Factory Automation, Labor Demand, and Market Dynamics

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Abstract

This study provides micro-level evidence on the labor market effects of historical automation technology by studying early 20th century powerloom adoption in Japan's silk-weaving industry. Relative to non-adopting factories in the same area, adopting factories employed more male mechanics but did not reduce female weaver employment. Meanwhile, wages rose only modestly despite large productivity gains. At the industry level, however, the exit of low-wage, low-productivity plants led to substantial net job losses—"technological unemployment"—and stronger overall wage growth. Nature of the technology, monopsony power, and market competition were all important in shaping these outcomes.

1 Introduction

Recent advances in automation technologies, including robotics and artificial intelligence, have reignited debates about their effects on workers in the labor market. Influential works frequently cite the displacement of hand spinning and weaving by automated machines during the Industrial Revolution as the canonical example of technological unemployment with deteriorating work conditions and pay (Acemoglu, 2002; Mokyr et al., 2015; Frey and Osborne, 2017; Acemoglu and Restrepo, 2019a,b; Johnson and Acemoglu, 2023). Evidence for this iconic case, however, relies heavily on anecdotal accounts or imprecise aggregate statistics (Bythell, 1969; Acemoglu and Johnson, 2024), leaving a scarcity of micro-level quantitative evidence on early industrial automation's labor market impacts. Such evidence is crucial for establishing causality and illuminating mechanisms, such as distinguishing direct effects on skill demand and wages within adopting firms from indirect effects mediated by shifts in market competition and dynamics (Aghion et al., 2022).

This paper fills this gap by leveraging newly digitized plant-level panel data to study the rapid adoption of powerlooms in the early twentieth-century silk-weaving industry of Fukui Prefecture, Japan. Fukui's silk-weaving sector flourished during Japan's Industrial Revolution through the export of a plain silk fabric known as *habutae*, employing primarily young female adult weavers, a small number of child trainees, and a few adult male mechanics. In the late 1900s, the industry underwent a major technological transition—from handlooms to powerlooms—spurred by electrification and improved domestic machinery, mostly in factories. Powerlooms replaced female weavers' manual tasks of operating handlooms with new tasks of supplying and monitoring mechanized powerlooms, more than doubling their labor productivity. To analyze the impact of this technological transition, we construct an unbalanced, plant-level panel by exploiting records of 1,317 factories with ten or more workers across 121 areas (towns or villages) in the Fukui *Statistical Yearbook*.

Our first step examines the plant-level effect of powerloom adoption by utilizing an event-study design that compares adopting and nonadopting plants within the same local area (by controlling for area-year fixed effects). This analysis isolates the impact on individual incumbent firms relative to their direct competitors, abstracting from broader market dynamics like entry and exit. We find that power-adopting plants substantially raised adult male employment by roughly 50% but did not significantly change adult female or child employment or daily operation hours. Moreover, adoption raised adult male and female daily wages by around 10%, whereas child wages showed insignificant declines. No discernible pre-trends appear in event-study plots, and results are robust across various estimators and sensitivity checks. We also discuss how the potential existence of spillover effects could affect our results.

These plant-level estimates contrast sharply with sector-level time-series trends showing a 20–30% drop in female employment and an over 20% rise in average real wages during the powerloom diffusion. To reconcile these findings, we examine how powerloom adoption shaped market dynamics. Regressing area-level market structure measures on powerloom intensity—using two-way fixed effects, instrumental variables (access to electricity stations), and long-difference specifications—reveals that an increase in the power penetration rate is associated with a significant net decline in the number of factories per area and a rise in market concentration. Further analysis shows that exited factories in power-diffused areas tended to be low-wage, low-productivity plants, while new power-adopting entrants paid notably higher wages relative to their productivity. This market selection—net exit of low-wage plants and entry of higher-wage ones—explains both the aggregate employment decline and the pronounced sectoral wage growth.

Drawing on economic theory and historical documents, we interpret these results as follows. First, the increased demand for male mechanics relative to other manual workers indicates a skill-biased dimension of this technical change that favored skilled workers who complemented machinery. Second, the absence of employment declines for female weavers in powerloom plants—despite the elimination of manual weaving tasks—reflects offsetting effects of displacement, reinstatement into new tasks, and productivity gains on labor demand. Technological unemployment did not arise within adopting plants because powerlooms still required a large manual workforce with handloom-like skills, combined with substantial productivity benefits. Third, rising female wages despite flat employment implies inelastic firm labor supply curves. Alternatively, this pattern reflects limited rent-sharing: The observed 10% wage gain represents a small pass-through of the 2–3 fold productivity increases. Both views imply significant monopsony power, allowing employers to capture most of the automation-generated surplus. Lastly, technological unemployment materialized indirectly through product and labor market competition: Expanding powerloom factories pushed out low-wage, low-productivity competitors by both intensifying product market competition and raising the labor costs required to retain and attract workers.

Literature and Contribution. Our study contributes to the literature on how historical technological changes shape labor markets through three perspectives. First, we provide micro-level causal evidence on one of the Industrial Revolution's most iconic advances—automated weaving, supplementing the rich aggregate-level findings.[1] The main debate is whether Industrial Revolution–era technologies were

[1]Most existing studies rely on decennial census tabulations and link capital or power intensity to labor market outcomes at aggregate levels (e.g., Goldin and Katz, 1998; Atack et al., 2004; Gray, 2013; Katz and Margo, 2014; Lafortune et al., 2019; Atack et al., 2023). Some recent works use instruments based on regional variations tied to natural resources or power facilities (De Pleijt et al., 2020; Leknes and Modalsli, 2020; Gaggl et al., 2021; Fiszbein et al., 2020; Molinder et al., 2021). Two notable exceptions are Chin et al. (2006), who leverage individual- and ship-level

skill-biased, skill-replacing, or featured more nuanced, task-biased effects. Although weaving automation has often been described as deskilling, our results show that it was both skill-biased (for male mechanics), and displacing and reinstating (for female weavers). This supports a flexible task-based perspective of technological changes, in line with evidence from aggregate statistics (Gray, 2013; Katz and Margo, 2014; Fiszbein et al., 2020), other historical contexts (Chin et al., 2006), and modern automation (Autor et al., 2003, 2006; Acemoglu and Autor, 2011). The key lies in which tasks the particular technology displaces and creates, and how different worker skills match these tasks.

Second, our findings underscore labor-market frictions and monopsony power in shaping the consequences of technological change. Most studies assume perfect labor market competition and attribute wage or employment outcomes solely to changes in factor marginal productivity. This view neglects the short-run struggles workers face to secure their jobs and a fair share of the gains from new machinery.[2] Instead, recent studies find that disruptive, labor-saving technologies often provoked labor unrest and conflicts (Caprettini and Voth, 2020; Molinder et al., 2021), indicating employers' power in the frictional labor market. Our results reveal an inelastic labor supply faced by factories and limited rent-sharing, reflecting monopsony power (Manning, 2003; Card et al., 2018), which dampened the potential employment and wage gains from technological advances.

Third, our results highlight the roles of market dynamics and market competition as key drivers of technological unemployment. While the displacement of hand spinners and weavers during industrialization is often cited, little is known about how this process unfolded at the factory and market levels. Recent studies of modern automation (Acemoglu et al., 2020, 2023; Aghion et al., 2023) show that displacement often occurs not within adopting firms, where employees shift to new tasks (Dauth et al., 2021; Battisti et al., 2023), but instead among less-productive competitors forced out by product market competition ("business stealing"). Our findings corroborate this pattern historically: Sectoral employment declined not through job losses in adopting plants but through exiting of low-wage, low-productivity factories driven out by intensified competition in product and labor markets.

2 Historical Background

Following the 1868 Meiji Restoration, the textile sector served as the cornerstone of Japan's early industrial transformation, much like in Britain's first Industrial Rev-

data to study the shift from sail to steam in merchant shipping industry, and Feigenbaum and Gross (2020), who track individual census records to study the displacement of female telephone operators by mechanical switching.

[2]This omission is particularly striking given that historical labor markets were long characterized by strong employer power and coercion (Acemoglu and Wolitzky, 2011; Delabastita and Rubens, 2022; Paker et al., 2025)

olution. This led to the adoption of Western technologies and organizations, and accounted for over one-third of manufacturing output until the 1930s. Within textiles, weaving constituted about 40% of total production, of which over one-third was silk weaving. Our analysis focuses on the silk-weaving industry in Fukui Prefecture during the 1900s and 1910s, where it dominated local manufacturing, accounting for nearly 80% of total output and employment. Over 95% of Fukui's silk-weaving production was a plain silk fabric, *habutae*, largely exported to Western markets. By this period, Fukui had become Japan's largest *habutae*-producing district, supplying over one half of the national output. Figure 1 presents key statistics on Fukui's silk weaving industry between 1905 and 1914, drawing on the Fukui *Statistical Yearbook*.[3]

Around the turn of the twentieth century, Fukui's weaving industry underwent two major transformations. The first was organizational: a shift from home production (under the putting-out system) to factory-based production. The second, our main focus, was technological: a rapid transition from handlooms to powerlooms. Although often treated as concurrent in the literature, in Fukui the organizational transformation preceded mechanization: By the mid-1900s, nearly one half of Fukui's weaving workforce was already in factories with ten or more workers, and subsequent powerloom diffusion occurred predominantly within these "disciplined" factories. Figure 1a illustrates this diffusion: Between 1905 and 1914, the number of powerlooms rose from near zero to over 7,000, while handlooms declined from more than 10,000 at their peak to around 2,000 by 1914. By 1914, over 70% of factories had adopted powerlooms. Historians commonly attribute this swift transition to access to electricity and domestic powerlooms.[4] This fast adoption within organized factories offers an ideal context for identifying its labor market impact, minimizing confounding shifts.

Powerlooms substantially altered production processes and worker tasks. During this period, distinct tasks were carried out by different demographic groups. Adult women formed the core workforce, operating hand-and-foot-driven looms to weave raw silk threads into fabric. Child workers constituted roughly 20% of the workforce, assisting with simple preparatory tasks until they reached weaving age.[5] Adult men, fewer than 10% of workers, primarily performed engineering tasks.[6] Under handloom production, each female weaver operated a single loom, executing routine manual steps in shuttle manipulation, warp regulation, and weft beating. Powerlooms auto-

[3] Appendix A provides a more detailed description of the historical context.

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

[5] A heavy reliance on female and child labor was also prevalent in British and American textile industries during early industrialization, typically as cheap, idle, and unskilled labor (Goldin and Sokoloff, 1982; Humphries and Schneider, 2019). Inoue (1913) instead attributes women's prevalence in silk weaving to their superior finger dexterity and patience with delicate work compared to men.

[6] Noshomusho (1903): "Male workers in weaving factories are generally limited to pattern designers and machine operators (who set up looms and repair equipment)."

mated these routines, freeing weavers to handle resupplying threads, knotting broken threads, and monitoring machine function. This allowed one worker to manage two or more powerlooms, breaking the nearly one-to-one relationship between the number of handlooms and female workers (Figure 1a). Despite being less routine, these new tasks required comparable or greater dexterity and attentiveness, drawing on many of the same skills used in handloom weaving.[7] Contemporary reports indicate a two- to threefold increase in labor productivity through faster machine speeds and multiple looms per worker, consistent with our calculations in Figure 1c showing annual *habutae* output per worker rising from 30 to 80 pieces.[8] Powerloom adoption also created new tasks for adult men—installing and maintaining power machinery—that required specialized skills.[9]

The labor supply of female workers in silk-weaving factories drew heavily from nearby peasant families, yielding segmented local labor markets within Fukui.[10] Labor turnover was high at the plant level, because most female workers were young and unmarried, seeking temporary employment before marriage, and remaining only a few years.[11] Factory owners commonly imposed obligation periods into labor contracts to deter departures and formed associations to curb poaching, though such agreements were not always binding.[12] Some also opened branch facilities in rural areas to secure additional, low-cost workers. Typically, female weavers were paid on a piece-rate basis, while men and child workers received daily or monthly wages. As shown in Figure 1d, adult males consistently earned about 20% more than adult females, and child workers received less than one half the adult rate.

3 Data

The *Statistical Yearbook* published by Fukui Prefectural Government provides annual data on factories with ten or more workers between 1904 and 1919. It reports

[7] Inoue (1913) notes that reconnecting broken silk threads demanded significant dexterity; workers trained on handlooms adapted better to powerlooms—a point often overlooked by short-sighted employers.

[8] Fukui Prefecture (1911) and Inoue (1913) estimate a worker with one handloom could produce 3–4 pieces (*biki*) of fabric per month, whereas operating two powerlooms yielded 14–16 pieces. Sanbe (1961) similarly finds that moving from one handloom to two powerlooms increased daily output of a worker from 1.5 to 4 rolls (*tan*). See also Okazaki (2021) for comparable estimates from production function estimations.

[9] Inoue (1913) observes that new "mechanical workers" were introduced alongside powerlooms to handle lubrication, repairs, and overall machine management, often drawn from graduates of local industrial training institutes.

[10] Fukui City (1994) and Fukushima Prefecture (1910) report that by the late 1900s, most female workers were commuting from nearby areas. Kandachi (1974) finds that most workers in Harue Village of Sakai County, a local weaving center, came from within the village or neighboring villages in the same county.

[11] Noshomusho (1903) reports that more than 90% of female workers were under 25 and had tenure under 5 years in 1901.

[12] Inoue (1913) notes that poaching occurred mainly when orders were high and the labor supply was short, and was achieved by luring skilled workers with higher wages.

plant specifics including plant name, location, owner's name, foundation year, major product, power source, daily operating hours, and, from 1913 onward, production values. It also records the number of male/female/child workers and their average daily wages. Adult workers were defined as those over 14 years until 1914, and over 15 years from 1915 onward. We hence focus on 1904–1914 to avoid both this definitional change and the World War I boom. We identify silk-weaving plants as those producing *habutae* or other silk fabrics. Among these, any plant reporting inanimate power use is classified as a "powerloom" plant, and others as "handloom" plants. Although steam and gas occasionally appeared, about 90% of power sources were electrical.

To construct our plant-level panel, we link plants across years using plant name, owner's name, location, and foundation year.[13] This yields 1,317 distinct plants and 4,622 plant-year observations spread across eight counties (including Fukui city) and 121 distinct areas (towns or villages).[14] The panel is unbalanced, with extensive entries and exits and an average of 3.5 observation years per plant. We define a plant's entry (exit) year as the first (last) year it appears in the data. Among 382 plants reporting power use in at least one year, only 133 appear initially with power (powered entrants), indicating most adoption occurred in incumbent handloom factories.[15]

4 Plant-level Analysis

We now investigate how powerloom adoption affected factory labor use and wages using event study and Difference-in-Differences (DiD) approaches. Our comparison contrasts adopting (treated) and nonadopting (non-treated) plants within the same local area (town or village), which presumably share similar labor demand and supply shifters aside from the new automation technology. For this exercise, we exclude 38 plants that discontinued power use after initially adopting it (treatment discontinuation) and 133 plants that entered the dataset already powered (no pre-treatment observations).

Specification. Let Y_{iat} denote the outcome (e.g. log employment, log average wages, or plant working hours) for plant i in area a at time t. Our event study

[13]Given possible documentation errors, we use a fuzzy-matching strategy. Plants in different years are treated as identical if they share the same location and at least two of the other three identifiers.

[14]We dropped 2 counties (Onyu, Oi) where the *habutae* industry was minimal. See Table A7 for summary statistics.

[15]Although some entries (exits) may reflect plants moving above (below) the 10-worker threshold, we find over two-thirds of these 133 list a foundation year matching or near their dataset entry year, suggesting that our entry measure reflects genuine plant start-up.

specification is:

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

where G_i is the first year plant i adopted power, α_i is a plant fixed effect, and δ_{at} is an area-by-year fixed effect. Coefficients γ_k capture the dynamic effects pre- and post-event, relative to the year -1 (which is normalized to zero). The area-by-year fixed effects control for unobserved shocks common to all factories in the same local area. Identification of the average treatment effects of treated requires that changes in Y_{iat} at nonadopting plants within area a provide a valid counterfactual for changes at adopting plants, i.e. the parallel trends assumption.[16] Because conventional two-way fixed effects (TWFE) estimators can incorporate undesired comparisons across different treatment cohorts, we use the Sun and Abraham (2021) estimator that explicitly utilizes never-treated and last-treated (1914) cohorts as the control groups. For completeness, we also report TWFE estimates from a pooled DiD specification:

$$Y_{iat} = \gamma D_{it} + \alpha_i + \delta_{at} + \epsilon_{it}, \tag{2}$$

where D_{it} is an indicator for being in the post-adoption period. This collapses all post-event dynamic effects into a single treatment effect, γ. Throughout, standard errors are clustered by plant.[17]

Results. Figure 2 plots the event-study estimates of γ_k for four periods before and after power adoption. Following powerloom adoption, male adult employment rises significantly: about 0.2 log points at the year of adoption, rising to 0.4 log points since the second year. Since treated plants employ 3.3 adult males on average before adoption, this translates into roughly 1.6 additional adult male workers one year after adoption.[18] In contrast, adult female employment remains essentially unchanged, with coefficients near zero apart from a small negative effect at the adoption year. Hence, replacing handlooms with powerlooms did not reduce the main workforce (averaging 21.4 adult females per plant pre-treatment) relative to

[16] Note that this assumption does not require the adoption to be exogenous and free of selection. In fact, adopting plants tend to have larger employment, on average (Figure A4b), mirroring modern results that larger, more productive firms are more likely to adopt automation robots (Koch et al., 2021; Acemoglu et al., 2022). As discussed in the theoretical framework in Appendix C, this selection is consistent with more efficient firms facing higher marginal labor costs, thus benefiting more from labor-saving technologies.

[17] All main findings are robust to clustering at the area level instead.

[18] We exclude plant-year observations with zero male workers from the log specification, so a shift from zero to a positive number is not captured. In a levels specification (zero observations retained) the estimated increase is two adult male workers, though that relies on parallel trends in levels, which can overstate the effect if the control group employs fewer male workers (Roth and Sant'Anna, 2023). A Poisson approach, which maintains a growth parallel-trend assumption and includes zeros, closely matches the log-employment results; see Appendix Table B1.

nonadopters. For child workers (6.8, on average, pre-treatment), coefficients are negative, but not statistically significant, in some post-treatment years. Operation hours also remain unchanged, hovering around 11.3 hours per day both pre- and post-treatment. Overall, the salient difference is a rise in male adult employment, with neither female employment nor operating hours systematically affected.

Turning to wages, Figure 2 indicates that both adult male and adult female log wages rise by about 0.05 log points in the adoption year, reaching roughly 0.1 log points from the second year onward. These parallel increases are statistically significant for most post-adoption periods. By contrast, child wages show a roughly 0.1 log point decline, yet only the immediate adoption-year estimate is significant due to larger standard errors in subsequent years. Hence, powerloom adoption is associated with a 10% wage gain for adult workers compared to their counterparts in non-adopting factories, while children experience no wage gains and possibly wage losses.

Table 1 corroborates these patterns and shows additional outcomes (plant overall employment and daily wage bills) using the DiD specification in Equation 2, which provides a single coefficient summarizing the treatment effect. The estimated coefficients are 0.33, 0, and -0.11 for adult male, adult female, and child employment, respectively, and 0.07, 0.07, and -0.04 for their average wages. Only adult male employment and the two adult wage coefficients are statistically significant. In addition, overall plant-level employment has a small positive but insignificant coefficient (0.04), reflecting the fact that the increase in male workers is modest relative to the stable female workforce. Average plant wages rise in line with adult wages. Finally, adult male wage bills (a product of employment and daily wages) increase by about 0.4 log points, while adult female wage bills increase by only 0.07 log points (not statistically significant). Total wage bills rise by 0.12 log points. Given the substantial capital costs of powerlooms, this implies a likely decline in the labor share of value added.[19]

Robustness. Our event-study plots reveal minimal evidence of pre-trends, suggesting that treated and control plants followed parallel paths (conditional on area-by-year fixed effects) prior to adoption. To further verify the parallel-trends assumption, we employ the sensitivity methods of Rambachan and Roth (2023), which assess how vulnerable our estimates are to potential parallel trends violations. The robustness checks in Figures B3 and B4 show that to overturn our significant post-treatment estimates, parallel-trend violations would have to exceed either the maximum observed pre-treatment deviation or the magnitude of the estimated treatment effects themselves.

We also verify the event-study findings using alternative estimators. Besides

[19]Table A4 shows a contemporary business accounting that compares handloom and powerloom operations and corroborates this finding.

our baseline approach (Sun and Abraham, 2021), we implement the procedures of Callaway and Sant'Anna (2021), De Chaisemartin and d'Haultfoeuille (2020), and Borusyak et al. (2021), as well as a standard TWFE regression (Figure B2). All yield similar results, suggesting the "negative weights" issue in staggered adoption is limited here, consistent with only moderate post-treatment dynamics. It also validates the simple TWFE estimator used in the pooled DiD specification.

Interpretation. We now interpret our plant-level findings through the lens of economic theories. A full theoretical account can be found in Appendices C and D.

First, relative to non-adopting, surviving competitors, powerloom adoption substantially increases the employment of adult male mechanics but leaves female and child employment unchanged. This pattern aligns with skill-biased (or routine-biased) technological change, as the new technology increases demand for skilled workers performing nonroutine mechanical tasks relative to routine manual labor. Although technological change during early industrialization is often portrayed as "deskilling" (Goldin and Katz, 1998; Acemoglu, 2002), our results complement other recent studies (Chin et al., 2006; Katz and Margo, 2014; Fiszbein et al., 2020) in highlighting a simultaneous upskilling dimension. The concentrated effect during the first two years of adoption is also consistent with the idea that skilled labor demand manifests most during the implementation of new technologies (Greenwood and Yorukoglu, 1997).

Second, the fact that female weavers are neither displaced nor in greater demand, despite a more than twofold increase in their productivity, can be well accounted for by offsetting effects in a task-based framework (Acemoglu and Restrepo, 2018, 2019a,b). On one hand, powerlooms completely automate the manual tasks of operating handlooms, reducing demand for female weavers ("displacement effect"), but on the other hand, they create new tasks of managing multiple powerlooms that the same workers can perform ("reinstatement effect"), and boost output per worker ("productivity effect"), both raising demand for female workers. When these effects are all sizable yet offset each other, the net change in labor demand can remain minimal even as average labor productivity significantly rises, reducing labor share, as observed in our case.

Third, the contrasting pattern of stable female employment but rising female wages implies that individual factories faced an inelastic labor supply. Under a perfectly competitive labor market with an infinitely elastic labor supply, an increase in a plant's labor demand would raise employment but not wages, resulting in no wage response observed from the event-study analysis. Instead, labor market frictions and monopsony power can yield the observed outcome, an interpretation consistent with historical accounts of limited mobility among female workers. By contrast, the adult male labor supply appears more elastic, as reflected in the larger rise in employment than wages, which is intuitive given their small overall presence in the silk weaving industry.

