopolistic labor market, expanding the labor force necessitates substantial wage increases, thus deterring firms from augmenting employment following the adoption of more efficient technologies. Therefore, our event study findings, which show a relative wage increase for female adult workers at adopting firms compared to non-adopters, alongside a subdued employment impact, could be attributed to the inelastic labor supply of female adult workers. In contrast, the marked increase in employment for male adult workers, disproportionate to their wage increase, may be ascribed to a more elastic labor supply and a more competitive labor market. This is consistent with the lower use of male adults in the weaving sector of the local labor markets. However, this explanation does not entirely capture the dynamics at play, as the event study outcomes derived from comparing treated and non-treated groups may also be shaped by strategic behavior under oligopsonistic competition, as explored subsequently.

To analyze the strategic responses of competitor firms upon the technology adoption by firm i, we can again use the equilbrium employment and wage that derive Equations (B14) and (B15), but now substituting firm i with firm $k \neq i$:

$$\begin{aligned}
\frac{d\ln W_{kS}}{dI} &= \underbrace{\frac{1}{1+\eta_S}\frac{d\ln\mu_{kS}}{de_{kS}}\frac{de_{kS}}{de_{iS}}\frac{de_{iS}}{dI}}_{+} + \underbrace{\frac{\eta_S-\phi_S}{\phi_S(1+\eta_S)}\frac{d\ln\mathbf{S}}{dS_i}\frac{dS_i}{dI}}_{+} \\
\frac{d\ln S_k}{dI} &= \underbrace{\frac{\eta_S}{1+\eta_S}\frac{d\ln\mu_{kS}}{de_{kS}}\frac{de_{kS}}{de_{iS}}\frac{de_{iS}}{dI}}_{+} + \underbrace{\frac{\phi_S-\eta_S}{\phi_S(1+\eta_S)}\frac{d\ln\mathbf{S}}{dS_i}\frac{dS_i}{dI}}_{-}
\end{aligned} \tag{B17}$$

. This shows us the second-round effect induced by the first-round own effect of technological adoption. Under Assumption (B11), the first term on the right hand side of two equations in Equation (B17) is positive, reflecting that a reduced market share encourages competing firms to offer higher wages and increase employment. However, the second term on the right hand side will be positive for wage (W_{kS}) but negative for employment (S_k), reflecting the firm's adjustment of optimal labor input choices under a less elastic labor supply curve resulted from the increased local market employment. It turns out that the effect of the second term, resulting from the changes in aggregate labor indexes (**L** and **H**), would dominate the effect of the first term. In other words, if a firm that has adopted new technology increases its employment to meet higher labor demand, then, under Assumption (B11), this would induce its competitors to reduce employment and increase wage levels. The intuition behind this result is simply that firms are strategic substitutes in employment and strategic complements in wage setting under Cournot competition. Consequently, in our context, any employment increase post power loom adoption observed in our event study analysis may be overestimated, as the competitors (i.e. the control group) are likely to respond simultaneously by reducing their employment. Conversely, the wage increase detected in the event study could be underestimated, given that competitors are correspondingly bidding up wages. This scenario is particularly pertinent for male adult workers, where we have observed a substantial rise in employment but only a relatively modest increase in wages. For female adult workers, the strategic responses of competitor firms are likely to be less pronounced due to a limited labor demand increase of adopted firms under highly inelastic labor supply (i.e. η_L is low and close to ϕ_L). This model characterization also predicts that, at (local labor) market level, we would observe a more subdued increase in employment and a more significant rise in wages as power loom adoption proliferates, compared to the plant-level results. This is exactly what we observe in our area-level results.

The strategic response of competitors upon a firm's adoption of new technology and subsequent labor demand increase thus introduces an intensive margin of the business stealing effects, akin to what is highlighted in monopoly or oligopoly settings (Acemoglu et al., 2020; Aghion et al., 2022). Facing a left-shifted labor supply curve, those competitors would have to reduce labor inputs and, consequently, their output and market shares. In addition, an extensive margin of business stealing, operating under a similar mechanism, also comes into play in our framework. To see this, note that the profit of a firm can be written as

$$\Pi_i = Y_i \left[1 - (1 + \mu_{iL})(I' - I) - (1 + \mu_{iH})(N - I')\right] \tag{B18}$$

. This profit is greater for more productive firm that achieve a larger production (Y_i) and higher markdowns (i.e. low values of μ_{iL} and μ_{iH}). Confronted with their competitors' automation and increased labor demand, "luddite" firms that refuse power adoption are forced to contend with more costly labor, resulting in reduced output, eroding market shares, and shrinking markdowns (i.e. increase in μ's). As a result, non-powered firms experience a continual decrease in profits along with intensified mechanization in the local market. This attrition could thus lead to the exit of the least productive firms when their profits turn negative or plummet below operational fixed costs. This extensive margin of business stealing works in the same direction as the intensive margin at the market level: it reduces overall market employment and possibly elevates market wages by stripping out low-pay firms.[22] This prediction again finds support in our area-level results, which indicate a significant reduction in area employment among female workers, despite plant-level data showing stable employment figures. Furthermore, we show direct evidence of a reduction in firm numbers and the exit of low-wage firms concurrent with the

[22] In this case, there is another counteracting effect on market wages: the exit of firms reduces labor market competition, potentially allowing surviving firms to exert greater labor market power and suppress wages. However, as the exiting entities are typically the least efficient and smallest firms, the net effect on market wages remains an empirical question.

diffusion of power looms.

Therefore, our model illustrates that even when new technologies intrinsically generate a sufficiently large productivity effect (and potentially also a reinstatement effect that we abstract here) and augment labor demand at adopting firms, the spillover effects—encompassing both the intensive and extensive margins of business steeling—could still dampen overall labor employment, leading to the observation of labor displacement at market level. In fact, in the case of perfectly elastic labor markets ($\eta_S, \phi_S \to \infty$), productivity-boosting technological adoption invariably enhances labor demand (see Equations (B14) and (B15)), and eliminates any spillover effects that would otherwise dampen market labor employment (see Equation (B17)). One potential force that could offset the negative spillover effects on market employment is the entry of high productivity and high wage firms with new technologies adopted. This behavior depends on fixed cost, entry cost, and the productivity draw of new firms, along with other market structure parameters. The net effect on market employment when all market dynamics are incorporated remains an empirical question although the market wage levels always rise up. We summarize the signs of all potential effects at market level in Table B1.

Table B1: Market-level Impact of Technological Diffusion

	Adoption Effect	Spillover Effect	Exit Effect	Entry Effect
Market Employment	+	-	-	+
Market Mean Wage	+	+	+	+

Notes: This table reports our model predictions of various effects of new automation technology diffusion on market employment and wage level under Assumption (B5) and Assumption (B11). The adoption effect depicts the direct first-round effect of the technology adoption of a firm. The spillover effect describes the strategic responses of competitors located in the same labor market induced by the adoption effect due to oligopsonistic competition. Exit effect indicates the exit of marginal firms further induced by this spillover effect that raises market wage. Finally, entry effect depicts the entry of new technology adopted firms, which have high productivity and wage levels.