Fourth, female weavers' wage gains can also be viewed as rent sharing. A simple calculation for doubled or tripled productivity but only a 10% wage increase suggests a pass-through rate of 5–10%, aligning well with the lower bound of the estimates in the rent-sharing literature (Card et al., 2018). Clear evidence of this low pass-through also comes from archival sources noting that piece rates for powerloom weavers were set at roughly half those for handloom weavers within the same year and factory (Fukushima Prefecture, 1910; Inoue, 1913; Fukui Prefecture, 1994). This illustrates that employers captured much of the automation-generated surplus.

Fifth, compensating differentials provide another possible explanation for wage increases if powerlooms changed working conditions. Yet we find no difference in operation hours between powerloom and handloom plants, and it was noted that young women preferred powerloom work for less physically demanding tasks and higher pay (Inoue, 1913). If anything, compensating differentials would have reduced wage gains rather than inflated them.

Lastly, even with pre-treatment parallel trends, treatment-induced equilibrium spillovers onto the control group can violate the stable unit treatment value assumption (SUTVA) required for valid post-treatment comparisons. Imperfect labor market competition, as discussed, makes such spillovers a relevant concern. While a direct estimation presents challenges, economic theory can help predict their signs and magnitudes (Minton and Mulligan, 2024). Berger et al. (2022) show that under an oligopsonistic market framework, one firm's increased labor demand can lead competing firms to reduce employment but raise wages, and the magnitude of these spillovers hinges on each firm's labor supply elasticity. Our DiD estimates of no net rise in female adult employment suggest minimal employment spillovers; otherwise, the estimated effect would likely be positive. In contrast, wage spillovers for adult females are more plausible and may cause us to underestimate the wage gains from powerloom adoption. For adult males, a higher labor supply elasticity likely tempers such spillovers. An event study using area-level adoption on non-adopting plants finds small yet significant spillovers only for female wages, aligning with these theoretical predictions (Figure E1). Thus, concerns about spillovers do not materially alter our discussions above. Nevertheless, because our analysis focuses on adopting and non-adopting plants that survived, it does not capture another potential spillover channel—plant exit—which we examine in the next section.

5 Market Dynamics

Our plant-level findings show that powerloom adoption raises male employment and leaves female employment unchanged, yet aggregate statistics reveal a decline in female employment coinciding with the diffusion of powerlooms (Figure 1a). Moreover, the sector-level wage in Figure 1d rises more sharply than our plant-level estimates suggest. The missing piece that can reconcile this discrepancy is likely market dynamics. Figure 1b shows a marked reduction in the number of silk-weaving factories soon after powerlooms spread, implying that market selection may drive both employment decline and stronger sectoral wage growth. In this section, we show that local areas experiencing faster power adoption underwent greater net exit and rising market concentration. This pattern was driven primarily by the exit of low-wage, low-productivity plants, whcih is attributable to intensified competition in product and labor markets.

Impact on Market Structure. To study how powerloom adoption affected market structure, we estimate variants of the specification:

$$Y_{at} = \mu E_{at} + \alpha_a + \delta_t + \epsilon_{at}, \tag{3}$$

where Y_{at} are measures of market structure at the area level, including the number of factories, Herfindahl-Hirschman Index (HHI), three-firm concentration ratio (CR3), and yearly exit rate. We define $E_{at} \equiv \sum_{i \in a} s_{it} D_{it}$ as employment-weighted power-adoption intensity in area a, where s_{it} is the employment share of plant i in area a. We now include all plants in the panel, including the power discontinuers and powered entrants excluded from the plant-level analysis. Area fixed effects α_a and year fixed effects δ_t absorb time-invariant area characteristics and common time shocks. The key coefficient μ captures the net effect of all power intensity changes, which arises mainly from three events: powered entrants, exit of non-adopters, and adoption by incumbents.[20] A potential threat to identification is the presence of unobserved factors affecting both power adoption and market structure, such as local shocks in product demand or labor costs. To address this, we employ two additional strategies. First, we instrument for area-level power intensity E_{at} using access to newly launched electricity stations. Over the sample period, four stations began operation at different locations, each covering a specific set of areas. Construction typically spanned two to three years and was subject to delays, making the timing plausibly exogenous to local market shocks. Second, we estimate a long-difference version of Equation (3), replacing Y_{at} and E_{at} with the differences between average values in the early (1904–1906) and late (1912–1914) periods. This specification focuses on longer-run variation, filtering out any confounding shorter-run market fluctuations. For all specifications, standard errors are clustered at the area level.

Table 2 Panel A reports the baseline OLS estimates of Equation (3). A shift in area power intensity from 0 (no adoption) to 1 (full adoption) is associated with

[20] Although changes in incumbent plants' employment and other events such as nonpowered entrants and powered exits can also affect intensity, these variations are either small or scarce in practice.

a net reduction of 1.1 plants (from a pre-treatment average of 5.3) and increases in HHI and CR3 of 0.07 and 0.08 (from 0.44 and 0.62), respectively, all statistically significant. For area exit rate, we add a quadratic intensity term to capture non-monotonicity; the estimated coefficients are 0.29 (linear) and -0.38 (quadratic), both significant, indicating exit rises with power intensity initially but declines at higher intensities.[21] Panel B and C present IV and long-difference estimates for the number of plants and concentration measures. These estimates point in the same direction but are larger in magnitude: For instance, the coefficient on the number of plants is -2.6 in the IV specification and -1.5 in the long-difference, each statistically significant. This suggests that some of the OLS variation may reflect confounding market forces operating in the opposite direction, while the larger IV coefficients may capture local average treatment effects associated with electricity introduction. Overall, these findings suggest that areas with greater powerloom adoption experienced net factory exit and higher market concentration relative to nonadopting areas. Since areas averaged about five plants before adoption and reached about 0.7 power intensity by the final year, the exit of one or two plants can account for much of the 20–30% aggregate employment decline observed in Figure 1a.[22] We next examine the characteristics of exiting factories to understand the mechanics of this market restructuring.

Characterizing Exit, Entry, and Competition. To understand which factories exited the market and why, we compare the wage and labor productivity distributions of exited plants, surviving plants, and power-adopting entrants. Exit, survival, and entry are defined annually, with exit or survival referring to a plant's status in the following year. We classify each area-year as "adopting" if any local plant reports power use, and "nonadopting" otherwise. Figure 3a pools data from 1907 to 1913 (the period of rapid diffusion) and shows real wage distributions for these three groups in adopting versus nonadopting areas. In nonadopting areas, exited and surviving plants display similar wage distributions. By contrast, in adopting areas, surviving that plants' wage distribution shifts rightward relative to exits, suggesting lower-wage establishments are disproportionately driven out. Moreover, power-adopting entrants in these areas exhibit a distribution further to the right, implying that they pay substantially higher wages than incumbents. Figures E3 and E4 confirm these patterns for individual years.

Figure 3b replicates this analysis for labor productivity in 1913—the only year

[21] The estimated quadratic relationship implies that the exit rate peaks at an area power intensity of $-(0.29)/(2 \times -0.38) \approx 0.38$, higher than the sample mean power intensity of 0.26.

[22] A potential concern is cross-area spillovers and a "missing intercept" issue. If nonadopting areas also experienced net exit due to inter-area competition, we might understate the local effects of adoption on market structure. Although such effects may help account for some of the sector-wide changes, comparing aggregate trends with our estimates suggests that these spillovers are relatively small, implying more intense within-area than between-area competition.

with both production values and entry/exit records. Although surviving plants have more right-skewed productivity than exits in both nonadopting and adopting areas, the gap is again larger in adopting areas. Notably, adopting entrants display a productivity distribution similar to that of survivors, suggesting their higher wages cannot be justified by productivity differences but indicate the existence of wage premiums. This again aligns with frictional labor-market theories, in which firms offer higher wages to attract workers. Taken together, the spread of powerlooms appears to induce strong selection, eliminating low-wage, low-productivity firms while admitting new entrants that pay elevated wages. This market-wide selection explains both why the drop in overall market employment occured and why market wages rose faster than our plant-level estimates indicate.

Historical accounts suggest that both product-market and labor-market competition contributed to these dynamics. Although *habutae* was largely a homogeneous export product, it varied in quality and was often sold as local brands by local associations. Powerloom production required higher-quality raw silk and produced more uniform, higher-grade goods (Fukushima Prefecture, 1910; Fukui Prefecture, 1994). As a result, expanding powerloom output likely eroded profits at smaller handloom factories through local monopolistic competition. Simultaneously, wage increases at power-adopting plants, especially among new entrants, put upward pressure on wages at handloom factories via oligopsonistic competition or higher workers' outside options. Less productive firms unable to match these higher wages could lose workers and ultimately exit. Contemporary sources confirm this pressure: "since powerloom diffusion, active recruitment is limited to handloom factories, which pay lower wages for more laborious work" (Inoue, 1913), and "handloom female weaver' wages could not possibly match those of powerloom operators" (Fukushima Prefecture, 1912).

6 Conclusion

Recent studies of modern automation often cite the mechanization of spinning and weaving during the Industrial Revolution as a classic example of technological unemployment, despite limited quantitative evidence. Exploiting a newly constructed plant-level panel dataset, this paper examines the rapid adoption of powerlooms in early twentieth-century Japan's silk-weaving sector and finds a more nuanced reality than standard accounts suggest. Although powerlooms automated handloom operation, displacing female weavers' core tasks, adopting factories did not reduce their female workforce. Instead, female workers were reinstated to newly created tasks of monitoring powerlooms, and additional adult male mechanics were hired to install and maintain power machinery. These surviving female weavers experienced wage gains, but these gains were modest relative to the surge in productivity, indicating limited rent-sharing and strong employer power. Moreover, overall industry employment declined significantly as low-wage, low-productivity factories exited under intensified product and labor market competition. These findings underscore that the nature of technology, monopsony power, and market dynamics all play critical roles in shaping the labor market impact of automation technologies.

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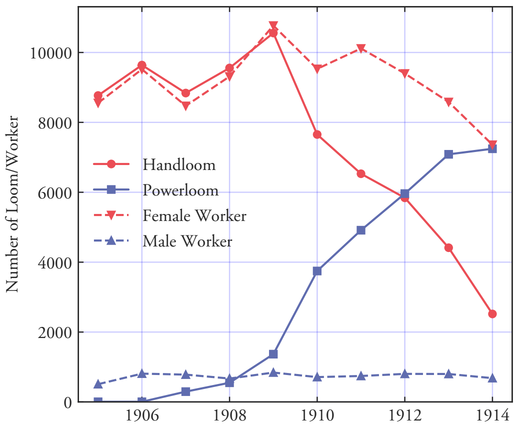
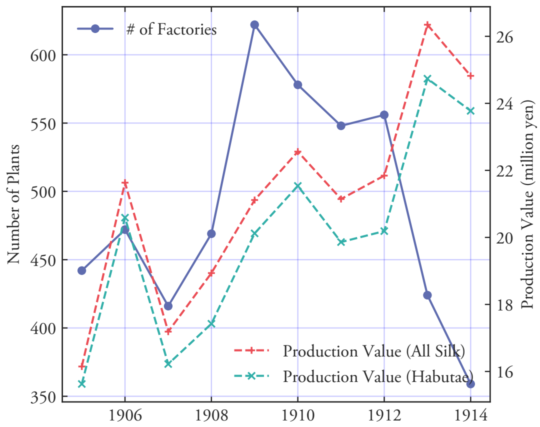
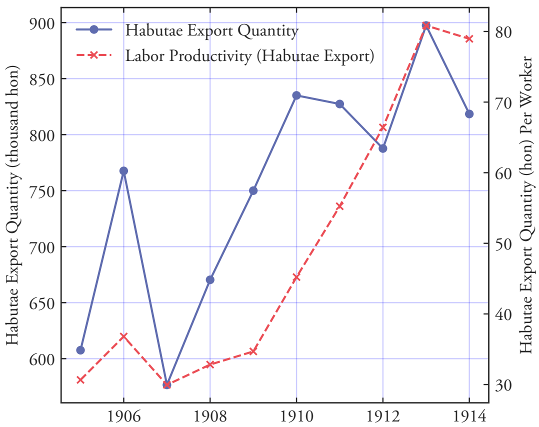
Figure 1: Trends of Fukui's Silk-weaving Industry



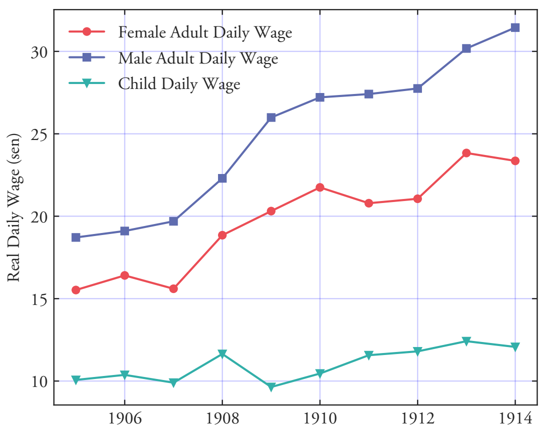
(a) Total Number of Machines and Workers



(b) Number of Factories and Total Output



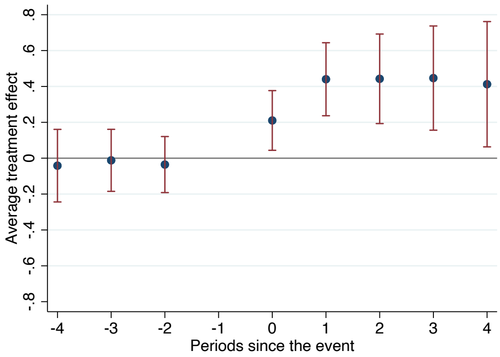
(c) Habutae Export Quantity and Labor Productivity



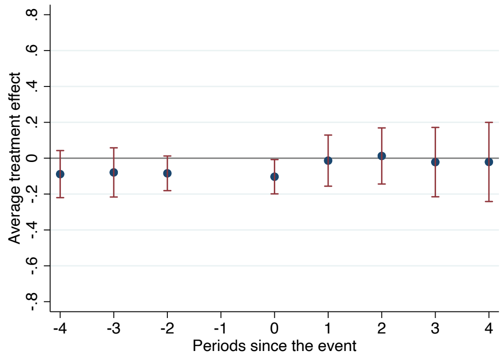
(d) Real Average Daily Wages

Note: All figures here use the data from the Fukui Prefecture *Statistics Yearbook*. The aggregate statistics of total machines and workers in Panel a and total number of plants in Panel b are for all factories in the silk-weaving industry of Fukui and are directly available in the statistics book. The *Statistics Yearbook* defines "factory" as any plants employing 10 or more workers, whereas plants with fewer workers are defined as home producers, whose trends are shown in Figure A2. The numbers of female and male workers in Panel a include both adult (older than 14 years old) and child workers. The production values in Panel b and the *habutate* export quantity in Panel c were also directly from the *Statistics Yearbook*, but they aggregate all types of business units and thus include the production of not only factories but also home producers and putting-out producers. The labor productivity in Panel c is calculated by dividing the total export *habutate* quantity by the total export *habutate* production workers. The real average daily wage in Panel d is not directly documented but calculated using the plant micro data collected from the same *Statistics Yearbook*. The wage is weight by plant employment and inflation-adjusted using the national price index published by Bank of Japan, with the year 1904 as the benchmark year.

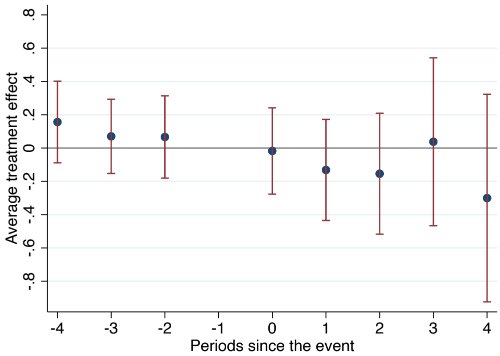
Figure 2: Plant-Level Impacts of Power Adoption on Employment and Wage



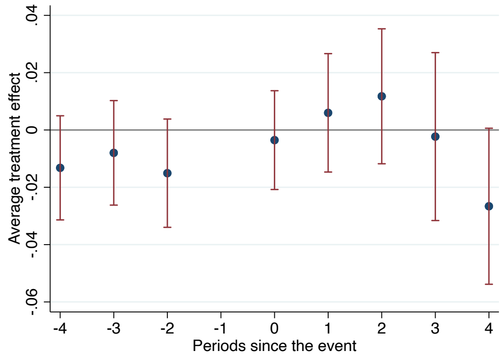
(a) ln(Male Adult Employment)



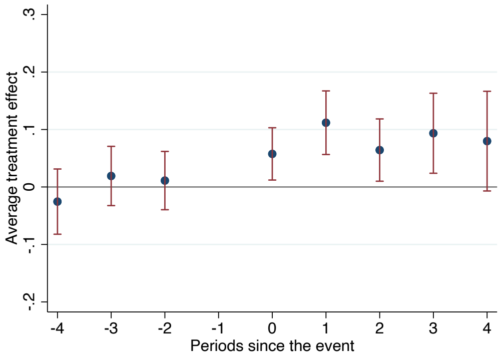
(b) ln(Female Adult Employment)



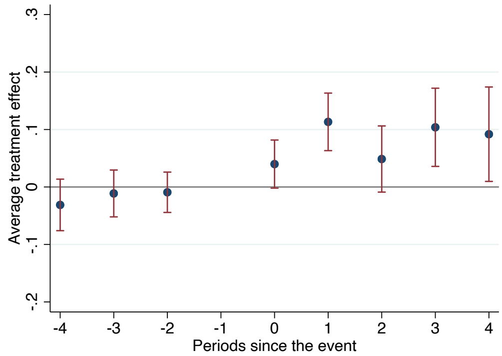
(c) ln(Child Employment)



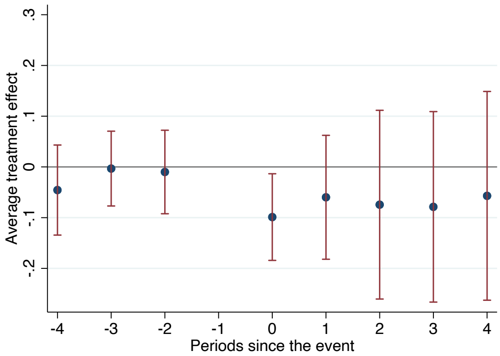
(d) ln(Operation Hours)



(e) ln(Male Adult Daily Wage)



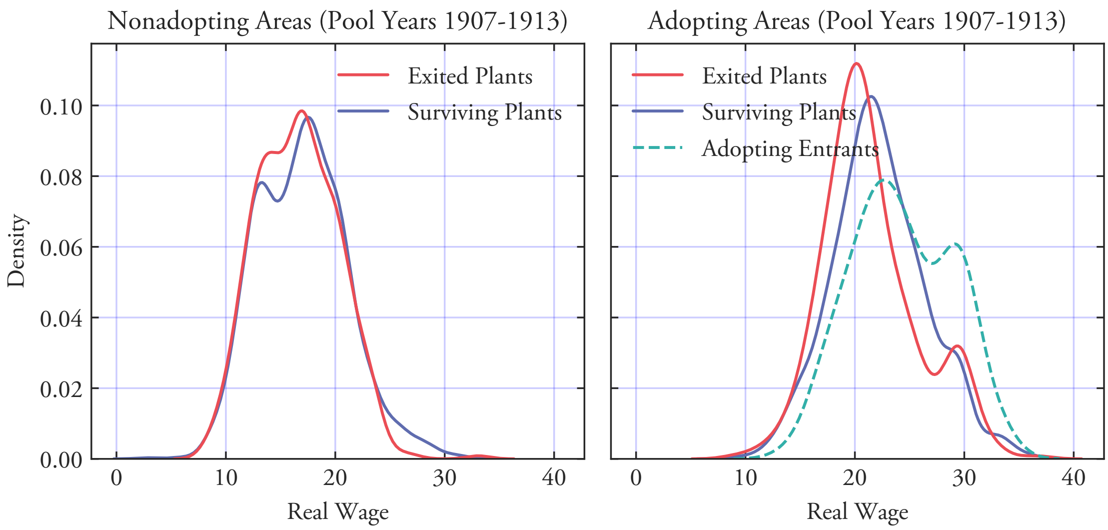
(f) ln(Female Adult Daily Wage)



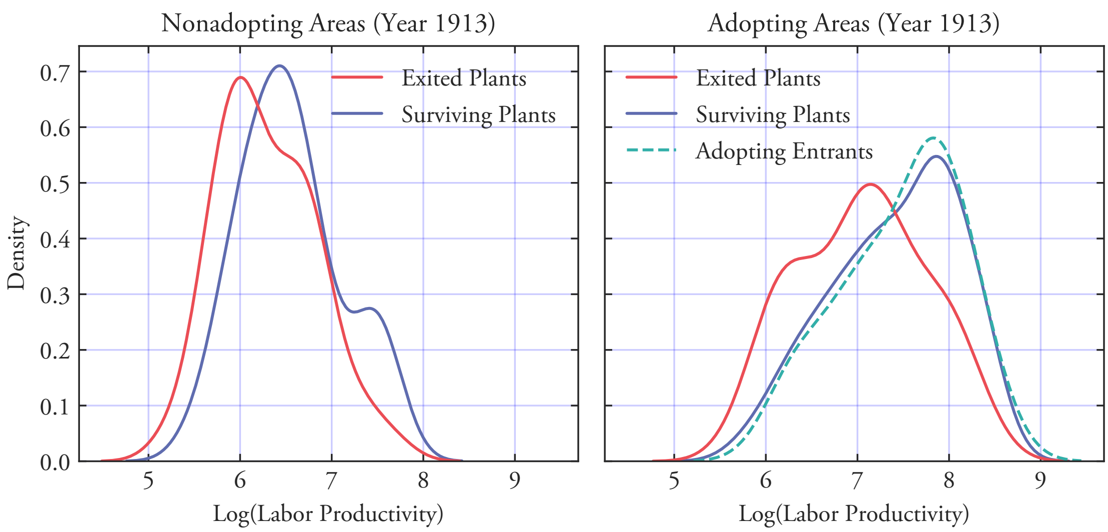
(g) ln(Child Daily Wage)

Note: This figure presents the results of the event-study specification in Equation (1) for various plant-level outcomes. Dots represent the estimated coefficients γ_k for each lead and lag event-time dummy relative to powerloom adoption, and error bars show 95% confidence intervals based on standard errors clustered at the plant level. Each regression includes plant fixed effects and area-by-year fixed effects. The estimation follows Sun and Abraham (2021), using never-treated plants and last-treated (1914) cohorts as control groups.

Figure 3: Wage and Productivity Distributions of Exited and Surviving Plants in Nonadopting versus Adopting Areas



(a) Real Wage Distribution



(b) Labor Productivity Distribution

Note: Panel a shows the distributions of real daily wages for plant-year observations from 1907 to 1913, deflated to 1904 levels using the Bank of Japan's national price index. Each area-year is classified as "nonadopting" if it has no powered plants, and "adopting" if at least one plant reports power use. For any year t, a plant is labeled "exited" if it no longer appears in year $t+1$; otherwise, it is "survived." "Adopting entrants" are newly observed powered plants in their first year. These classifications are time-variant and not mutually exclusive: The same plant can be "survived" and "adopting entrants" in one year and "exited" in the next. Panel b plots the distributions of labor productivity in 1913, measured as a plant's total production value divided by total employment.

Table 1: 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 Ln(Employment)				
Power	0.329	0.000	-0.110	0.047
	(0.071)	(0.050)	(0.117)	(0.043)
Pre-treatment Mean	3.33	21.42	6.76	28.24
N	2,171	3,484	2,068	3,488
Panel B: Effect on Ln(Operation Hours)				
Power				0.008
				(0.007)
Pre-treatment Mean				11.30
N				3,485
Panel C: Effect on Ln(Daily Wages)				
Power	0.071	0.071	-0.044	0.076
	(0.020)	(0.016)	(0.037)	(0.016)
Pre-treatment Mean	24.90	19.93	11.61	19.27
N	2,167	3,483	2,035	3,488
Panel D: Effect on Ln(Wage Bills)				
Power	0.401	0.072	-0.111	0.123
	(0.077)	(0.053)	(0.126)	(0.048)
Pre-treatment Mean	83.59	429.13	80.69	540.17
N	2,167	3,483	2,035	3,488

Note: This table reports DiD estimates (γ) from Equation (2) for various plant-level outcomes. Panel A considers log employment, Panel B operation hours, Panel C log average wages, and Panel D log wage bills (employment multiplied by average daily wage), each by worker category. The unit of observation is a plant-year. "Pre-treatment mean" refers to the average of the dependent variable in levels (non-logarithmic units) for eventually treated plants prior to adoption. Observations with missing or zero values for the outcome are excluded. All specifications include plant fixed effects and area-by-year fixed effects. Standard errors are clustered at the plant level and reported in parentheses.

Table 2: The Area-Level Effect of Power Introduction on Market Structure

	(1) # of Plants	(2) HHI	(3) CR3	(4) Exit Rate
Panel A: OLS				
Area Power Intensity	-1.076	0.073	0.083	0.289
	(0.328)	(0.037)	(0.032)	(0.127)
Area Power Intensity^2				-0.380
				(0.125)
Pre-treatment Mean	5.32	0.44	0.62	0.18
N	941	941	941	941
Panel B: IV				
Area Power Intensity	-2.648	0.333	0.323	
	(1.269)	(0.098)	(0.107)	
First-stage F	102.73	102.73	102.73	
Pre-treatment Mean	5.32	0.44	0.62	
N	941	941	941	
Panel C: Long-difference				
Area Power Intensity	-1.512	0.134	0.124	
	(0.651)	(0.071)	(0.069)	
Pre-treatment Mean	4.93	0.51	0.67	
N	81	81	81	

Note: Panel A reports OLS estimates (μ) of the two-way fixed effects specification (TWFE) in Equation (3), regressing market-structure outcomes on area-level power intensity. Area power intensity is defined as the employment-weighted average of plant-level power indicators within each area and year. Panel B shows IV estimates using an indicator of power-station availability as an instrument for area power intensity. Panel C presents long-difference estimates, where both the outcome and power-intensity variables are replaced by their differences between the average values in early period (1904–1906) and the late period (1912–1914). "Pre-treatment mean" is the average of the dependent variable for adopting areas prior to adoption. All regressions include area and year fixed effects, and standard errors (in parentheses) are clustered by area.

Online Appendices

A Historical Background: More Detail

This section provides additional historical context on the silk-weaving industry in Fukui, Japan during the early twentieth century.

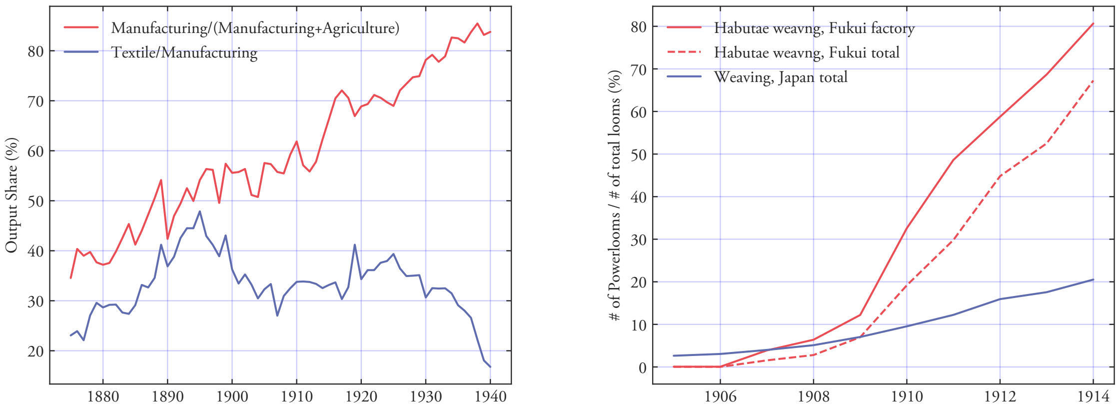
General Background. Japan's transformation from a feudal society to a global industrial power began following the Meiji Restoration of 1868, which catalyzed the adoption of Western technologies and institutions. This period marked a significant economic acceleration, with real GDP per capita growth rising to 1.68% during 1870–1920 from just 0.19% in 1820–1870 (Maddison Historical Statistics). Manufacturing's share of overall economic production more than doubled during this period, underscoring industrialization's central role in Japan's modern economic growth. Mirroring Britain's earlier industrialization pattern, the textile industry served as the cornerstone of Japan's industrial transformation, accounting for over 30% of total manufacturing output between 1880 and 1930 (Figure A1a). The textile industry comprised two principal subsectors: thread production (silk reeling and cotton spinning) and fabric production (silk and cotton weaving). The weaving industry alone contributed 39% of textile production and 12% of total manufacturing output in 1909, rising to 42% and 13%, respectively, by 1914 (Table A1).

The early twentieth century witnessed profound organizational and technological transformations within Japanese manufacturing, particularly in the weaving industry. Factories—defined in official Japanese statistics as plants employing 10 or more workers—proliferated during this period. In 1905, only 12.3% of weaving workers were employed in factories (Table A2), but by 1914, this proportion had more than doubled to 26.7%, highlighting the sector's rapid industrialization. Concurrent with this organizational transition was a marked technological shift as powerlooms became increasingly prevalent. The ratio of powerlooms to total looms (including both powerlooms and handlooms) rose from merely 2.6% in 1905 to 20.5% by 1914 (Figure A1b). This percentage was substantially higher within factories, suggesting a strong complementarity between factory-based production systems and mechanization.

Fukui and *habutae*. Among Japan's exported silk fabrics in the late 19th and early 20th centuries, the most prominent product was a plain silk fabric called *habutae*.[23] While the earliest export attempts occurred in the Kiryu area of Gunma

[23] The name is believed to derive from either "bird feathers layering" or "two warps layered like feathers."

Figure A1: Trends of Industrial Output and Mechanization in Weaving



(a) Composition of Sector Output (b) Ratio of Powerlooms to Total Looms

Sources: Panel (a): Umemura et al. (1966), p.146; Shinohara (1972), pp.140-143. Panel (b): Noshomusho (Ministry of Agriculture and Commerce) Statistics; Fukui *Statistical Yearbook*.

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

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

Table A2: Number of Workers in the Weaving Industry by Type of Production Organization

Organization Type	A. National Weaving Industry		B. Fukui Silk-weaving Industry	
	1905	1914	1905	1914
Total	772,858	630,675	24,031	11,934
	(100.0%)	(100.0%)	(100.0%)	(100.0%)
Factory	94,964	168,653	9,063	8,041
	(12.3%)	(26.7%)	(37.7%)	(67.4%)
Home Workshop	230,864	178,487	12,828	2,398
	(29.9%)	(28.3%)	(53.4%)	(20.1%)
Putting-out System	447,030	283,535	2,140	1,495
	(57.8%)	(45.0%)	(8.9%)	(12.5%)

Sources: National data: Ministry of Agriculture and Commerce, Nōshōmu Tōkei Hyō (1905-14); Fukui data: Compiled from Fukui Prefecture statistics.
Note: Production organizations are defined as follows: *Factory* refers to establishments with 10 or more workers (including family members); *Home Workshop* includes smaller operations with fewer than 10 workers; and *Putting-out System* encompasses both thread suppliers who provided materials to outworkers and outsourcing weavers who produced fabrics in their own home.

Prefecture in the late 1880s, Fukui Prefecture quickly emerged as the principal center of *habutae* weaving, eventually establishing itself as a major hub for this specialized export textile. Fukui's success in developing its *habutae* weaving industry has been attributed to its adoption of Western-style "pattan" looms, which are well-suited for *habutae* weaving, and to its product inspection system—first implemented by local guilds and later by the prefectural government—which ensured consistent quality (Fukui Prefecture, 1994). As shown in Table A1, by the first decade of the 20th century, Fukui accounted for 53–60% of Japan's national *habutae* production and 21–24% of national silk production. Silk and *habutae* weaving dominated Fukui's industrial landscape, with more than 70% of the prefecture's manufacturing output being silk fabric, of which over 96% was *habutae*.

As the national center for *habutae* weaving and export, Fukui also spearheaded an organizational and technological transformation across the country. While nationally only 12.3% of weaving workers were employed in factories in 1905, rising to 26.7% by 1914, the corresponding figures for Fukui's silk weaving sector were substantially higher at 37.7% and 67.4%, respectively (Table A2). Thus, while home producers—including both home workshops with fewer than 10 workers and putting-out systems where outworkers produced goods at home as side jobs—still constituted the majority of employment in the national weaving sector through the mid-1910s, approximately 40% of workers in Fukui's silk weaving sector had already transitioned to large factories by 1905, a figure that rose to around 70% within just a decade.[24] Furthermore, Fukui's silk-weaving sector led in the adoption and diffusion of powerlooms. As shown in Figure A1b, the ratio of powerlooms to total looms in Fukui's *habutae* weaving sector rose from near zero in 1905 to over 65% across all producers by 1914, substantially outpacing the national trend. This adoption was even more pronounced among Fukui's silk-weaving factories, reaching approximately 80% by 1914. The relative share of home producers in Fukui's silk-weaving sector declined to marginal levels during this period of powerloom diffusion.

Fukui's successful development of its silk weaving industry was initially driven by a surge in *habutae* production in Fukui City, followed by rapid diffusion into surrounding counties. While in 1889 Fukui City alone accounted for over 95% of the prefecture's total silk weaving production, this figure fell to approximately 42% by 1904, with seven local counties accounting for nearly 60% of output. Table A3 shows that this distribution largely persisted thereafter, though with fluctuations within certain counties. Figure A3 illustrates the spatial distribution of silk-weaving production (in pink) across Fukui Prefecture in 1922, with each circle representing a local area within a county and its size indicating the relative production value. The figure demonstrates the concentration of production in Fukui City (the largest circle in the middle) and its neighboring areas.

Table A3: Regional Distribution of Silk-weaving Production in Fukui Prefecture

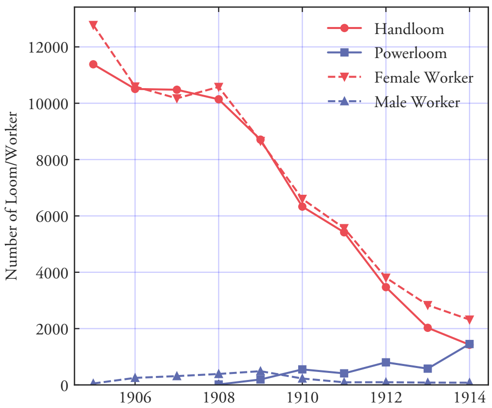
Year	Production Value	Regional Distribution (%)							
		Fukui City	Asuwa County	Yoshida County	Sakai County	Ono County	Imadate County	Niu County	Nanjo County
1889	694	95.5	0.2	1.2	0.4	0.4	1.8	0.0	0.4
1892	2,996	54.5	6.2	11.7	2.3	3.8	12.7	2.0	6.4
1899	14,879	54.8	5.0	16.8	8.6	3.7	7.0	1.4	2.4
1904	22,351	41.7	5.7	17.6	10.7	4.9	11.9	2.1	5.2
1905	16,149	44.1	6.1	14.1	9.6	5.9	13.8	2.4	3.7
1906	21,634	44.5	7.4	12.9	8.7	6.4	12.5	2.4	4.1
1907	17,188	42.5	5.7	14.0	12.4	7.2	12.9	2.0	3.2
1908	18,936	41.0	7.6	15.4	9.9	7.0	12.0	2.9	4.2
1909	21,116	42.8	6.1	13.7	10.7	6.1	14.5	2.2	3.9
1910	22,560	48.3	5.8	14.1	10.0	6.1	10.0	2.2	3.5
1911	21,146	43.8	6.6	11.1	12.3	8.7	10.0	2.0	5.5
1912	21,844	41.9	4.2	12.5	16.5	9.0	10.5	1.3	4.2
1913	26,347	35.9	4.1	11.9	19.6	9.6	13.1	1.2	4.7
1914	24,821	41.1	2.4	9.9	19.7	9.6	12.0	0.7	4.7
1915	31,690	41.1	2.6	8.9	18.9	9.3	13.8	0.7	4.6

Source: Fukui Statistical Yearbook and Fukui Industry Annual Report.

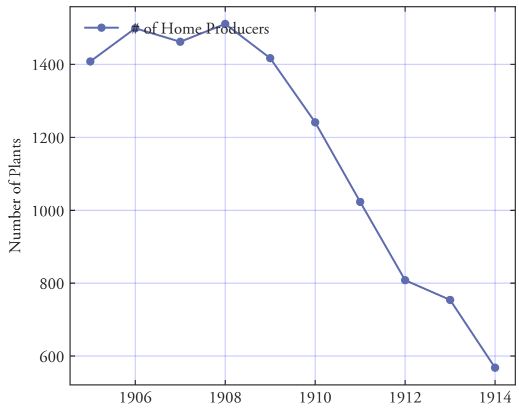
Powerloom Adoption. While powerlooms for cotton weaving had been well developed and widely diffused during Britain's early 19th century industrial revolution

[24]The strong presence of large-scale factories in Fukui's silk weaving sector is presumably attributable to the sector being largely established and funded by local merchants, as well as small- and mid-scale landlords (Kandachi, 1974).

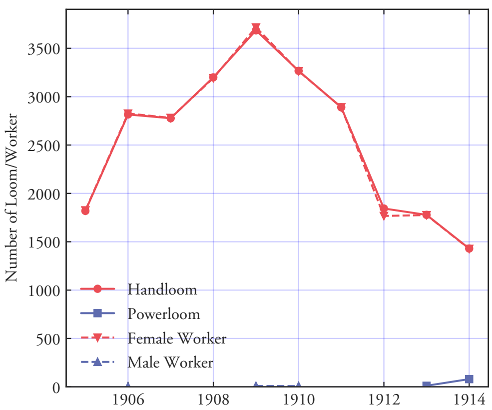
Figure A2: Trends of “Home-Producers” in Fukui’s Silk-weaving Industry



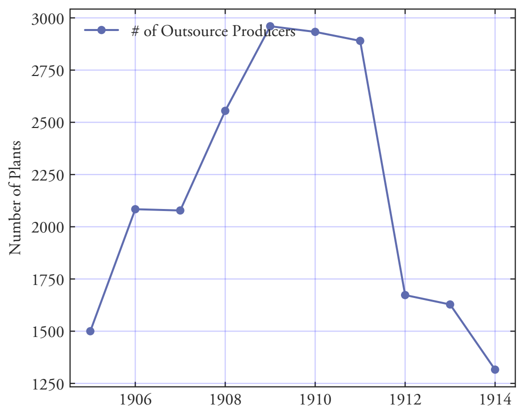
(a) Total Number of Machines and Workers (Home Workshops)



(b) Total Number of Producers (Home Workshops)



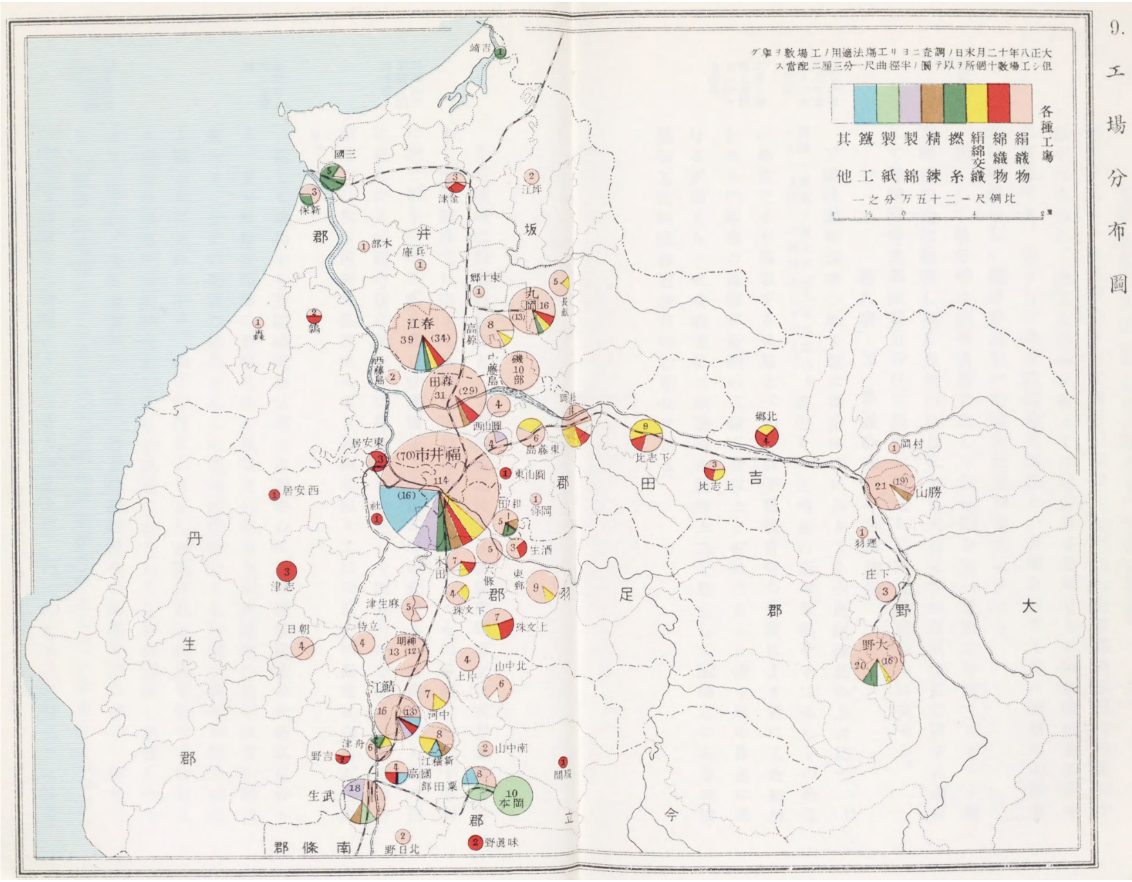
(c) Total Number of Machines and Workers (Putting-out System)



(d) Total Number of Producers (Putting-out System)

Note: The figures use the statistics documented in the Fukui Prefecture Statistics Yearbooks. Home workshops are defined as silk-weaving plants with less than 10 workers. Putting-out systems refer to both thread suppliers who provided materials to outworkers and outsourcing weavers who produced fabrics in their own home for piece rates.

Figure A3: The Spatial Distribution of Fukui Manufacturing Production in 1922



Source: The History of Fukui Prefecture, 1922, Vol. 3.

(Bythell, 1969), powerlooms for automated silk weaving remained underdeveloped for large-scale production until the late 19th century, primarily due to the more delicate and precise operations required for silk weaving and the prohibitively high costs of silk-weaving powerlooms (Federico, 2009). The rapid diffusion of powerlooms in Japan, and particularly in Fukui from the late 1900s onward, was facilitated primarily by two factors: the availability of domestically manufactured powerlooms and access to electrical power.

In 1906, the Fukui Prefectural Industrial Experiment Station conducted experiments with domestically manufactured powerlooms and concluded that, though still prototypical, Japanese machines were simple yet comparable to imported alternatives. These machines were subsequently promoted to weaving factory owners and received an overwhelmingly positive response (Fukui Silk Association, 1921). Recognizing the imminent shift toward mechanized weaving, leading silk-weaving factory owners in Fukui City purchased powerlooms from other prefectures in 1907. After installation, they discovered that these machines reduced labor expenses while simultaneously standardizing product quality, prompting them to expand their usage (Fukui City, 1994). By 1909, several powerloom ironworks and shops had been established in Fukui, and locally developed powerlooms better suited to Fukui's silk fabrics were invented or refined, resulting in the further rapid spread of cheaper and more efficient powerlooms from Fukui City to surrounding rural districts.[25]

Beyond the diffusion of domestic powerlooms, access to electricity during this period was equally crucial for powerloom adoption. Although powerlooms could operate using waterpower, steam, petroleum engines, electric motors, or gas engines, electricity proved superior in terms of stable supply and operational costs. Electricity was first introduced to Fukui in 1899 by the Kyoto Electric Company's Fukui branch, which initially had a capacity of 80 kW (later expanded to 160 kW). This supply was limited to Fukui City, however, and focused primarily on electric lighting, with only 30 horsepower allocated for manufacturing power use (Inoue, 1913).[26] Beginning in 1907, the company undertook significant expansion, launching a new Hydroelectric Station (800 kW) in July 1908 and an additional plant (900 kW) in November 1911. The company extended its supply area to include the outskirts of Fukui City, introduced a convenient motor rental service, and lowered tariffs—all of which facilitated powerloom adoption (Inoue, 1913). Concurrent with Kyoto Electric's policy shift, another firm, Echizen Electric, was established in 1908 and began operations with an output of 250 kW in August 1909, distributing both lighting and power to southern areas of Fukui. Furthermore, several additional electric compa-

[25] Hashino (2012) notes that the price of a domestic powerloom was one-seventh to one-twelfth the cost of an imported powerloom, making it economically feasible for factories to adopt this transformative technology.

[26] Kogita (2000) cites a 1906 report stating that rates for lighting and motive power were relatively high, and although local investors attempted to negotiate with the company for its sale, it refused further negotiations due to its substantial profitability.

nies established electricity stations between 1909 and 1914, providing electricity to previously unserved outlying counties (Figure A6). Consequently, most powerlooms adopted in the silk-weaving sector during this period were electrically powered, with only a few exceptions using gas power.

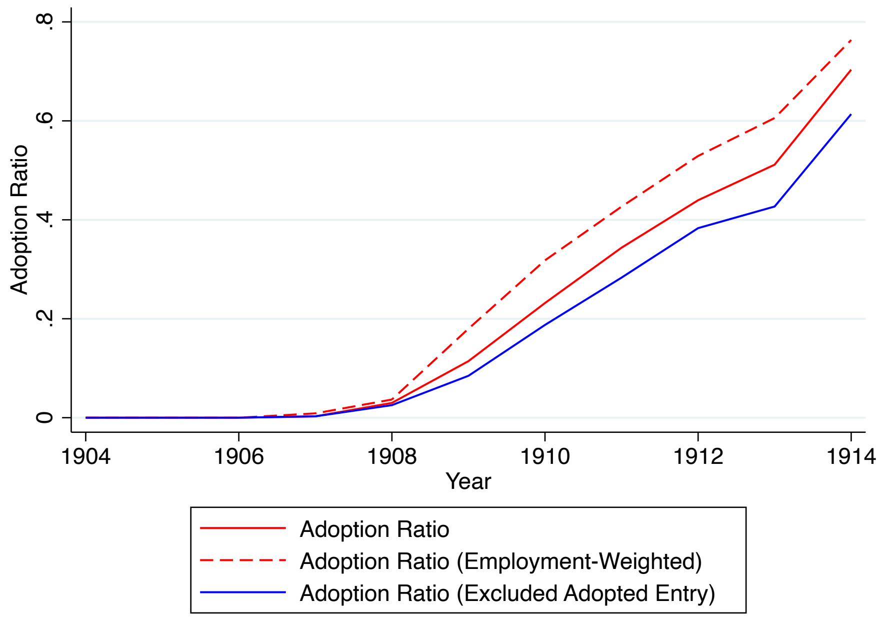
Beyond these external conditions, contemporary reports and subsequent studies consistently cite labor cost reduction as a primary driver behind Fukui's rapid powerloom adoption. For instance, Fukui City (1994) notes, "it is well known that powerlooms save manpower and reduce labor" and "the profits generated from manufacturing a certain amount of products using powerlooms can never be matched by manual machines." Similarly, Fukui Prefecture (1994) observes that "Fukui Prefecture has made rapid progress in the use of powerlooms in order to reduce *habutae* production cost." Notably, the fixed capital investment for powerlooms was estimated to be at least six times greater than that for handlooms, not including power costs and depreciation of other accompanying machinery and equipment (Hashino, 2012). Therefore, the rapid adoption of powerlooms must have been motivated by factory owners' expectations of substantial economic gains. These economic advantages of powerloom automation appear to have been greatest for larger factories, as adoption was concentrated among incumbent larger handloom factories (Figure A4) and remained rare among home-based producers (Figure A2).

Business Accounting. A particularly valuable historical source for understanding the economic implications of powerloom adoption in silk weaving is the comparative business accounting records preserved in contemporary reports. One such detailed accounting document comes from a 1910 survey conducted by Fukui's export textile inspection institution (Fukui Prefecture, 1911), presented in Table A4. This record compares the monthly financial performance between operations using 10 handlooms versus 20 powerlooms. The data collection periods (March and May) were sufficiently close that product prices per unit of weight remained identical, presumably reflecting comparable product quality. The production volumes achieved by these two operations, however, differed substantially. The output per loom was 50% higher for powerlooms (6 pieces) compared to handlooms (4 pieces). Moreover, powerloom products featured greater fabric width than handloom products, resulting in more than a twofold difference in total production between a single powerloom and a handloom. This productivity differential directly translated into a more than twofold difference in per-loom revenue between the two technologies.

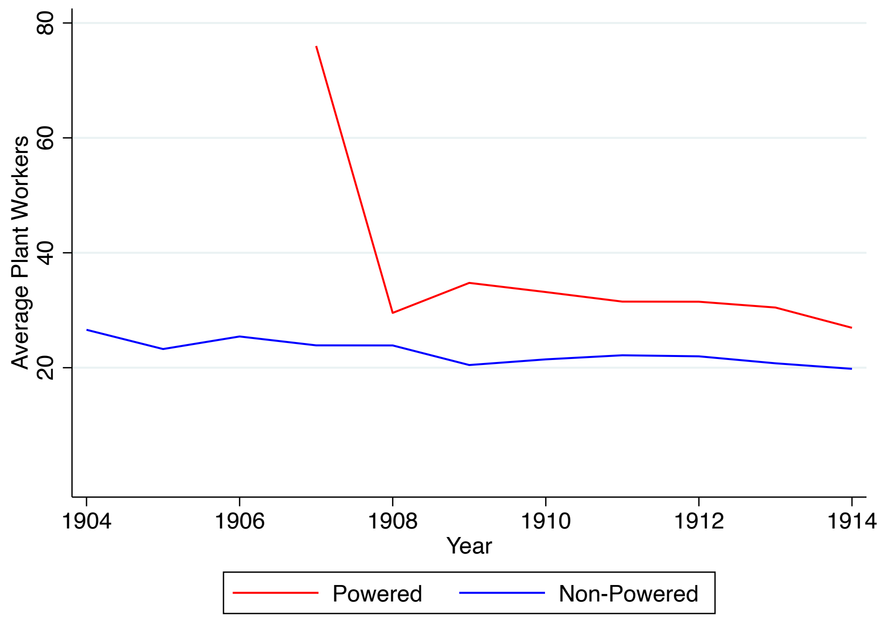
Raw silk (warp and weft threads) constituted the primary cost component, accounting for over 80% of revenue from *habutae* sales. Table A4 indicates that raw material costs represented a slightly higher proportion of revenue in powerloom operations than in handloom operations (85.4% versus 83.7%), possibly reflecting powerlooms' requirement for higher-quality raw silk to ensure smooth operation

Figure A4: Trends of Powerloom Plants

(a) Trend of Power Adoption

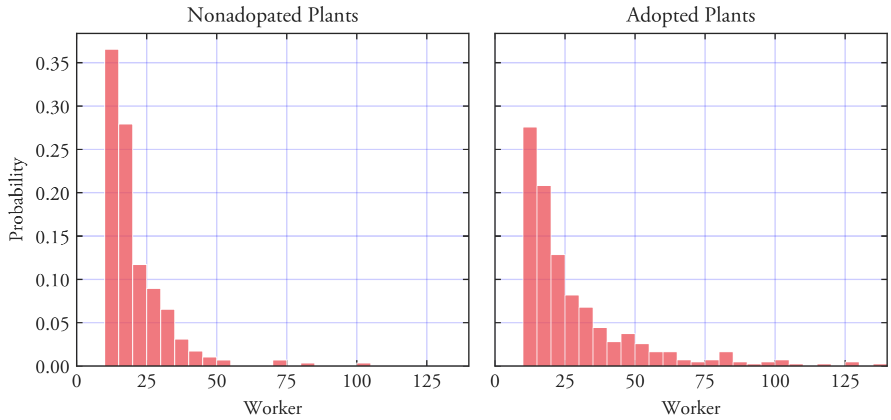


(b) Average Plant Size by Power



Source: The panel dataset used in the main text.

Figure A5: Plant Size Distribution by Power Adoption



Source: The panel dataset used in the main text.
Note: The cutoff at 10 workers is because the micro data published in the Fukui Prefecture *Statistics Yearbook* only includes plants with 10 or more workers and regards them as factories to distinguish them from small-scale home producers.

Figure A6: The Provision of Electricity by Electric Companies in Fukui

Source: Illustrated History of Fukui Prefecture

(Fukui City, 1994).[27]

Labor costs constituted the largest component of the remaining expenses, with weaving wages representing the largest share, followed by preparation wages. While operating 20 powerlooms required higher total weaving and preparation wages than operating 10 handlooms, these increases were disproportionately small relative to the revenue differential. Weaving wages accounted for 7% of revenue under handloom operations but only 2.5% under powerloom operations. Notably, the piece rate for powerloom silk weaving was just 0.6 yen, half the 1.2 yen piece rate for handloom silk weaving. Similar proportional reductions appeared in preparation wages. Consequently, despite additional labor costs such as supervisor and machine operator salaries, total labor costs represented a substantially smaller share of revenue under powerloom operations compared to handloom operations. Conversely, both capital costs and operating expenses increased slightly as a proportion of revenue. Powerloom operations required higher capital costs—including powerloom depreciation, equipment interest, factory expenses, and waste-thread depreciation—than the fixed capital depreciation under handloom operations. Operating expenses necessarily included additional power costs for powerloom operations. The enhanced profitability of powerlooms thus derived entirely from reduced labor costs. The labor share of value-added declined from 55.4% under handloom operations to 38.2% under powerloom operations, while the profit share of value-added increased from 9 to 17%.

Given that raw-silk costs exceeded 80% of total *habutae* sales under either production mode, the silk weaving industry operated on thin margins and remained highly vulnerable to fluctuations in raw-silk and *habutae* prices. Figure A7 illustrates the *habutae* export price and raw thread price during our study period. Raw thread prices declined gradually by approximately 20% after 1906, while *habutae* export prices fluctuated, experiencing 20% spikes around 1909 and 1914. Thus, while business cycles certainly affected the industry, overall product market conditions generally remained favorable for *habutae* exports. As Fukui Prefecture (1994) reports: "Although commercial and industrial circles languished during the Russo-Japanese war (1904-1905), *habutae* alone saw robust overseas demand... once the economy turned lively from 1907 (Meiji 40) onward, both electric and other mode of power use rapidly multiplied... Meanwhile, as the number of powerlooms surged, handlooms markedly declined, and with stricter enforcement of inspections and so

[27] Federico (2009) explains: "The speed increased the stress on the silk and therefore the chances that it could break at any weak point. Of course, the yarn had to be knotted by hand, wasting both time in having to stop the machine and precious silk. Moreover, the worker had to correct by hand any defect of the silk (loose threads, dirty spots etc.) which otherwise would have spoiled the appearance of the cloth. Therefore, the use of an inferior silk required more labour and could hamper the increase of the number of looms per worker—that is, of the productivity of labour. The hand-loom had none of these constraints, and could use any kind of silk profitably. The stress was less intense and any breaking or defect could be corrected by the weaver himself. In other words, mechanization shifted, ceteris paribus, the average quality of silk upwards."

forth, many small-capital producers were forced out, giving rise to a 'consolidated' structure. Thus, in 1913, sales of output were extremely favorable, exceeding 23 million yen—truly the highest price levels since the industry's inception."

Table A4: Comparison of Monthly Income and Expenditure for Handlooms vs. Powerlooms (1910)

	Handlooms		**Powerlooms**	
Operation Details	10 looms, May 1910		20 looms, March 1910	
Production				
Fabric Width		1.8 shaku		2.4 shaku
Production Volume		40 hiki		120 hiki
Production per Loom		4.0 hiki		6.0 hiki
Finished Weight		8 kan 400 momme		34 kan 650 momme
Price		8.20 yen 100 momme		8.20 yen 100 momme
	Yen	**%**	**Yen**	**%**
Income				
Sales Revenue	**688.80**	**100.0**	**2,841.30**	**100.0**
Raw Materials				
Warp Threads	286.20	41.6	1,250.64	44.0
Weft Threads	290.00	42.1	1,175.04	41.4
Subtotal Materials	**576.20**	**83.7**	**2,425.68**	**85.4**
Labor Costs				
Weaving Wages	48.00	7.0	72.00	2.5
Preparation Wages	16.40	2.4	41.76	1.5
Supervisor Salary	—		20.00	0.7
Machine Operators	—		15.00	0.5
Bonus	—		6.00	0.2
Transportation Allowance	—		7.80	0.3
Subtotal Labor	**64.40**	**9.3**	**162.56**	**5.7**
Capital Costs				
Working Capital Interest (2.25%/yr)	6.75	1.0	24.00	0.8
Fixed Capital Depreciation	11.25	1.6	—	
Powerloom Depreciation	—		10.80	0.4
Equipment Interest (1.75%/yr)	—		3.00	0.1
Preparation Equipment Depreciation	—		3.72	0.1
Insurance Fee	—		2.40	0.1
Factory Expenses	—		10.60	0.4
Machine Repair	1.20	0.2	3.90	0.1
Heddle, Reed, Shuttle Depreciation	3.40	0.5	10.20	0.4
Waste-Thread Cost Depreciation	—		37.80	1.3
Subtotal Capital	**22.60**	**3.3**	**106.42**	**3.7**
Operating Expenses				
Power Costs	—		18.00	0.6
Starch / Sizing	2.80	0.4	10.80	0.4
Mineral Oil	—		1.20	0.0
Refining Fees	9.44	1.4	33.96	1.2
Sales Commission	2.00	0.3	6.00	0.2
Lighting and Fuel	2.00	0.3	7.20	0.3
Public Taxes	2.00	0.3	6.00	0.2
Consumable Supplies	0.40	0.1	1.20	0.0

Continued on next page

Table A4 – *Continued*

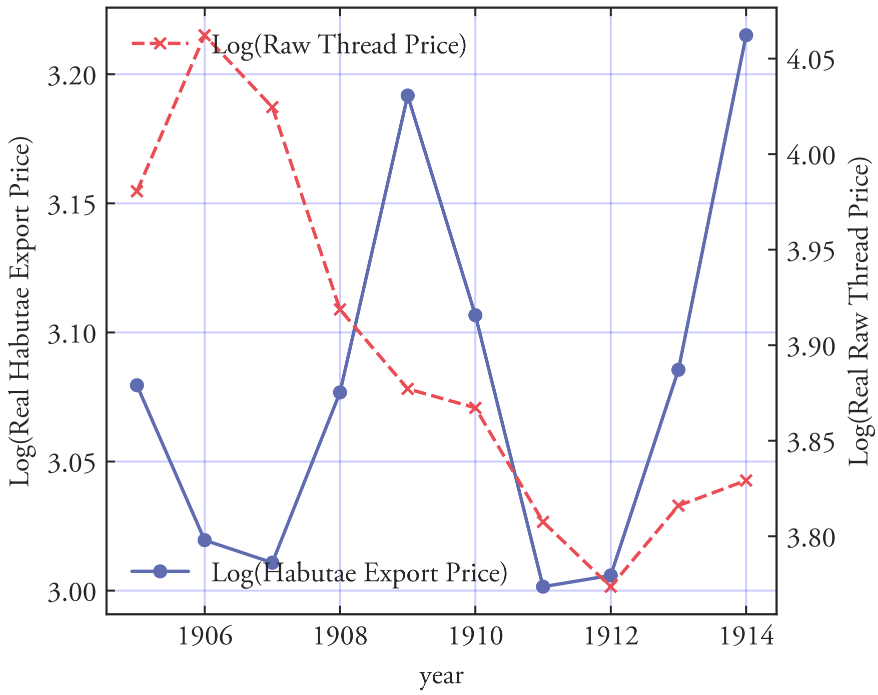
Operation Details	Handlooms 10 looms, May 1910		Powerlooms 20 looms, March 1910	
Subtotal Operating	**18.64**	**2.7**	**84.36**	**3.0**
Total Expenses	**681.84**	**99.0**	**2,779.02**	**97.8**
Net Profit from Operations	**6.96**	**1.0**	**62.28**	**2.2**
Additional Income (waste yarn etc.)	3.50	0.5	10.32	0.4
Total Net Profit	**10.46**	**1.5**	**72.60**	**2.6**
Key Performance Indicators				
Revenue per Loom		68.88		142.07
Value-Added (Rev.−Mat.) per Loom		11.26		20.78
Labor Cost per Loom		6.44		8.13
Capital Cost per Loom		2.26		5.32
Operating Expense per Loom		1.86		4.22
Profit per Loom		1.05		3.63
Weaving Wage per Output (Piece-rate)		1.20		0.60
Labor Cost per Output		1.61		1.35
Operating Expense per Output		0.47		0.70
Profit per Output		0.26		0.61
Labor Share of Value-Added		55.4%		38.2%
Capital Share of Value-Added		19.5%		25.0%
Operating Exp. Share of Value-Added		16.1%		19.8%
Profit Share of Value-Added		9.0%		17.0%

Note: This table compares the monthly financial performance of handloom operations (10 looms) versus powerloom operations (20 looms) based on accounting records from surveys in 1910 (Fukui Prefecture, 1911). Conversions for Japanese historical units: 1 kan = 3.75 kg, 1 momme = 3.75 g, 1 shaku ≈ 30.3 cm, 1 tsubo ≈ 3.3 m^2. Weaving/preparation wages were 1.20/0.41 yen per piece on handlooms and 0.60/0.34 yen on powerlooms. Refining fees were paid to refining factories as a service cost. For handlooms, working capital interest reflects working capital of 900 yen at a 2.25% annual rate (9 shu). Fixed capital depreciation includes land/buildings (40 tsubo, 800 yen) and 10 looms/tools (200 yen), totaling 1,000 yen depreciated over 10 years with 1.75% annual interest (7 shu). For powerlooms, working capital interest assumes a 1.75% annual rate (7 shu), depreciation assumes a 10-year life, and factory expenses reflect fixed capital of 2,550 yen (including 1,500 yen financed at 1.75% interest) depreciated over 20 years. Percentages in the main body refer to the share of each cost item in total sales revenue. Some expense categories differ between the two operations due to their different production systems.

Worker Tasks and Productivity. The silk-weaving industry during this period employed three primary categories of workers: weavers, preparation workers, and mechanics. Weavers constituted the core workforce and consisted predominantly of adult female workers. Using handlooms, each weaver operated a single loom, transforming raw silk threads into fabric. This operation involved the repetitive execution of three manual tasks: manipulating the shuttle, operating the pedals/heddles to control the warp threads, and using the reed/batten to beat the weft threads into place. Though seemingly routine, this work demanded considerable finger dexterity and patience with delicate materials (Inoue, 1913), typically requiring approximately three years of on-the-job training to develop the necessary skills (Kogita, 2000).[28]

[28] The importance of skill accumulation is evidenced by the practice of local silk-weaving associations rewarding long-term, highly productive workers, with ceremonies often attended by the local Governor (Fukui Prefecture, 1994).

Figure A7: *Habutae* Export Price and Raw Thread Price



Source: Fukui Prefecture Statistics Yearbook.

Preparation work—involving tasks such as spooling, rewinding, and sizing—was typically performed by child or adolescent apprentices who would eventually progress to become weavers upon reaching appropriate age and skill levels. Despite the relatively lighter nature of preparation work compared to weaving, these younger workers typically maintained similar working hours as their adult counterparts (Noshomusho, 1903). In some instances, preparation tasks were also performed by adult female workers or even male workers in Fukui (Inoue, 1913). Finally, a small contingent of male workers served as mechanics, responsible for setting up and repairing weaving equipment.

The adoption of powerlooms fundamentally transformed the production process by mechanizing the routine manual tasks previously performed by female weavers. Freed from the physical constraints of handloom operation, weavers' responsibilities were redirected toward newer, less routine tasks associated with powerloom management. These new tasks included halting looms for thread resupply, repairing broken threads, and monitoring multiple machines for contingencies (Uchida, 1960; Sanbe, 1961; Tsunoyama, 1983; Hunter, 2003). (See Figure A8 for a visual comparison of the two types of machines and production processes.) Inoue (1913) observes that these new responsibilities required equal or greater finger dexterity and attentiveness than handloom operation—particularly for quickly and precisely reconnecting broken silk threads during machine weaving—and that skills developed through handloom operation transferred effectively to powerloom work. This skill transferability helps explain the sustained demand for manual workers in silk weaving, distinguishing it from industries like iron manufacturing or cotton spinning, where extensively automated production required only minimal machine monitoring. Contemporary sources also indicate that the training period for powerloom weavers was reduced to approximately six months, and that female workers generally considered powerloom weaving less physically demanding than handloom work. While documentation on how powerlooms affected preparation tasks is comparatively sparse, at least one source indicates that power was increasingly applied to preparation work as well, enhancing the efficiency of warp preparation processes (Fukushima Prefecture, 1910). Concurrently, powerlooms expanded the responsibilities of mechanical workers, who now managed comprehensive maintenance operations including lubricating powerlooms and resolving all types of mechanical issues (Inoue, 1913). Specialized training proved advantageous, as more progressive factory owners reportedly employed graduates from the Fukui Industrial Training Institute as powerloom operators, entrusting them with overall machinery management.

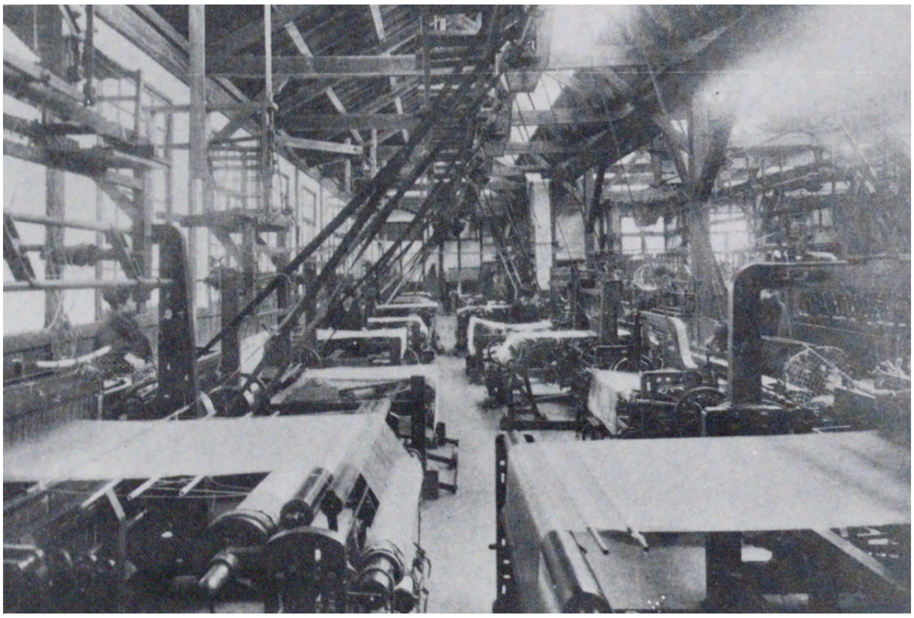
Powerloom adoption significantly enhanced weaver productivity through two mechanisms: increased production per loom in a given time period, and an increased number of looms operable by a single weaver. Sanbe (1961) documents that while a worker operating a hand-and-foot-driven handloom could produce 1.5 rolls (tan) of silk fabric daily, a worker managing approximately two powerlooms could produce 2 rolls with each machine. The combined effect yielded a 2.67-fold increase in labor productivity. Similar evidence appears in a 1911 survey conducted by the Fukui Chamber of Commerce (Table A5), which reported per-loom productivity approximately 1.45 times higher for powerlooms than handlooms. With two powerlooms typically assigned per worker, total labor productivity under powerloom production was approximately 2.9 times that of handloom production. Further statistical evidence of this productivity differential is provided by Okazaki (2021), who utilized prefecture-, county-, and plant-level data to estimate production functions for the Japanese silk weaving industry during this period, finding that powerlooms increased labor productivity by approximately two to three times after controlling for organizational changes. This substantial productivity enhancement explains how Fukui's silk sector could increase output volumes despite declining total employment during the period of powerloom diffusion (Figure 1).

Labor Supply. The workforce in Fukui's silk weaving sector consisted predominantly of young, unmarried females from local agricultural and lower-income families. While approximately one-third of female workers in Fukui were recruited from outside the prefecture (primarily from neighboring Ishikawa Prefecture) around 1900, by 1904 most female weavers originated from Fukui's own rural districts, with only a small minority from the Kanazawa area (the silk center of Ishikawa) (Fukui Prefecture, 1994; Fukui City, 1994). The industrial weaving sector's expansion placed considerable pressure on agricultural labor markets, making it "gradually

Figure A8: Handloom Production and Powerloom Production

(a) Handloom Operation

(b) Powerloom Operation



(c) Powerloom Operation in a Fukui Factory

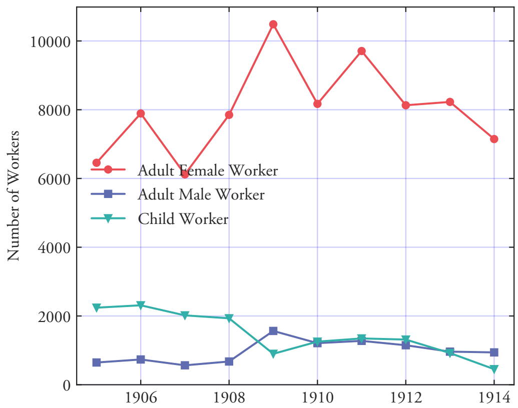
Source: https://commons.wikimedia.org/wiki/File:Hand-weaving_in_factory._(19329323753).jpg (left panel); https://monk.radford.edu/viewer/7281/ (right panel); https://dl.ndl.go.jp/pid/9539681/1/35 (bottom panel)
Note: Panel (a) is a photo of hand-weaving factory from a set of color-tinted transparencies depicting life in Japan around 1910. Panel (b) is a photo of Kiryu Textile Company in the 1910s or 1920s, equipped with imported powerlooms from the U.S. It was claimed to be the first machinery factory in Kiryu, Gunma Prefecture, another main production place along with Fukui at that time. Panel (c) is a photo of Matsui Loom Factory in 1910, a workshop with 35 workers run by Buntaro Matsui, a raw silk and *habutae* merchant in Fukui City. This factory had a single 6 horse power electric motor installed and a belt transmitting power from the drive shaft above the photo to each powerloom. Another photo of Matsui Loom Factory: https://www.library-archives.pref.fukui.lg.jp/fukui/07/zusetsu/D14/d1412.jpg.

Table A5: Comparison of Powerloom and Handloom Worker Productivity and Wages in Fukui (1911)

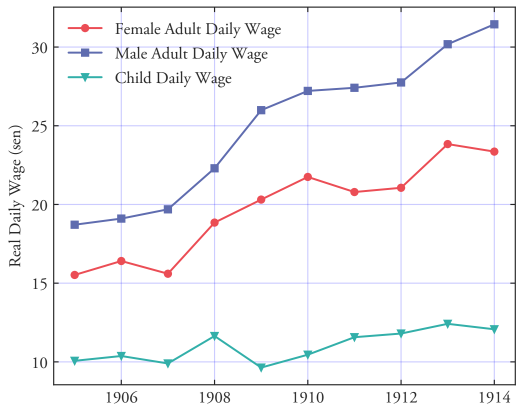
Category	Powerlooms	Handlooms
Number of Looms		
Total Looms (December 1911)	5,326	11,106
Export-oriented Looms	5,326	9,441
Domestic Market Looms	0	1,665
Production Capacity (per Loom)		
Hourly Production	2.9 shaku	2.0 shaku
Daily Production (12 hours)	35 shaku	25 shaku
Monthly Production (28 days)	8.2 hiki	5.5 hiki
Annual Production	98 hiki	70 hiki
Production Efficiency Ratio	1.45	1.00
Labor Efficiency		
Looms per Worker	2	1
Labor Productivity Ratio	2.90	1.00
Wages (per Worker)		
Hourly Wage (sen)	2.6	1.7
Daily Wage (sen)	32	20.7
Monthly Wage (yen)	8.98	5.80
Annual Wage (yen)	117.76	70.00
Wage Ratio	1.68	1.00
Labor Cost Analysis		
Workers per 1,000 hiki Production	5.1	14.3
Labor Cost per 1,000 hiki (yen)	747	1,234
Cost Efficiency Ratio	1.00	1.65

Notes: This table compares the production capabilities of powerlooms and handlooms based on a survey conducted by the Fukui Chamber of Commerce in 1911. For powerlooms, one worker could operate two machines, while hand looms required one worker per loom. The production efficiency ratio and labor productivity ratio use hand looms as the baseline (1.00). 1 yen equals 100 sen. For Japanese units: 1 kan = 3.75 kg; 1 momme = 3.75 g; 1 shaku = approximately 30.3 cm; 1 hiki is a standard bolt of fabric (approx. 1.8 shaku width by 25-28 yards length).

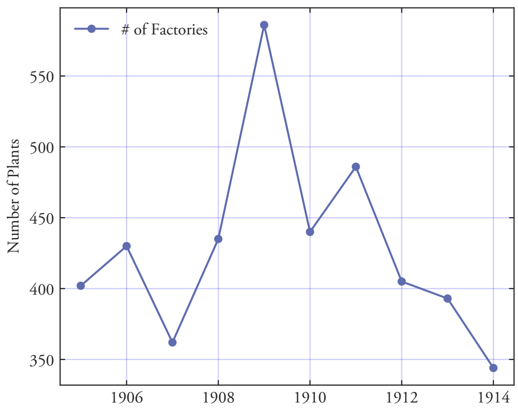
Figure A9: Trends of Fukui's Silk-weaving Industry (Factory Micro-data)



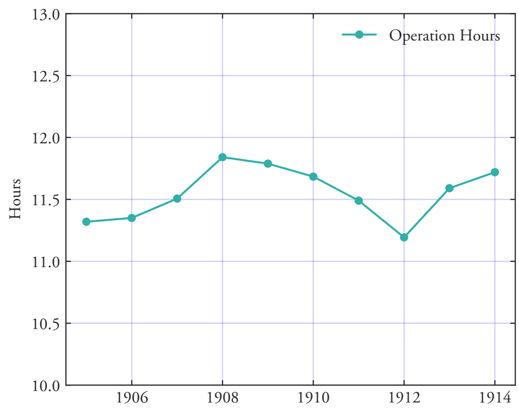
(a) Total Plant Workers



(b) Average Plant Wages



(c) Number of Plants



(d) Average Plant Operation Hours

Note: All figures here use the data from the Fukui Prefecture *Statistical Yearbooks*. Different from Figure 1, where the data used (except the wage series in Figure 1d) are the aggregate statistics directly documented, here all statistic trends are calculated using the plant micro data, which are used for the main analysis. The "plants" defined in the *Statistical Yearbooks* are any plants employing 10 or more workers, whereas plants smaller than this scale are defined as home producers. Both average wages and average operation hours are weighted by corresponding employment. Average wage is inflation-adjusted using the national price index published by Band of Japan, with 1904 as the benchmark year.

difficult to procure hired labor for farming" and forcing those seeking indentured servants to "look beyond their own villages to other towns or counties." Labor supply also became increasingly localized during this period, as evidenced by the declining prominence of the boardinghouse system. For instance, around 1904 in Fukui City, "female workers were half commuting, half boarding" (Fukui City, 1994), but by 1909, multiple factories reported that "all the workers are commuting" or "both male and female workers commute, with hardly any boarding female workers" (Fukushima Prefecture, 1910). Similarly, Inoue (1913) observed that "only a very small fraction [of workers] are exchanged among the three Hokuriku prefectures as their fortunes rise or fall, with almost none from farther away. Moreover, in Fukui City, the local underclass supplies the female labor: all are girls from nearby, sufficing to fill the ranks." This localization trend has been attributed to the introduction of powerlooms in rural areas of Fukui Prefecture (which had previously supplied female labor to Fukui City) and to female workers' general preference to remain in their home regions.

Most young women entered factory employment with the aim of accumulating savings for marriage or acquiring silk-weaving skills for post-marriage income supplementation. Upon marriage, they typically left factory employment, with some relocating elsewhere (Inoue, 1913; Fukui City, 1994). Some workers, lured by promises of high wages or pressured by family circumstances, found themselves unable to endure the demanding work conditions in silk-weaving plants and subsequently departed (Noshomusho, 1903). This pattern resulted in high workforce turnover at the plant level and created a persistent need to replenish and attract workers. Table A6 illustrates the age and tenure distribution of workers in Fukui's silk-weaving industry around 1902, based on a survey conducted by the Ministry of Agriculture and Commerce (Noshomusho, 1903). The largest cohort of female workers was aged 14 to 19 (41%), followed by those aged 10 to 13 (30%) and those aged 20 to 24 (18%).[29] Female workers over age 25 constituted just 8% of the total female workforce. Regarding tenure, over 40% of female workers had been employed for approximately one year or less, and over 80% for less than three years. Only 20% had a tenure of five years or more. The survey noted that worker departures were most frequent among those with less than two years' tenure and declined progressively among longer-tenured workers.

Silk-weaving plant owners employed various strategies to reduce worker turnover and attract new employees. First, worker contracts frequently included obligation periods, typically ranging from one to five years depending on worker age (Noshomusho, 1903).[30] Second, local weaving factory owners often formed asso-

[29] Inoue (1913) notes the absence of age or education restrictions or requirements, observing that "most are poor people's daughters working to support the family, the entire system has drifted toward laissez-faire."

[30] According to Inoue (1913), "so-called apprentices who came in not knowing weaving might depart for another mill as soon as they acquired proficiency, leaving the previous employer to bear

ciations or unions that prohibited worker poaching and regulated wages (Fukui Silk Association, 1921).[31] They also occasionally rewarded workers with long service records or outstanding technical skills. The practical effectiveness of these strategies, however, remains empirically uncertain. Inoue (1913) observed that "terms-of-service contracts often proved a dead letter, and as soon as workers ran off midterm to another factory, one could do nothing but let it go." Regarding anti-poaching measures, the same source noted that "that phenomenon occurred only when there were many orders and a shortage of female workers, so it was not so severe at present. When the shortage became serious enough to send recruiters into villages, the method of poaching involved quietly instructing one's own female workers to lure their experienced friends with higher pay. Since these women were easily swayed, they would immediately transfer to another factory if the deal was better, ignoring guild rules." Thus, these contractual and rule-based strategies for limiting worker movement likely achieved only partial success. Finally, evidence suggests that silk-weaving factory owners occasionally established branches in local areas, potentially to secure additional workers. Indeed, one owner responded to a 1910 interview by stating, "We have a shortage of workers. Hence the necessity of establishing branch sites."

Table A6: Worker Demographics in the Fukui Silk-weaving Industry

Panel A: Workers by Age Group				
Age Group	**Male**	**%**	**Female**	**%**
Under 10 years	0	0.0%	511	3.1%
10-13 years	2	0.9%	4,840	29.7%
14-19 years	132	56.7%	6,665	40.9%
20-24 years	52	22.3%	2,932	18.0%
25-50 years	47	20.2%	1,338	8.2%
Total	**233**	**100.0%**	**16,286**	**100.0%**
Panel B: Workers by Years of Tenure				
Tenure	**Male**	**%**	**Female**	**% s**
Less than 6 months	32	13.7%	1,730	10.6%
1 year	64	27.4%	5,117	31.4%
2 years	45	19.2%	3,526	21.7%
3 years	37	15.8%	2,581	15.9%
5 years	18	7.7%	2,168	13.3%
More than 5 years	38	16.2%	1,164	7.1%
Total	**234**	**100.0%**	**16,286**	**100.0%**

Source: Noshomusho (1903)

the loss. As a result, it was customary to impose a two- or three-year obligation to discourage abrupt departures."

[31] These associations typically established rules stipulating that "no worker from House A may be employed by House B for any reason without House A's permission, except that re-employment by the previous owner is not forbidden."

Wage System. The silk-weaving sector employed distinct compensation methods based on worker roles and tasks (Fukui Prefecture, 1911). Weavers were predominantly compensated through piece rates, while workers engaged in preparatory processes typically received daily or monthly wages. Supervisors and mechanics were likewise paid monthly wages. The piece-rate system for weavers reflects economic logic: Worker productivity varied substantially, and *habutae* products differed in size and grade, necessitating performance-based pay to both elicit effort and ensure equitable compensation. Even for preparatory and male workers, employers implemented ability-based daily or monthly wage systems (Noshomusho, 1903). Preparatory workers, particularly child apprentices and trainees, typically received lower wages than other workers, while adult male workers generally commanded higher compensation than adult female workers (see our microdata in Figure A9).[32] Inoue (1913) observes that beyond product type, wages were determined by factory customs and dynamic factors such as product market prices.

Of particular relevance to our study is the comparison between wages under handloom and powerloom production during the period when both technologies coexisted in the market. Our business accounting evidence in Table A4 indicates a piece rate of 0.6 yen (per hiki) under powerloom production versus 1.2 yen under handloom production in 1910. Since revenue increased fourfold under the assumption that a worker operated two powerlooms, this translates to a doubling of powerloom wages relative to handloom wages. A more direct comparison appears in Table A5, which includes survey data on per-worker wages. Compared to a labor productivity ratio of 2.9 between powerlooms and handlooms, the wage ratio was only 1.68, further suggesting significantly lower piece rates under powerloom production. Inoue (1913) similarly noted that handloom piece rates were approximately double those for powerloom weaving, while productivity was 3-4 times higher with powerlooms for workers who could manage two machines after one year of training. Consistent evidence appears even within individual factories. For instance, Fukushima Prefecture (1910) reports that at Nakajima machinery factory, the powerloom weavers' piece rate for heavy products was 0.65 yen, while handloom weavers received 1.6 yen for producing the same weight of product. After accounting for productivity differences, powerloom weavers earned slightly higher wages than their handloom counterparts. Thus, while different entrepreneurs established varying piece rates, a common approach was to reduce powerloom piece rates (and perhaps also to raise handloom piece rates) such that total wage disparities among workers

[32] Fukui Prefecture (1911) notes that while first-rate, second-rate, and third-rate preparatory workers were paid 50, 40, and 25 sen (0.50, 0.40, and 0.25 yen) daily, respectively, apprentices received only 15-16 sen. Noshomusho (1903) indicates that high/mid/low-level male workers earned 40/30/25 sen daily, while corresponding female workers earned 33/20/15 sen. The majority of men earned below 30 sen daily, and the majority of women below 20 sen. Inoue (1913) reports that compared to the 30-40 sen daily wage for powerloom weavers, preparatory worker wages ranged between 10 sen (for trainees) and 30 sen, while adult males earned 3 to 9 yen per month.

Table A7: Summary Statistics of Plant Panel

	NonPowered Plants (Mean)	Powered Plants (Mean)	Powered - NonPowered
Total Workers Per Plant	22.99	30.57	7.58
	[20.23]	[27.73]	(0.79)
- Male Adult Workers	1.79	3.94	2.15
	[2.64]	[4.92]	(0.12)
- Female Adult Workers	17.28	24.22	6.94
	[16.48]	[22.13]	(0.64)
- Child Workers	3.92	2.41	-1.51
	[6.45]	[5.18]	(0.22)
Work Hours Per Day	11.42	11.56	0.13
	[1.39]	[1.17]	(0.05)
Average Daily Wage Per Plant	17.13	23.65	6.52
	[4.17]	[4.19]	(0.15)
- Male Adult Workers	22.33	30.60	8.27
	[5.87]	[5.43]	(0.23)
- Female Adult Workers	17.87	23.77	5.90
	[4.01]	[4.18]	(0.15)
- Child Workers	10.59	12.51	1.92
	[2.86]	[3.38]	(0.15)
Observations	3651	971	4622

Note: This table reports the summary statistics of the plant-level panel datasets used in the main text. Means across all plants in the panel-data set are reported. Standard deviations are reported in square brackets; standard errors are reported in parentheses.

remained relatively moderate or not as large as productivity disparities.

Facing widening wage gaps between powerloom and handloom weavers, handloom-based operations likely encountered increasing difficulty in securing and retaining workers. While direct evidence from Fukui is scarce, narrative evidence from neighboring Ishikawa Prefecture, which experienced similar powerloom diffusion during this period, is instructive. When asked by visitors how to maintain worker satisfaction amid powerloom proliferation, the owner of a large handloom factory with over 300 handlooms responded: "Because female workers' income under handlooms can scarcely match that with powerlooms, we have reduced to 150 handlooms and now are switching gradually to powerlooms." This experience supports the argument that "in the Kanazawa area in the early 1910s, competition in wages with factories adopting powerlooms essentially forced handloom-based factories to either introduce powerlooms or cease operations" (Matsumura, 2010).

B Robustness Analysis

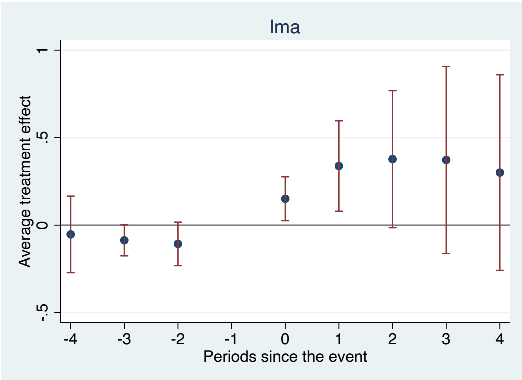
B1 Robustness on Plant-level Estimation

Table B1: The Plant-Level Effect of Power Introduction on Employment

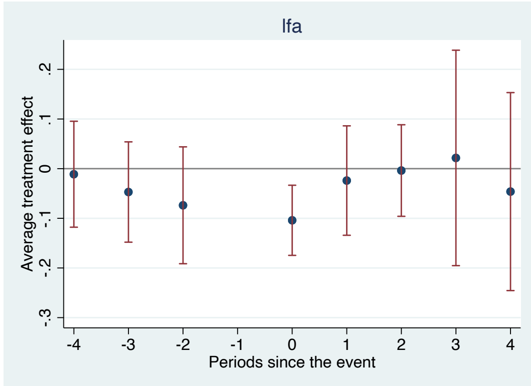
	(1) Male Adult	(2) Female Adult	(3) Child	(4) Overall
Panel A: Regression on Employment				
Power	1.996	2.395	-0.835	3.558
	(0.614)	(1.943)	(0.697)	(2.281)
Pre-treatment Mean	2.32	21.89	4.44	28.65
N	3,487	3,488	3,488	3,488
Panel B: Poisson Regression on Employment				
Power	0.337	0.028	0.165	0.102**
	(0.063)	(0.063)	(0.153)	(0.052)
Pre-treatment Mean	2.32	21.89	4.44	28.65
N	2,923	3,488	2,923	3,488
Panel C: Regression on 1(Employment > 0)				
Power	-0.004		0.032	
	(0.035)		(0.039)	
Pre-treatment Mean	0.72		0.68	
N	3,488		3,488	

Note: This table reports the alternative estimations of Equation (2) with the dependent variables to be plant employment levels (Panels A and B) and an indicator of non-zero employment (Panel C). Panels A and C estimate the model using a TWFE regression same as in the main text, while Panel B estimates the model using a Poisson pseudo-likelihood regression. All estimations here differ in the sample used from the main text estimation, as now zero employment of male adult and child workers is no longer dropped. The unit of observation is plant-year. Clustering robust standard errors against the plant-level correlations are reported in parentheses. All specifications include plant and area-year fixed effects.

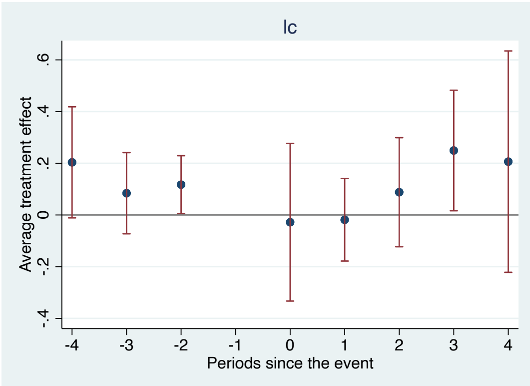
Figure B1: The Plant-level Impacts of Power Adoption on Employment and Wage (Country-Year Fixed Effects)



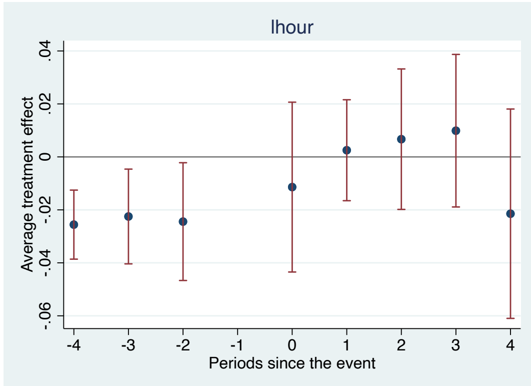
(a) ln(Male Adult Employment)



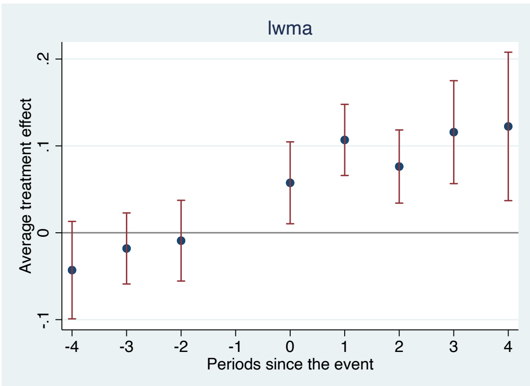
(b) ln(Female Adult Employment)



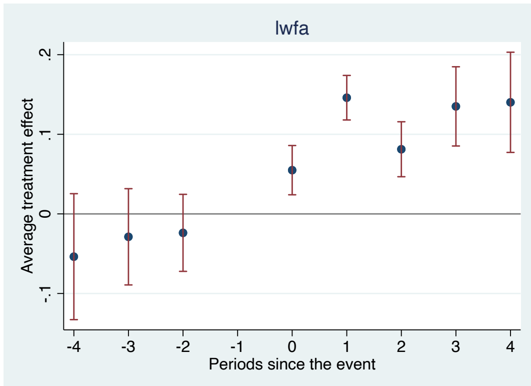
(c) ln(Child Employment)



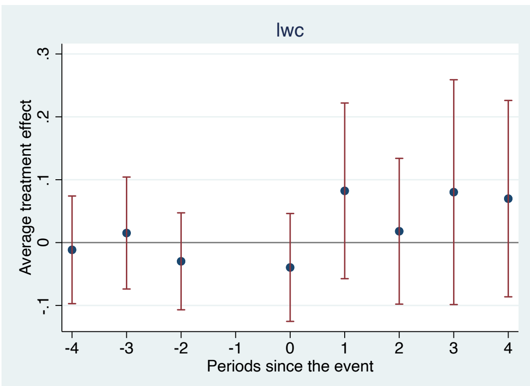
(d) ln(Operation Hours)



(e) ln(Male Adult Wage)



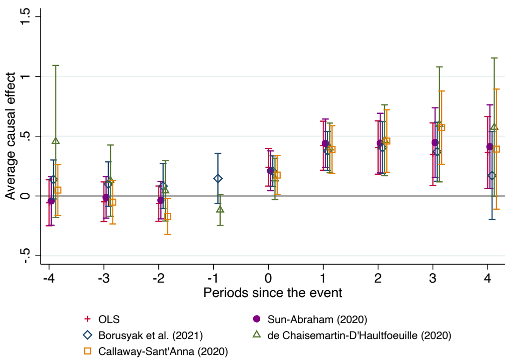
(f) ln(Female Adult Wage)



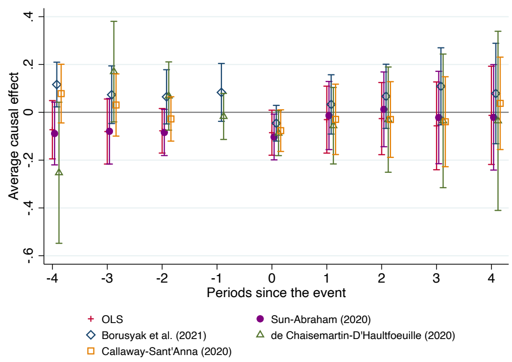
(g) ln(Child Wage)

Note: This figure reports the results of plant-level event studies on employment and wages specified in Equation (1), but with country-year fixed effects instead of more restrictive area-year fixed effects. See the note of Figure 2 for more details.

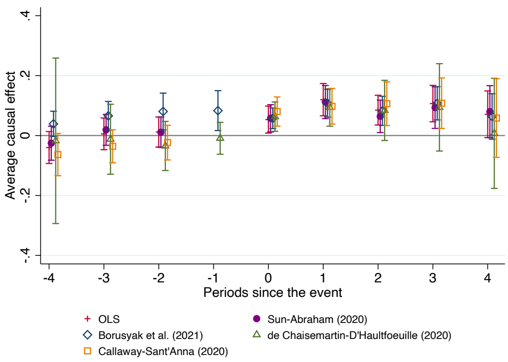
Figure B2: Comparison of Estimators for Plant-level Event-study Estimations



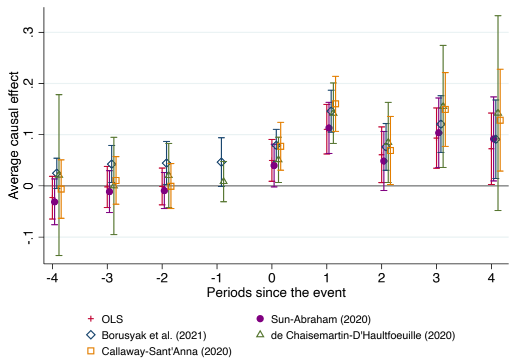
(a) ln(Male Adult Employment)



(b) ln(Female Adult Employment)



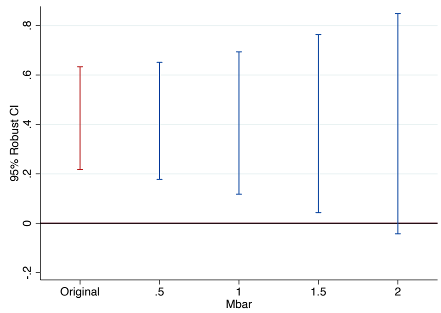
(c) ln(Male Adult Wage)



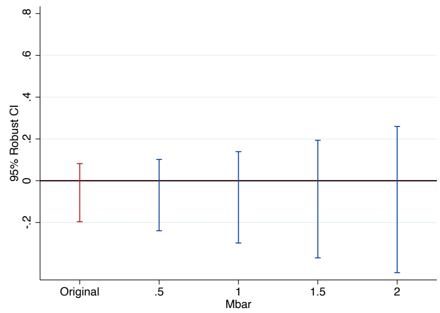
(d) ln(Female Adult Wage)

Note: This figure reports a robustness check of the plant-level event study estimations in Figure 2 under different estimators. In particular, we test with five estimators that have 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 the Callaway and Sant'Anna (2021) estimator, we also include the not-yet-adopting 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.

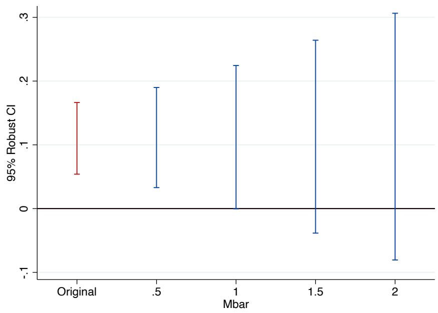
Figure B3: Sensitivity Analysis on Parallel Trends Using Relative Magnitudes Restrictions



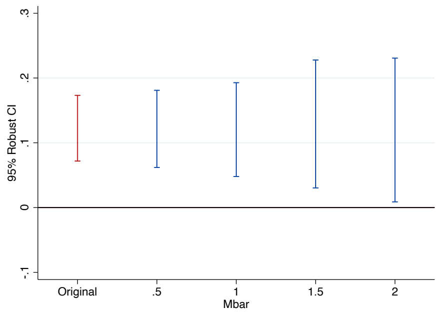
(a) Male Adult: Log Employment



(b) Female Adult: Log Employment



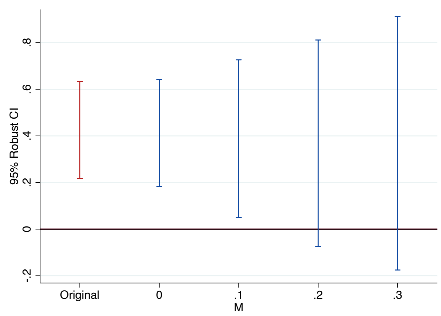
(c) Male Adult: Log wage



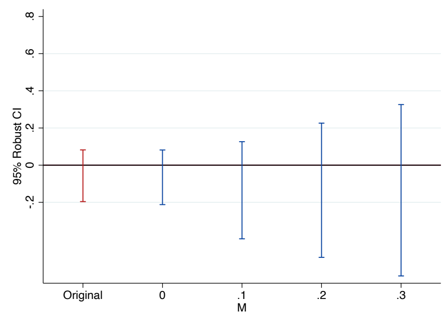
(d) Female Adult: Log wage

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 on male and female adult log wages.

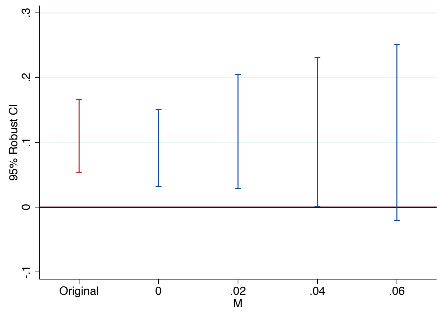
Figure B4: Sensitivity Analysis on Parallel Trends Using Smoothness Restrictions



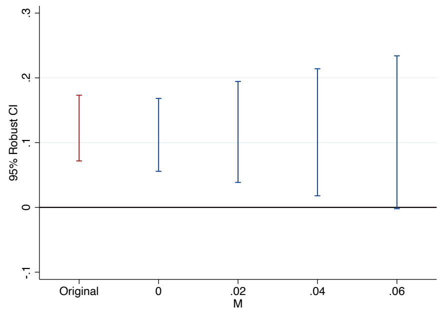
(a) Male Adult: Log Employment



(b) Female Adult: Log 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.

C Theoretical Framework: Task Automation and Oligopsonistic Competition

This section develops a theoretical framework to formalize the theoretical underpinnings of the interpretations we advanced for our empirical findings in the main text. The framework unifies the task-based technological change perspective of Acemoglu and Restrepo (2018, 2019a) with the oligopsonistic labor-market competition model of Berger et al. (2022). Our aim is twofold. First, we demonstrate how a task-based approach can capture the nuances of automation's labor market impact in a manner consistent with our empirical findings. Second, we show that imperfect labor market competition shapes how these automation effects manifest, and that such frictions are critical for reconciling several of our empirical patterns. In the main text, we argue that both product- and labor-market competition likely played roles in driving exits of low-wage, low-productivity factories. To keep the exposition tractable, however, we assume perfectly competitive product markets here and focus on the implications of the labor market's imperfect competition.[33] Despite this, we show that automation can induce a "business stealing" force via local labor-market competition similar to the one via product market competition (Acemoglu et al., 2020; Aghion et al., 2022). For convenience, we use "firm" hereafter instead of "factory" or "plant" as in the main text.

C1 Production Technology

Consider a firm i operating in a local labor market j populated with n_j firms. All firms produce a homogeneous good with its price normalized to one. Each firm's production requires completing a set of differentiated tasks indexed by a continuum from $N-1$ to N. Formally,

$$\ln Y_i = \ln z_i + \int_{N-1}^{N} \ln y_i(x)dx, \tag{C1}$$

where Y_i is total production of the good, $y_i(x)$ is production per task x, and z_i is a firm-specific productivity term. Each task is produced according to the following technological regime:

$$y_i(x) = \begin{cases} \gamma_L(x)l_i(x) + \gamma_M(x)m_i(x) & \text{if } x \in [N-1, I] \\ \gamma_L(x)l_i(x) & \text{if } x \in (I, I') \\ \gamma_H(x)h_i(x) & \text{if } x \in [I', N], \end{cases} \tag{C2}$$

[33] Models that assume perfectly competitive labor markets but monopolistic product markets include Acemoglu et al. (2020) and Koch et al. (2021). Such frameworks produce only market-level wage shifts—individual firms all face the same wage—and generate spillovers primarily through employment levels rather than wages. This contrasts with our empirical findings, which emphasize variation in wages at the plant level and strong local labor-market frictions.

where I and I' represent the "technological" and "skill" thresholds, respectively. The functions γ_M, γ_L, and γ_H measure the productivities of three inputs—machinery (m_i), L-type labor (l_i), and H-type labor (h_i), respectively—across different tasks. Tasks in $[N-1, I]$ can be performed by either L-type labor or machinery, which are assumed to be perfectly substitutes. Beyond I, tasks must be carried out by human labor, so I marks the technological constraint of existing automation technology. A further constraint imposes separate tasks domains for L- and H-type labor in $(I, I']$ and $[I', N]$, respectively, which could arise from distinct comparative advantages between the two worker types. Under this setup, the adoption of new automation technology modeled as an increase in I would directly displaces the tasks of L-type labor, without affecting the tasks of H-type labor. The critical differences between L- and H-type labor, therefore, lie in their distinct task ranges and whether their tasks can be mechanized. For our empirical context, we interpret L-type labor as female weavers and H-type labor as male mechanics.[34].

To simplify the setup, we assume machinery m is competitively supplied by external producers at a fixed rental rate R. By contrast, both types of labor inputs (l and h) are supplied elastically within the local labor market. Denoting their wages by W_{iL} and W_{iH}, respectively, each firm features an upward-sloping labor supply curve that depends on firm i's total employment of the labor type across tasks, as well as local labor market conditions, as outlined in the next subsection. To simplify the discussion, we further assume that $\frac{\gamma_L(x)}{\gamma_M(x)}$ is a non-decreasing continuous function of x on the interval $[N-1, I']$ and that

$$\frac{MC_{iL}}{\gamma_L(I)} > \frac{R}{\gamma_M(I)} \ \forall i \tag{A1}$$

, where MC_{iL} is the marginal cost or shadow price of L-type labor for firm i.[35] These assumptions guarantee that all firms find it more efficient (cost saving) to use

[34]Although it is common (and convenient) to label L-type labor as "low-skilled" and H-type labor as "high-skilled," we prefer more neutral terminology that highlights the task-based nature of workers within this framework. Skill is inherently multidimensional, and wages—often used as an empirical proxy for skill—are endogenously determined in labor markets. In the model here, wage levels depend on the range of tasks performed and the labor supply, as discussed later. Indeed, under certain conditions, L-type workers may earn higher wages than H-type workers prior to automation if demand for tasks in $(I, I']$ is sufficiently higher than supply. Once I expands, automating those tasks, the wage ordering can reverse. Consequently, the distinction between L- and H-type labor really lies in whose tasks can be automated (and whose tasks can be retained or even extended) rather than in any fixed notion of "skill." In this sense, it is perhaps most suitable to refer to L type labor as "displaceable" and H-type labor as "non-displaceable."

[35]Assumption A1 departs from the typical condition in the task-based framework of Acemoglu and Restrepo (2018, 2019a) in the use of the marginal cost MC_{iL} instead of the wage rate W_{iL}. In their setup, tasks are supplied by competitive producers, so all final-good firms face a flat labor supply curve and the same market wage rate if labor is used for the task. Here, however, workers are employed directly by the final-good producer, which faces an upward-slopping labor supply curve and thus holds monopsony power. Hence, an additional unit of labor for the production of a task not only incurs the current wage rate but also raises the cost for existing workers of that type employed on other tasks.

machinery for tasks in $[N-1, I]$ rather than L-type labor, and that the automation boundary I is binding across all firms so that a marginal increase in I would lead them to replace more human labor tasks with machine tasks. Relaxing our assumption to allow for an endogenous machine use threshold below I would generate endogenous selection into automation adoption, as larger firms facing higher marginal labor costs would be more likely to reach the threshold and thus have greater incentives to adopt automation.[36]

The log-aggregator production function implies, through standard arguments of cost-minimization, that the optimal use of each task's input is in inverse proportion to its marginal cost:

$$\begin{aligned} m_i(x) &= \frac{Y_i}{R} && \text{for } x \in [N-1, I] \\ l_i(x) &= \frac{Y_i}{MC_{iL}} && \text{for } x \in (I, I') \\ h_i(x) &= \frac{Y_i}{MC_{iH}} && \text{for } x \in [I', N] \end{aligned} \tag{C3}$$

.[37] Because the firm faces a single shadow price for each input across tasks, any given input is used in the same quantity in all tasks where that input is applied. The production function in (C1) can thus be rewritten in terms of total firm-level input usage:

$$Y_i = B_i\left(\frac{M_i}{I-N+1}\right)^{I-N+1}\left(\frac{L_i}{I'-I}\right)^{I'-I}\left(\frac{H_i}{N-I'}\right)^{N-I'}, \tag{C4}$$

$$\text{where } M_i = \int_{N-1}^{I} m_i(x)dx, L_i = \int_{I}^{I'} l_i(x)dx, H_i = \int_{I'}^{N} h_i(x)dx, \text{ and}$$
$$B_i = z_i \exp\left(\int_{N-1}^{I} \ln\gamma_M(x) + \int_{I}^{I'} \ln\gamma_L(x) + \int_{I'}^{N} \ln\gamma_H(x)dx\right).$$

As a typical result of the task-based framework, the technological threshold I

[36] Specifically, in practice, firms with lower marginal wage rates or higher capital rental rates may find that Assumption A1 does not hold, resulting in an interior threshold $I_i^* < I$ where only tasks in $[N, I_i^*]$ are performed by machines. The prediction that larger, more productive firms are more likely to be technologically constrained and therefore to adopt new automation technologies following a technological breakthrough is also consistent with our data. While this endogenous technological adoption implication is interesting and noteworthy, we abstract from it to focus on how an exogenous expansion of I affects labor demand on those automated firms.

[37] For a log aggregate production function, each task's output $y_i(x)$ also scales inversely with its marginal cost: $y_i(x) = \frac{Y_i}{MC_i(x)}$. Here, each task's marginal cost again incorporates the firm's rising labor costs due to an upward-sloping labor supply, rather than a flat task/wage rate in a perfectly competitive task/labor market. Specifically,

$$MC_i(x) = \begin{cases} \frac{R}{\gamma_M(x)} & \text{if } x \in [N-1, I] \\ \frac{W_{iL}}{\gamma_L(x)} & \text{if } x \in (I, I') \\ \frac{W_{iH}}{\gamma_H(x)} & \text{if } x \in [I', N]. \end{cases}$$

directly enters the exponent for L_i, corresponding to the set of labor tasks that can be displaced by machinery. As I expands (reflecting more advanced automation), a larger share of tasks shifts from L-type labor to machinery, reducing the labor share of output (the "displacement effect"). By contrast, factor-augmenting technological changes (i.e., increases in γ-functions) only shift the factor-neutral term B_i and thus boosts overall labor demand without altering factor shares.

C2 Labor Market

Assume a representative household in local labor market j that solves the following utility maximization problem:

$$\max_{C_i, L_i, H_i} U_j \left(\mathbf{C} - \frac{\mathbf{L}^{\frac{\phi_L+1}{\phi_L}}}{\frac{\phi_L+1}{\phi_L}} - \frac{\mathbf{H}^{\frac{\phi_H+1}{\phi_H}}}{\frac{\phi_H+1}{\phi_H}} \right)$$

$$\text{s.t. } \mathbf{C} = \sum_{i \in j} W_{iL} L_i + \sum_{i \in j} W_{iH} H_i + \mathbf{\Pi}_j, \ \mathbf{L} = \left(\sum_{i \in j} L_i^{\frac{\eta_L+1}{\eta_L}} \right)^{\frac{\eta_L}{\eta_L+1}}, \text{ and } \mathbf{H} = \left(\sum_{i \in j} H_i^{\frac{\eta_H+1}{\eta_H}} \right)^{\frac{\eta_H}{\eta_H+1}}, \tag{C5}$$

where $\mathbf{\Pi_j}$ denotes the aggregated firm profits of all firms in market j. The aggregator terms $\mathbf{L}$ and $\mathbf{H}$ capture the household's disutility from supplying L-type and H-type labor, respectively, and serve as a tractable way for modeling oligopsonistic labor-market competition among the m_j firms in market j. As shown in Berger et al. (2022), such an aggregate labor supply setup can be micro-founded from a discrete-choice setting in which heterogeneous workers choose employers based on idiosyncratic firm preferences. The elasticity parameters $\eta_L > 0$ and $\eta_H > 0$ govern the degree of substitution across employers in the local labor market, analogous to the elasticity of substitution in frameworks of monopolistic or oligopolistic competition. These parameters capture the intensity of employer competition within an area: Larger values of η_L or η_H indicate less employer differentiation and more competitive local labor markets. In the limiting case where $\eta_L \to \infty$ or $\eta_H \to \infty$, the local labor market approaches perfect competition, with firms' marginal products equalized at a single market wage. Meanwhile, parameters $\phi_L > 0$ and $\phi_H > 0$ determine the market-level labor supply elasticities, reflecting households' tradeoffs between market work and outside options (leisure or home production), as well as potential competition across geographic markets. Since we do not explicitly model between-market competition, we henceforth omit the subscript j and focus our analysis on a single local labor market.

Solving the household problem yields the labor supply curve that each firm i faces for $S \in \{H, L\}$:

$$W_{iS} = \mathbf{S}^{\frac{1}{\phi_S} - \frac{1}{\eta_S}} S_i^{\frac{1}{\eta_S}} \text{ for } S \in \{H, L\}, \tag{C6}$$

, where $\mathbf{S}$ is the aggregator ($\mathbf{L}$ or $\mathbf{H}$), and S_i denotes the employment of labor type S at firm i.[38] Since $\mathbf{S}$ incorporates the employment levels of all firms in the local labor market, a firm's optimal employment depends not only on its own wage but also on the wages and employment levels of competing firms. Following Berger et al. (2022), we impose:

$$\eta_S > \phi_S \text{ for } S \in \{H, L\} \tag{A2}$$

. This assumption states that the elasticity of substitution across firms within the local labor market exceeds the market-level labor supply elasticity. Intuitively, Assumption A2 implies that attracting workers from competitors within the market is relatively more efficient than expanding the total market labor supply—a condition that holds in most empirical settings and drives firms' strategic responses under oligopsonistic competition

C3 Equilibrium

Combining the production function (Equation (C4)) and the labor supply function (Equation (C6)), we formulate the firm's profit maximization problem:

$$\Pi_i = \max_{H_i, L_i, M_i} Y_i(H_i, L_i, M_i) - W_{iH}H_i - W_{iL}L_i - RM_i - \Omega \tag{C7}$$

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

, where S_k^* $(k \neq i)$ represents the optimal employment levels of other firms in the same local labor market, and Ω is a fixed operation cost that does not affect input choices. Each firm takes competitors' actions as given and a Nash equilibrium is achieved when all firms in the local labor market make optimal choices. The first order conditions are:

$$\frac{\partial Y_i}{\partial M_i} = R \tag{C8}$$

$$\underbrace{\frac{\partial Y_i}{\partial S_i}}_{\text{Marginal product: } MP_{Si}} = \underbrace{W_{iS} + \left.\frac{\partial W_{iS}}{\partial S_i}\right|_{S_{-i}^*} S_i}_{\text{Marginal cost: } MC_{Si}} \text{ for } S \in \{H, L\}. \tag{C9}$$

[38] This specification of labor supply function nests several special cases. Under perfect competition in the local labor market ($\eta_S \to \infty$), Equation (C6) simplifies to $W_{iS} = \mathbf{S}^{\frac{1}{\phi_S}}$, where all firms pay identical wages that depend on solely on aggregate employment. When, instead, $\eta_S = \phi_S$, Equation (C6) reduces to $W_{iS} = \mathbf{S_i}^{\frac{1}{\eta_S}}$, corresponding to the monopsony case. Similarly, if there is only one firm ($\mathbf{S} = S_i$), we obtain $W_{iS} = \mathbf{S_i}^{\frac{1}{\phi_S}}$.

Following the derivation in Berger et al. (2022), we can express Equation (C9) as:

$$MP_{iS} = MC_{iS} = W_{iS}/\mu_{iS}, \text{where } \mu_{iS} = \frac{\varepsilon_{iS}}{\varepsilon_{iS}+1},$$
$$\varepsilon_{iS} := \left[\left. \frac{\partial \ln W_{iS}}{\partial \ln S_i} \right|_{S_{-i}} \right]^{-1} = \left[(1-e_{iS}) \frac{1}{\eta_S} + e_{iS} \frac{1}{\phi_S} \right]^{-1} \text{ and } e_{iS} = \frac{W_{iS} S_i}{\sum_i W_{iS} S_i}. \tag{C10}$$

Here, μ_{iS} denotes firm i's markdown on input $S \in \{H, L\}$, ε_{iS} represents the inverse of the firm's wage elasticity of labor supply for input S, and e_{iS} is the firm's share of input S's wage bill in the local labor market. Under Assumption A2, firms with higher marginal products (e.g., due to higher productivity z_i) offer higher wages, employ more workers, capture a larger share of the labor market, and end up facing a less elastic labor supply curve—resulting in a wider markdown and greater labor market power.

Using Equations (C4), (C6) and (C10), we can express the entire system of labor demand and labor supply functions as:

$$\begin{aligned} W_{iL}(L_i) &= \mu_{iL}(I' - I) Y_i / L_i && \text{(labor demand for } L) \\ W_{iL}\left(L_i, L^*_{-i}\right) &= \mathbf{L}^{\frac{1}{\phi_L} - \frac{1}{\eta_L}} L_i^{\frac{1}{\eta_L}} && \text{(labor supply for } L), \end{aligned} \tag{C11}$$

and

$$\begin{aligned} W_{iH}(L_i) &= \mu_{iH}(N - I') Y_i / H_i && \text{(labor demand for } H) \\ W_{iH}\left(H_i, H^*_{-i}\right) &= \mathbf{H}^{\frac{1}{\phi_H} - \frac{1}{\eta_H}} H_i^{\frac{1}{\eta_H}} && \text{(labor supply for } H). \end{aligned} \tag{C12}$$

From the labor demand equations we can derive the labor shares as:

$$\begin{aligned} s_{iL} &\equiv \frac{W_{iL} L_i}{Y_i} = \mu_{iL}(I' - I); \\ s_{iH} &\equiv \frac{W_{iH} H_i}{Y_i} = \mu_{iH}(N - I'). \end{aligned} \tag{C13}$$

The market equilibrium for this local economy is defined as a set of firm-specific input allocations $\{M_i, L_i, H_i\}_{i \in j}$ and wages $\{W_{iL}, W_{iH}\}_{i \in j}$ such that, given the machine rental rate R, Equations (C8), (C11) and (C12) are satisfied for each firm i in the local labor market j.

C4 Automation Impact

Our framework settled above allows us to examine how automation adoption affects both a firm's own labor demand and that of its competitors, providing a theoretical account for our empirical findings. We characterize an automation event as an increase in the I for a specific firm i while holding constant the technological parameters of competing firms. We first analyze the direct (first-round) effect of this technology adoption on the adopting firm's labor demand—how changes in I_i

affect firm i's optimal labor allocation and wages immediately. We then characterize the triggered (second-round) equilibrium spillover effects arising from labor market competition.[39]

Labor Demand. From the labor demand equations in Equations (C11) and (C12), we can decompose the direct effect of marginal automation on the adopting firm's labor demand:

$$\begin{aligned}\frac{d\ln(W_{iL}L_i)}{dI} &= \underbrace{\frac{d\ln\mu_{iL}}{dI}}_{\text{Markdown effect } \lesseqgtr 0} + \underbrace{\frac{d\ln(I'-I)}{dI}}_{\text{(Net) Displacement effect } <0} + \underbrace{\frac{d\ln(Y_i)}{dI}}_{\text{Productivity effect } >0}; \\ \frac{d\ln(W_{iH}H_i)}{dI} &= \underbrace{\frac{d\ln\mu_{iH}}{dI}}_{\text{Markdown effect } \lesseqgtr 0} + \underbrace{\frac{d\ln(Y_i)}{dI}}_{\text{Productivity effect } >0}.\end{aligned} \tag{C14}$$

Equation (C14) reveals that automation generates a negative displacement effect ($\frac{d\ln(I'-I)}{dI} = -\frac{1}{I'-I}$) on L-type labor demand by directly reducing their task range.[40] Counterbalancing this, automation also produces a productivity effect through more efficient production under automation. We can further decompose this productivity effect as:

$$\begin{aligned}\frac{d\ln Y_i}{dI} &= \underbrace{\left.\frac{d\ln Y_i}{dI}\right|_{M,L,H}}_{\text{Pure productivity effect}} + \underbrace{\frac{\partial \ln Y_i}{\partial M}\frac{dM_i}{dI} + \frac{\partial \ln Y_i}{\partial L}\frac{dL_i}{dI} + \frac{\partial \ln Y_i}{\partial H}\frac{dH_i}{dI}}_{\text{Re-optimization effect}}, \\ \left.\frac{d\ln Y_i}{dI}\right|_{M,L,H} &= \ln\left(\frac{W_{iL}}{\mu_{iL}\gamma_L(I)}\right) - \ln\left(\frac{R}{\gamma_M(I)}\right) > 0.\end{aligned} \tag{C15}$$

The pure productivity effect (productivity gains from automation holding input quantities fixed) is positive under Assumption A1, and the re-optimization effect must also be positive given profit optimization. Under our assumption of perfectly elastic machine supply, the total productivity effect can fully offset the negative displacement effect. To see this, we can derive automation's impact on average labor productivity in the simplified case where $I' = N$ (i.e., no H-type labor is used):

$$\frac{d\ln(Y_i/L_i)}{dI} = \frac{\ln\left(\frac{W_{iL}}{\mu_{iL}\gamma_L(I)}\right) - \ln\left(\frac{R}{\gamma_M(I)}\right)}{I'-I} + \frac{1}{I'-I} > 0. \tag{C16}$$

The second term in Equation (C16) precisely cancels out the displacement effect, yielding a positive net effect. When machines' supply or use is subject to constraints due to production limitations, financial frictions, or other constraints, however, the displacement effect may dominate and reduce labor demand. This analysis highlights how labor market frictions could hamper automation's productivity effects. More

[39] Subsequent ripple effects are of lower orders and do not qualitatively alter our conclusions.

[40] This can represent a net effect, incorporating both task displacement and reinstatement into new tasks, assuming unchanged γ_L across the interval (I, I').

frictional labor markets reduce productivity gains from re-optimization, thereby limiting a potential increase in labor demand. Finally, Equation (C14) includes a markdown effect whose sign depends on the net impact of displacement and productivity effects. When this net effect is positive and increases labor demand, it raises the firm's market share e_{iS} and labor elasticity $1/\varepsilon_{iS}$, widening the markdown (reducing μ_{iS}) under Assumption A2. This creates an additional dampening force on potential labor demand gains from automation, though this second-order effect cannot reverse the sign of the overall impact.

These results formalize our interpretations in the main text. First, the absence of a displacement effect indicates a stronger (and always positive) effect on the labor demand of H-type workers compared to L-type workers (male mechanics versus female weavers in our empirical context). Moreover, when new tasks are created for H-type workers, a reinstatement effect further augments their labor demand:

$$\frac{d\ln(W_{iH}H_i)}{dN} = \underbrace{\frac{d\ln\mu_{iH}}{dN}}_{\text{Markdown effect }\lesseqgtr 0} + \underbrace{\frac{d\ln(N-I')}{dN}}_{\text{Reinstatement effect }>0} + \underbrace{\frac{d\ln(Y_i)}{dN}}_{\text{Productivity effect }>0}, \tag{C17}$$

where the productivity effect is positive when $\frac{R}{\gamma_M(N-1)} > \frac{MC_{iH}}{\gamma_H(N)}$. Thus, increased demand for "skilled" workers that is traditionally attributed to skill-biased technological change in factor-biased frameworks can instead be re-interpreted as a joint result of productivity and reinstatement effects within the task-based framework. Second, when the displacement effect is substantial and factor supply (machinery and labor) faces frictions, the productivity effect for L-type workers may not fully offset the displacement effect, resulting in muted or even negative impacts on their labor demand. Nevertheless, labor productivity always increases, substantially when the direct cost savings from machine-replaced tasks are large. This is consistent with our findings for female silk weavers following powerloom adoption. Lastly, Equation (C13), demonstrates that automation (increased I) directly reduces the labor share of L-type workers while raising the factor shares of other inputs. Enhanced employer monopsony power (reduced μ_{iL}) could further suppress labor's share. Both predictions are consistent with female weavers' experience in our empirical analysis.

Employment versus Wage. Combining the labor demand and labor supply equations in Equations (C11) and (C12) to derive equilibrium employment and wages, we can decompose the labor demand effect into employment and wage components:

$$\begin{aligned}
\frac{d\ln W_{iL}}{dI} &= \frac{1}{1+\eta_L}\left(\frac{d\ln\mu_{iL}}{dI} + \frac{d\ln(I'-I)}{dI} + \frac{d\ln Y_i}{dI}\right) + \frac{\eta_L-\phi_L}{\phi_L(1+\eta_L)}\frac{d\ln\mathbf{L}}{dI} \\
\frac{d\ln L_i}{dI} &= \frac{\eta_L}{1+\eta_L}\left(\frac{d\ln\mu_{iL}}{dI} + \frac{d\ln(I'-I)}{dI} + \frac{d\ln Y_i}{dI}\right) + \frac{\phi_L-\eta_L}{\phi_L(1+\eta_L)}\frac{d\ln\mathbf{L}}{dI},
\end{aligned} \tag{C18}$$

and

$$\begin{aligned}\frac{d\ln W_{iH}}{dI} &= \frac{1}{1+\eta_H}\left(\frac{d\ln \mu_{iH}}{dI}+\frac{d\ln Y_i}{dI}\right)+\frac{\eta_H-\phi_H}{\phi_H(1+\eta_H)}\frac{d\ln \mathbf{H}}{dI} \\ \frac{d\ln H_i}{dI} &= \frac{\eta_H}{1+\eta_H}\left(\frac{d\ln \mu_{iH}}{dI}+\frac{d\ln Y_i}{dI}\right)+\frac{\phi_H-\eta_H}{\phi_H(1+\eta_H)}\frac{d\ln \mathbf{H}}{dI}\end{aligned} \tag{C19}$$

.[41] From Equations (C18) and (C19), it is clear that the relative magnitude of automation's impact on employment versus wages depends critically on the labor elasticity parameters—both within-market (η) and across markets (ϕ). In fact, we can express this relationship as:

$$\frac{d\ln(W_{iS})}{dI} = \left(\frac{1-\tilde{s}_{iS}}{\eta_S}+\frac{\tilde{s}_{iS}}{\phi_S}\right)\frac{d\ln(S_i)}{dI} \text{ for } S\in\{H,L\}, \tag{C20}$$

where $\tilde{s}_{iS} \equiv S_i^{\frac{\eta_S+1}{\eta_S}} / \sum_k S_k^{\frac{\eta_S+1}{\eta_S}} \in (0,1]$. Thus technological change affects employment more than wages when η or ϕ is larger—that is, when labor markets are more competitive either within or across local areas, with their relative importance determined by the firm's employment share in the local market. This result is intuitive: In more competitive labor markets, productivity-enhanced firms can attract workers from competitors without substantial wage increases. Conversely, in monopsonistic or oligopsonistic settings where firms face upward-sloping labor supply curves, expanding employment necessitates significant wage increases, dampening the employment response to productivity-enhancing technologies.

Our empirical findings of significant wage increases (10%) for female weavers with minimal employment changes at adopting firms suggest an inelastic plant-level labor supply for these workers. This indicates significant monopsony power, which can be manifested by wide markdowns (Equation (C10)) and low labor shares (Equation (C13)). In contrast, the pronounced increase in male employment relative to their wage growth indicates a more elastic labor supply, which is consistent with their limited presence in the silk-weaving sector before powerloom diffusion. We next show that these implications, derived from event-study analyses comparing adopting and non-adopting plants within local markets, remain valid even when accounting for strategic behavior under oligopsonistic competition.

Spillover Effects. To analyze competitors' strategic responses to firm i's technology adoption, we derive the indirect cross-effects on firm $k \neq i$ from equilibrium

[41] The explicit formulas for equilibrium employment and wages are

$$W_{iL} = (\mu_{iL}(I'-I)Y_i)^{\frac{1}{1+\eta_L}}\mathbf{L}^{\frac{\eta_L-\phi_L}{\phi_L(1+\eta_L)}},\ L_i = (\mu_{iL}(I'-I)Y_i)^{\frac{\eta_L}{1+\eta_L}}\mathbf{L}^{\frac{\phi_L-\eta_L}{\phi_L(1+\eta_L)}};$$
$$W_{iH} = (\mu_{iH}(N-I')Y_i)^{\frac{1}{1+\eta_H}}\mathbf{H}^{\frac{\eta_H-\phi_H}{\phi_H(1+\eta_H)}},\ H_i = (\mu_{iH}(N-I')Y_i)^{\frac{\eta_H}{1+\eta_H}}\mathbf{H}^{\frac{\phi_H-\eta_H}{\phi_H(1+\eta_H)}}.$$

employment and wage equations:

$$\begin{aligned}\frac{d\ln W_{kS}}{dI} &= \underbrace{\frac{1}{1+\eta_S}\frac{d\ln \mu_{kS}}{de_{kS}}\frac{de_{kS}}{de_{iS}}\frac{de_{iS}}{dI}}_{+} + \underbrace{\frac{\eta_S-\phi_S}{\phi_S(1+\eta_S)}\tilde{s}_{iS}\frac{d\ln S_i}{dI}}_{+} \\ \frac{d\ln S_k}{dI} &= \underbrace{\frac{\eta_S}{1+\eta_S}\frac{d\ln \mu_{kS}}{de_{kS}}\frac{de_{kS}}{de_{iS}}\frac{de_{iS}}{dI}}_{+} + \underbrace{\frac{\phi_S-\eta_S}{\phi_S(1+\eta_S)}\tilde{s}_{iS}\frac{d\ln S_i}{dI}}_{-}.\end{aligned} \tag{C21}$$

This represents the second-round effect induced by the impact of the first-round direct effect of technological adoption (Equations (C18) and (C19)) on labor market aggregators. Under Assumption A2 and assuming a positive direct effect on employment ($\frac{d\ln S_i}{dI} > 0$), the first term in the right hand side of both equations of Equation (C21) is positive, reflecting that reduced market share and hence increased labor elasticity incentivize competing firm k to raise wages to attract more workers. The second term is positive for wages (W_{kS}) but negative for employment (S_k), however, reflecting firm k's optimal adjustment of labor input choices under a tighter labor market (higher $\mathbf{S}$) and a less elastic labor supply curve resulting from increased market-wide employment. Under plausible parameter values and firm shares, the second term's effect on aggregate labor indexes typically dominates the first term for employment, yielding an overall negative effect.[42] Consequently, if automation adoption increases the adopting firm's employment to meet higher labor demand, it induces competitors to reduce employment while increasing wages. This result emerges because firms are strategic substitutes in employment decisions but strategic complements in wage setting, analogous to Cournot competition. In such cases, a standard event-study analysis would overestimate the employment effect and underestimate the wage effect of automation adoption.

Applying these insights to our empirical context, spillover effects on adult female weavers' employment are likely minimal given our estimated null employment effects. This is because if significant negative employment spillovers existed, such that nonadopting competitors respond by simultaneously reducing their workforce, the employment gap between adopting and nonadopting firms would widen, yielding a positive and significant treatment effect on employment, which we do not observe. Conversely, our estimated wage increases for adult female weavers may underestimate the true effect of automation adoption, as competitors likely bid up wages to retain their workers. For adult male mechanics, spillover effects are probably limited despite significant direct effects in our event study analysis. This is because the size

[42] By solving the derivatives in the second equation of Equation (C21), we obtain

$$\frac{d\ln S_k}{dI} = \frac{1}{1+\eta_S}(\eta_S-\phi_S)\frac{1}{\phi_S}\left[\mu_{kS}e_{kS}e_{iS}\left(1+\frac{1-\tilde{s}_{iS}}{\eta_S}+\frac{\tilde{s}_{iS}}{\phi_S}\right)-\tilde{s}_{iS}\right]\frac{d\ln S_i}{dI}.$$

Under Assumption A2, the sign of employment spillovers depends on the sign of the term in brackets, which is likely negative in most cases.

of both terms in Equation (C21) depends on the labor market shares of firm i and k (e_{iS}, e_{kS}, $\tilde{s}_{iS}$). When firms command only negligible shares in the labor market, they will have minimal impact on labor market aggregates and are themselves minimally affected by changes in these aggregates. These theoretical predictions also align with our supplementary event study analysis in FigureE1, which compares nonadopting plants in adopting areas versus those in nonadopting areas; the analysis finds significant positive spillover effects only for adult female wage, lending support to the relevance of our theoretical framework.

Business Stealing. The strategic responses of competitors with respect to a firm's technology adoption and subsequent labor demand increase generate a business stealing effect via labor market competition, akin to what can be found in monopolistic or oligopolistic settings where product market competition plays the role (Acemoglu et al., 2020; Aghion et al., 2022). In oligopolistic labor markets, when one firm increases productivity and shifts its labor demand curve rightward, its competitors have to face a leftward-shifted labor supply curve, thus reducing their labor inputs while raising wages in the new equilibrium. This intensive margin of business stealing can also lead to an extensive margin of business stealing, by driving low-productivity, low-profit firms our of the market. To demonstrate this, we derive a firm's equilibrium profit using optimal input choices:

$$\Pi_i = Y_i \left[(1 - \mu_{iL}) (I' - I) + (1 - \mu_{iH}) (N - I') \right] - \Omega. \tag{C22}$$

Since Y_i depends on idiosyncratic productivity z_i and μ_{iS} depends on labor market wage bill share e_i, Equation (C22) reveals that the profit is greater for more productive firms (higher z) through two channels: a larger output (higher Y_i) and a wider markdown (lower values of μ_{iL} and μ_{iH}). As discussed earlier, more productive firms realize larger productivity and labor cost gains from automation and are thus more likely to adopt new technology, leaving non-adopting firms disproportionately concentrated among low-productivity, low-wage, and low-profit establishments.[43] New technology diffusion squeezes non-adopting firms' profits by forcing them to contend with more costly labor, resulting in reduced output (Y_i) and narrower markdowns (μ_{iS}). This competitive pressure can thus trigger the exit of the least productive firms when their gross profits fall below fixed operating costs (Ω), leading to zero or negative net profits.

We propose that this labor market competition, driven by both incumbent adoption and entry of powered plants, partially explains the observed simultaneous exit

[43] Perhaps interesting, Equation (C22) also indicates that automation (increased I) reduces profit because all profit in our setting stems from monopsony power, and labor-saving technology that reduces labor use also reduces this source of profit. For automation to be profitable, however, the increase in production must be large enough to counteract this effect. Additional gains from the product market are also available in a more general setting that incorporates monopoly power.

of less productive, low-wage "luddite" factories alongside powerloom diffusion. The process reduces overall market employment while elevating market wages (through both intensive and extensive business stealing margins).[44] In a more general model incorporating monopolistic or oligopolistic product markets, product market competition would similarly drive out low-productivity firms, further intensifying market dynamics. Thus, technological displacement can materialize at the market level even when strong productivity effects (combined with task reinstatement) prevent employment declines within adopting firms. While entry of high-productivity, high-wage firms equipped with new technologies could potentially offset reduced market employment, such entry may take time to materialize and, at least in our empirical context, was insufficient to fully mitigate the technological unemployment arising from short-run market churning.[45]

Table C1: Market-level Impact of Technological Diffusion

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

Note: This table presents model predictions for various effects of automation technology diffusion on market employment and wages under Assumptions A1 and A2. The adoption effect captures the direct first-round effect of a firm's technology adoption. The spillover effect reflects competitors' strategic responses within the same labor market due to oligopsonistic competition. The exit effect indicates the exit of marginal, low-wage firms induced by rising market wages. The entry effect represents the entry of new technology-adopting firms with high productivity and wages.

[44] There also exists a counteracting effect on market employment and wages stemming from this market dynamics: Firm exit reduces labor market competition, potentially shifting labor supply curves of surviving firms leftward and allowing them to pay lower wages while employing more workers. This force, however, may be suppressed by downward wage rigidity, which prevents substantial wage declines at the firm level due to worker incentives or fairness concerns. The relative importance of these offsetting forces remains an empirical question worthy of further investigation.

[45] We summarize the signs of all potential effects at the market level in Table C1.

D Alternative Theoretical Framework: Worker Effort and Wage Contract

This section develops an alternative theoretical framework based on worker effort and piece-rate wage contracts to demonstrate how automation technology reduces rent-sharing with workers by allowing employers to lower the piece rates required to elicit effort. This analysis thus solely targets on the main workforce in our empirical context—female weavers—and abstracts from other labor. Although we primarily examine a single firm-worker match, we implicitly assume a frictional, imperfectly competitive labor market where workers' outside options do not fully capture the entire match surplus.

Consider a mass L of homogeneous workers and a unit mass of homogeneous firms, all risk neutral. Workers and firms are initially randomly matched. Assuming that production follows constant return to scale, firm size is irrelevant, allowing us to focus on a worker-firm pair.[46] Each worker-firm match produces according to the production function:

$$y = f(k, e) = zk^{1-\alpha}e^{\alpha}, \quad 0 < \alpha < 1, \tag{D1}$$

where z is firm productivity, k is capital or machinery, and e is worker effort. The parameter α represents labor factor share, but can also be interpreted as task share for labor, as we have seen within the task-based framework in Appendix C. The production function is increasing and strictly concave. Effort cost is private and the cost function $c(e)$ is increasing and strictly convex. The firm cannot directly observe effort but can infer it indirectly through output y, as the production function is deterministic and there is no other uncertainty.[47] At the beginning of the match, the firm sets and commits to an output-dependent wage contract, $w(y)$, in order to discipline the worker's effort. We assume that this wage contract is restricted to be a pure piece rate with a fixed component,

$$w(y) = \beta y, \quad 0 \leq \beta \leq p. \tag{D2}$$

While restrictive, this wage-setting approach does match historical accounts of female silk weavers during our study period, and can be theoretically justified in settings where employers need to hire multiple workers with heterogeneous productivity (Lazear, 2000).[48] The worker, anticipating this wage contract, will choose e

[46] This setting is particularly appropriate for our context of silk-weaving factories, where equipment was fully independent and the scale and scope economies were negligible.

[47] The setting—hidden action without uncertainty—results in a principal-agent model with trivial information asymmetry, as the hidden action can be perfectly and costlessly detected, allowing first-best effort to be easily achieved. Yet, this aligns with our empirical setting, where uncertainty in silk weaving was minimal.

[48] We abstract from worker heterogeneity in productivity again given that the production of

to maximize her utility:

$$U = w(f(e;k)) - c(e), \tag{D3}$$

where we assume the cost function takes the simple convex form:

$$c(e) = e^{\gamma}, \ \gamma \geq 1. \tag{D4}$$

The worker also has an outside option, U_0, such that she will reject the wage contract if the expected utility falls below this value. If the worker accepts, the firm earns profit:

$$\begin{aligned} \pi &= pf(k,e) - w(f(e,k)) - rk \\ &= (p-\beta)f(k,e) - rk, \end{aligned} \tag{D5}$$

where p is the price of the production good, and r is the capital rental rate. We assume a homogeneous good with a perfectly competitive product market, so p is taken exogenous to the firm. Capital price r is also assumed to be competitively determined and thus constant. Similarly to Assumption 1 in Appendix C, we impose the following condition on the rental price:

$$\frac{r}{1-\alpha} < (pz)^{\frac{\gamma}{\gamma-\alpha}}, \tag{A3}$$

, which would ensure that automation (reduced α) is cost-efficient for the firm.[49]

Given the wage contract, the worker's optimal effort choice, e^*, is derived from the first-order condition of her utility maximization problem:

$$\begin{aligned} & w'(f(e;k))f'(e;k) = c'(e) \\ \Rightarrow \ & e(\beta,k) = \left[\frac{\alpha}{\gamma}\beta z k^{1-\alpha}\right]^{\frac{1}{\gamma-\alpha}}. \end{aligned} \tag{D6}$$

This equation forms the worker's incentive compatibility (IC) condition faced by the firm. The firm's problem is to choose the wage parameter, β, and capital level, k, to maximize profit, π, subject to the IC constraint and the participation constraint (PC),

$$w(f(k,e)) - c(e) \geq U_0. \tag{D7}$$

Assuming that PC is not binding, which is possible given our linear piece-rate re-

silk-weaving—our focus here—is perfectly divisible.

[49]Notably, more productive firms are again more likely to find automation beneficial and thus have stronger incentives to adopt, similar to results from the framework in Appendix C.

striction on the wage contract, we can solve the interior solution of the firm problem:

$$\begin{aligned}\beta^* &= \frac{\alpha}{\gamma} p, \\ k^* &= (pz)^{\frac{\gamma}{\alpha(\gamma-1)}} \left(\frac{\Gamma}{r}\right)^{\frac{\gamma-a}{a(\gamma-1)}}, \\ e^* &= \left(\frac{\alpha}{\gamma}\right)^{\frac{2}{\gamma-\alpha}} (k^*)^{\frac{1-\alpha}{\gamma-\alpha}}.\end{aligned} \tag{D8}$$

where $\Gamma = (1-\alpha)\left(\frac{\alpha}{\gamma}\right)^{\frac{2\alpha}{\gamma-\alpha}}$ is a constant.[50]

The most significant insight from Equation (D8) is that automation—manifested as a decrease in α as suggested by the task-based framework—results in a reduction in the optimal piece rate β^*. This occurs because automation diminishes workers' importance in production, thereby reducing the need for high-powered performance pay to elicit effort. By contrast, factor-augmenting or factor-neutral technological changes (e.g. increases in firm productivity z) do not affect the piece rate, though they increase capital use k^* and, through this, the equilibrium effort executed by the worker. Similarly, business fluctuations that affect product price p influence optimal input levels but leave the piece rate unchanged. Notably, a decline in the marginal cost of exerting effort (decreased γ) would actually increase the piece rate rather than reduce it, contrary to predictions from compensating differential models. This occurs because higher piece rates and lower effort costs serve as complementary tools for eliciting worker effort, generating a force that can potentially counteract firms' incentives to reduce wages due to compensating differentials. Thus, automation emerges as the only factor in our framework that reduces piece rates, consistent with our empirical observations in the powerloom weaving context.

Despite facing reduced piece rates under automation, a worker's total wages may still increase as she operates more machines and produces greater output. This can

[50] If instead we allow firms to set arbitrary wage contracts, the PC would necessarily bind, because the IC constraint can be satisfied at no additional costs. This occurs because in a principal-agent model with no uncertainty, such as the one here, the firm can implement the "first-best" (efficient) effort, e^{fb} such that

$$pf'(e^{fb}; k) = c'(e^{fb}), \tag{D9}$$

by setting the optimal wage function near the efficient effect e^{fb} as

$$\begin{aligned} w(y;k) &= \frac{c'\left(e^{fb}\right)}{f'\left(e^{fb};k\right)} y + \left(c(e^{fb}) + U_0 - \frac{c'\left(e^{fb}\right)}{f'\left(e^{fb};k\right)} f\left(e^{fb};k\right)\right) \\ &= py + \left(c(e^{fb}) + U_0 - pf\left(e^{fb};k\right)\right). \end{aligned} \tag{D10}$$

, where the terms in brackets represent a constant (i.e. the intercept of a linear piece-rate wage contract) chosen so that the worker's payoff at e^{fb} exactly equals U_0. In other words, the marginal return from effort only needs to fully accrue to workers in the neighborhood of the first-best solution to satisfy the IC constraint, while the level of the entire wage profile can be adjusted by the firm to reduce the equilibrium wage to the outside option level. This thus allows firms to capture the entire joint surplus with zero left to workers.

be demonstrated through a decomposition similar to that in Appendix C:

$$-\frac{d\ln w}{d\alpha} = \underbrace{-\frac{d\ln \beta}{d\alpha}}_{\text{Displacement effect}=-1} \qquad \underbrace{-\frac{d\ln y}{d\alpha}}_{\text{Productivity effect}>0} \tag{D11}$$

, and

$$\begin{aligned} -\frac{d\ln y}{d\alpha} &= \underbrace{-\left.\frac{d\ln y}{d\alpha}\right|_{k,e}}_{\text{Pure productivity effect}} \qquad \underbrace{-\left(\frac{\partial \ln y}{\partial \ln k}\frac{d\ln k}{d\alpha} + \frac{\partial \ln y}{\partial \ln e}\frac{d\ln e}{d\alpha}\right)}_{\text{Re-optimization effect}}, \\ -\left.\frac{d\ln y}{d\alpha}\right|_{k,e} &= \ln k - \ln e = \frac{\gamma}{\alpha(\gamma-\alpha)}\ln(pz) + \frac{1}{\alpha}\ln\left(\frac{1-\alpha}{r}\right) > 0. \end{aligned} \tag{D12}$$

The last equation uses optimal input choices, and the inequality holds under Assumption A3. This productivity effect is larger when productivity (z) or product price (p) is high and when the convexity of the effort cost function (γ) is low.[51]

Next, using the optimal solutions, the firm's equilibrium profit can be written as:

$$\pi = py - w - rk = \frac{\alpha}{\gamma}(\gamma-\alpha)py, \tag{D13}$$

which yields a wage-to-profit ratio of:

$$\frac{w}{\pi} = \frac{1}{\gamma-\alpha}. \tag{D14}$$

Thus, a decrease in α induced by automation reduces this wage-to-profit ratio, indicating that automation allows employers to capture a greater share of the gains relative to workers—consistent with our observations in the Japanese silk-weaving industry.[52]

[51] The reason why less convex effort cost functions yield larger pure productivity effects is that they imply lower marginal productivity of labor effort, resulting in greater productivity gains when these inputs are replaced by more efficient machines.

[52] The share of quasi-rent captured by workers involves a slightly more complex relationship. The quasi-rent of a worker-firm match, denoted as Q, is:

$$Q = py - rk - c(e) - U_0 \tag{D15}$$

, where we assume the firm's outside option is zero for simplicity. Using the first-order conditions, i.e.

$$\begin{aligned} e^{*\gamma} &= \frac{\alpha^2}{\gamma^2}py^*, \\ rk^* &= p\frac{\gamma-\alpha}{\gamma}(1-\alpha)y^*. \end{aligned} \tag{D16}$$

, the worker's share of this quasi-rent can be written as

$$\frac{w - c(e) - U_0}{Q} = \frac{py\frac{\alpha(\gamma-\alpha)}{\gamma^2} - U_0}{py\frac{\alpha(\gamma-\alpha)(1+\gamma)}{\gamma^2} - U_0}. \tag{D17}$$

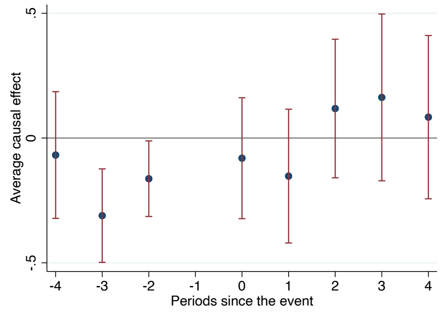
. This ratio equals a constant $\frac{1}{\gamma}$ when $U_0 = 0$ and increases with α when $U_0 > 0$, provided that

Finally, since wage (w) is a linear function of output, firms with low productivity (z) may more frequently face binding the participation constraint (see the numerator of Equation (D17)), requiring them to pay wages equal to workers' outside options. When the outside options (U_0) are determined by alternative employment opportunities, automation diffusion among high-productivity competing firms can thus force wage increases at nonadopting low-productivity firms—creating wage spillover effects. This wage pressure reduces profits at these less productive firms, potentially triggering their exit from the market.

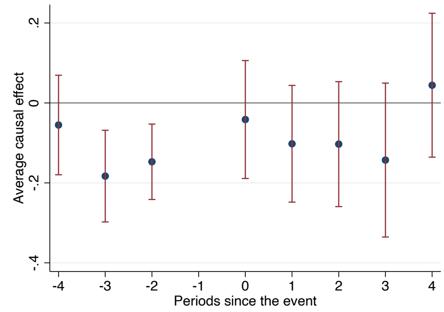
$\alpha < \gamma/2$ or $\gamma > 2$. Thus, in most cases, automation, via reducing workers' production share parameter α, also reduces the share of quasi-rent accrued to workers.

E Additional Figures and Tables

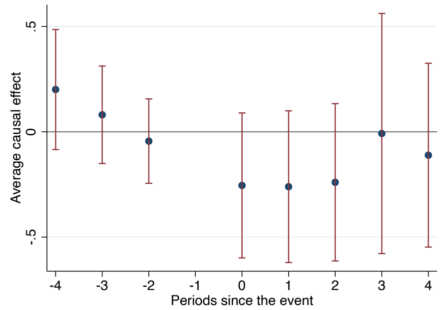
Figure E1: The Impacts of Area-level Power Adoption on Never-adopting Plants' Employment and Wage



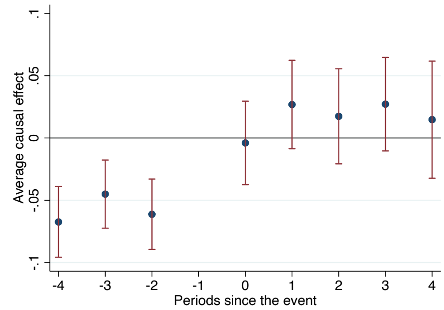
(a) ln(Male Adult Employment)



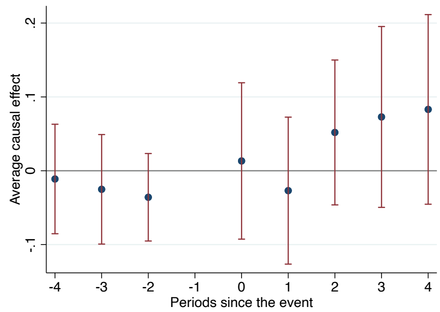
(b) ln(Female Adult Employment)



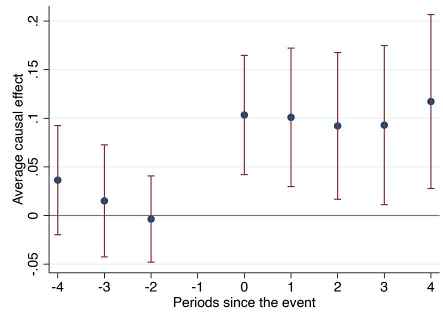
(c) ln(Child Employment)



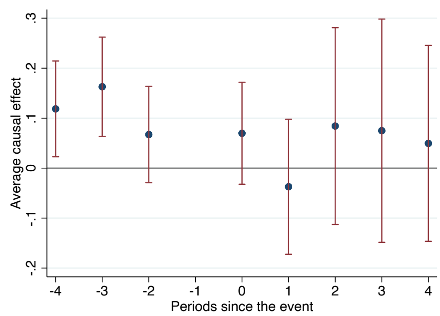
(d) ln(Operation Hours)



(e) ln(Male Adult Wage)



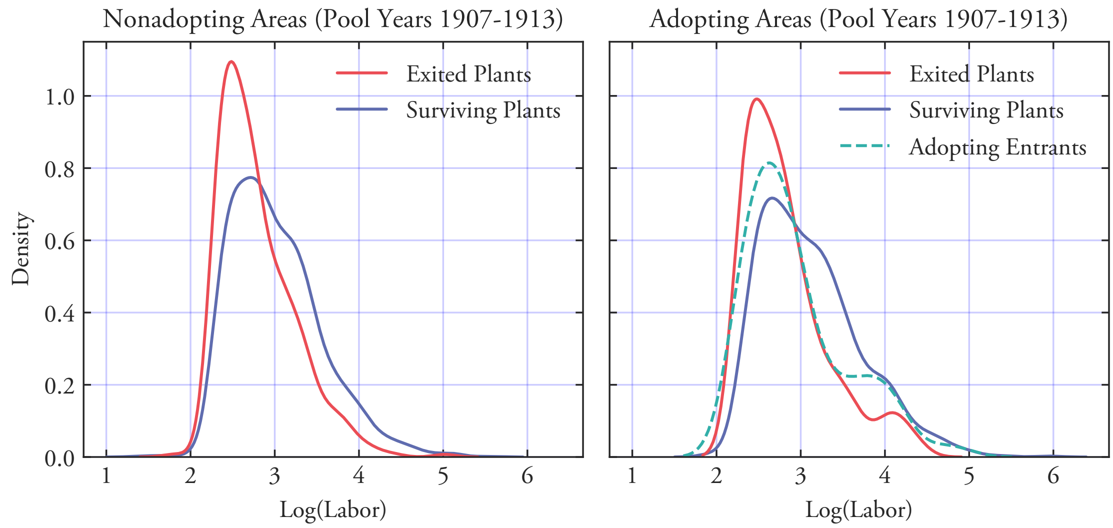
(f) ln(Female Adult Wage)



(g) ln(Child Wage)

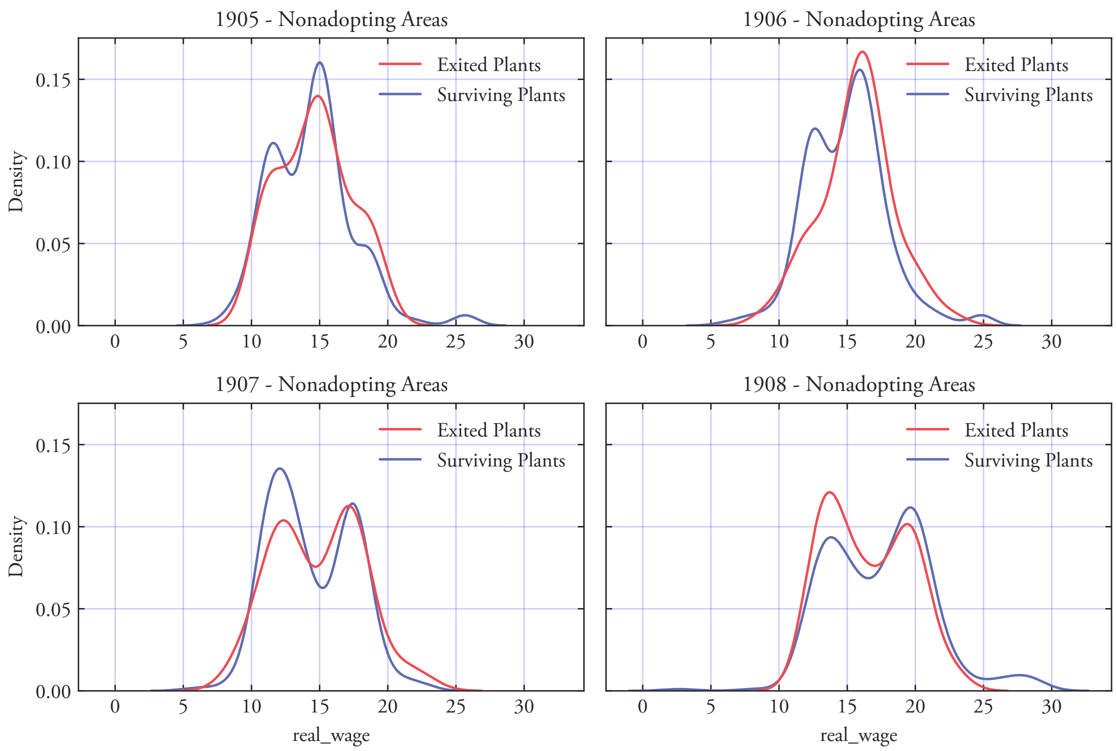
Note: This figure reports the plant-level event study results of area-level adoption events on never-adopting plants' employment and wages across different worker categories. In particular, the specification here replaces the plant-level treatment in Equation (1) with an area-level treatment defined as the first time an area adopted power. Given that the treatment is at the area level, we also replace the area-by-year fixed effects in Equation (1) with a simple year fixed effects. All other notes are the same as in Figure 2.

Figure E2: Employmen Size Distribution of Exited and Surviving Plants in Non-adopting Areas versus Adopting Areas (Pool Years)



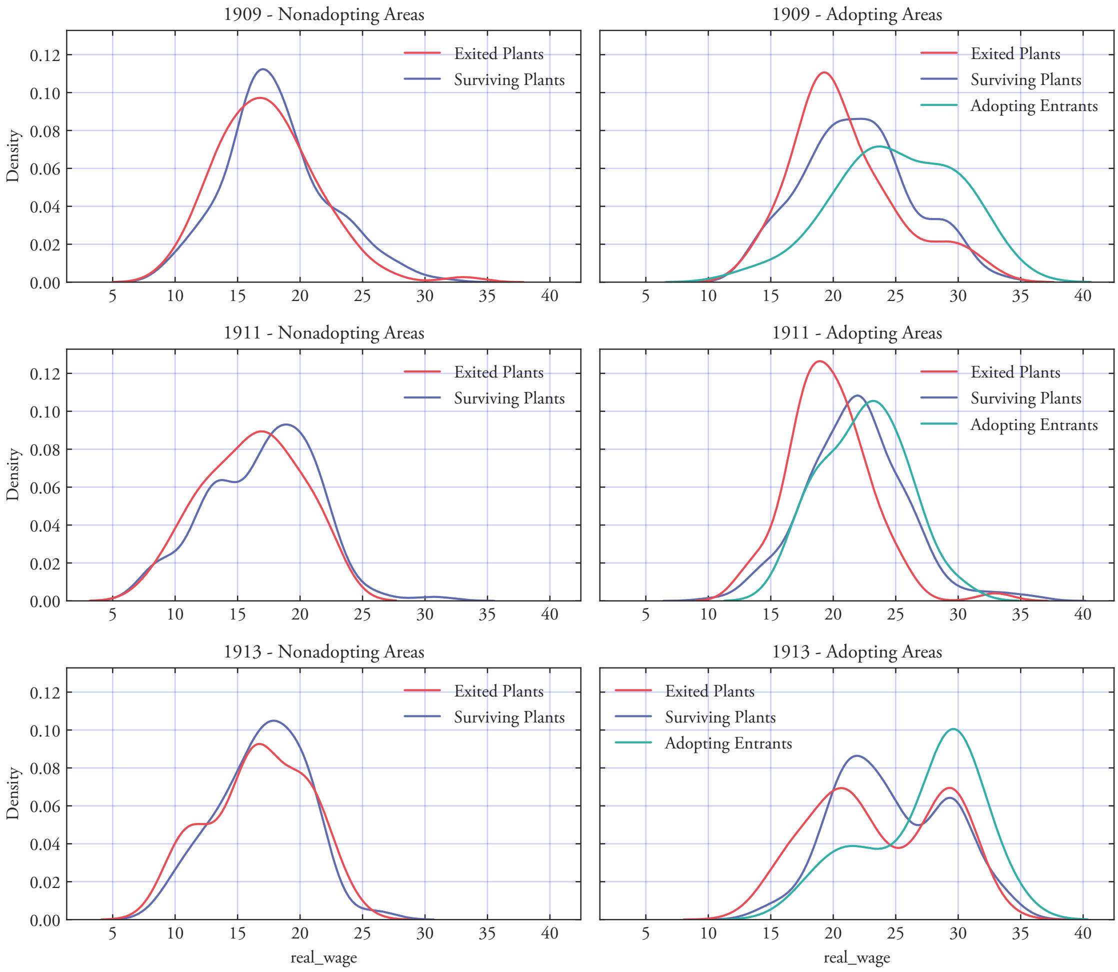
Note: See the note of Figure 3.

Figure E3: Wage Distribution of Exited and Surviving Plants in Nonadopting Areas (Individual Years; 1905-1908)



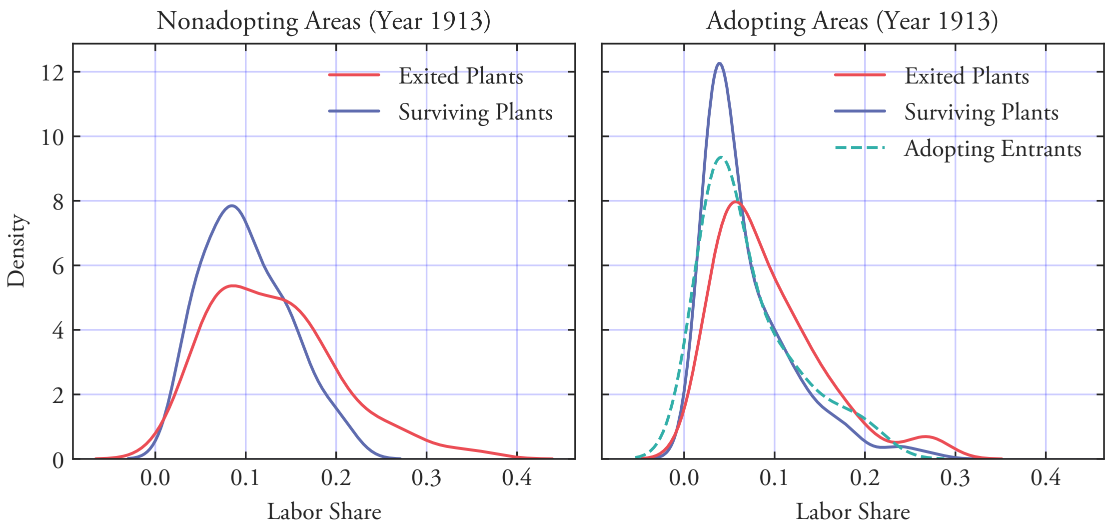
Note: See the note of Figure 3.

Figure E4: Wage Distribution of Exited and Surviving Plants in Nonadopting versus Adopting Areas (Individual Years; 1909-1913)



Note: See the note of Figure 3.

Figure E5: Labor Share Distribution of Exited and Surviving Plants in 1913



Note: Labor share is calculated as yearly wage bills (daily wages × workers × 320 days) divided by yearly production values (including raw input costs) at plant level. See the note of Figure 3 for other details.