COVID-19, Migrants, and Automation in China *

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Abstract

We study whether transient policy-induced labor supply shocks can permanently redirect technological change. China's zero-COVID mobility restrictions provide a natural experiment: between 2020 and 2022, hundreds of millions of rural migrants were blocked from urban manufacturing centers, generating a nearly 60% collapse in migrant labor supply. Exploiting cross-county variation in pre-pandemic migrant dependence, we find that more exposed counties experienced sharp post-COVID growth in robotics patenting, with no corresponding change in total patenting activity. The response is concentrated in tight local labor markets where native workers could not substitute for absent migrants, consistent with binding quantity constraints rather than wage-driven substitution. Displaced migrants bear persistent earnings and employment losses. The results show that temporary restrictions on labor mobility can have lasting effects on the direction of innovation.

JEL Codes: J61, O33, R23, J24, O14
Keywords: Migration, Labor Shortage, Automation, COVID-19, Directed Technological Change

*We thank Peking University for the China Family Panel Studies (CFPS) survey data. We thank all the comments from conference participants from CHLR 2025. This work was supported by JSPS KAKENHI Grant Number 250700000082. All errors are our own.

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1 Introduction

While directed technical change theory predicts that factor scarcity redirects innovation toward labor-saving technologies (Acemoglu, 2002), the empirical literature has largely focused on settings where labor supply adjusts gradually, through immigration waves (Lewis, 2011; Danzer et al., 2024) or demographic transitions (Acemoglu et al., 2022). This paper asks whether sudden labor supply shocks, compounded by persistent policy uncertainty over workers' mobility, can similarly redirect innovation. We argue that when unexpected mobility restrictions can instantly sever firms' access to workers, human capital ceases to be a flexible input and becomes a source of acute operational fragility. Under such conditions, automation serves not merely as a factor substitution response but as a hedge against operational risk. Using China's COVID-19 mobility restrictions as a sudden and exogenous shock to internal migration flows, we identify how unpredictable labor supply constraints drive the country's rapid and persistent surge in industrial automation.

China provides an ideal setting for isolating this high-frequency mechanism for three reasons. First, it operates the world's largest system of internal labor migration: approximately 292 million rural *hukou* holders, representing 39% of the national workforce, form the backbone of China's manufacturing sector.[1] Second, the enforcement of China's zero-COVID policies replaced a stable labor market with extreme policy uncertainty. Because local governments frequently initiated abrupt, zero-warning lockdowns to meet strict political mandates, human labor became fundamentally unpredictable. This triggered an unprecedented collapse in the out-migration rate of more than half relative to its pre-pandemic level.[2] Third, China dominates global automation: robot installations nearly doubled between 2019 and 2022 while the rest of the world stagnated (Figure 1). Whether this surge was caused by the labor supply collapse, or merely coincided with it, is the central question this paper resolves.

To analyze these dynamics, we construct a dataset that spans two levels of aggregation, linking individual labor supply decisions to regional innovation outcomes. At the individual level, we use the China Family Panel Studies (CFPS) to track migration decisions and employment status across the 2018, 2020, and 2022 waves, thereby identifying the specific demographic groups most affected by mobility restrictions. At the county level, we construct a panel of patent applications from the China National Intellectual Property Administration (CNIPA) covering more than 40 million records spanning 2,200 counties

[1] Data from the National Bureau of Statistics of China (National Bureau of Statistics of China, 2021). The *hukou* system creates institutional segmentation that makes migrant mobility observable, regulable, and sharply affected by policy.

[2] The 76-day Wuhan lockdown (January 2020) and the 61-day Shanghai lockdown (spring 2022) imposed sudden, severe constraints on worker movement, reinforced by a color-coded QR code system embedded in WeChat and Alipay that required a green code to access workplaces and public transport.

over a ten-year period. By classifying patents using text-based algorithms targeting keywords such as "robot" and "manipulator" (robotic arm), this dataset allows us to measure the direction of indigenous technical change at a granular spatial level and test whether the pandemic redirected innovation toward labor-saving technologies rather than spurring broad inventive activity.

First, we establish the structural bias of the labor supply shock. Using individual-level survey data, we document that the pandemic reduced cross-regional mobility for workers in migrant-intensive sectors, relative to those in sectors with low migration dependence, with migrant labor supply falling by nearly 60% during the peak restriction period, as shown in Figure 2.[3] Critically, this contraction was not a generalized withdrawal of labor. The shock fell exclusively on low-skilled workers, effectively severing the supply of routine manual labor to urban manufacturing centers while high-skilled professionals remained largely insulated. Firm-level evidence from the Enterprise Survey on Innovation and Entrepreneurship in China (ESIEC), collected in early 2020, corroborates this picture: firms in regions with higher pre-pandemic migrant shares were significantly less likely to have resumed operations, faced more severe labor shortages, and were more likely to have raised wages to attract or retain workers.[4]

Second, we provide causal evidence that the labor supply shock redirected innovation toward automation. Counties more reliant on migrant labor experienced significant post-COVID increases in robotics and automation patenting, while non-automation patents remained unchanged, confirming directed technical change rather than a generalized innovation boom (Acemoglu, 2002). This pattern is corroborated by cross-country robot installation data: Chinese robot installations nearly doubled between 2019 and 2022 while the rest of the world stagnated, with the surge concentrated in migrant-intensive industries such as electronics and construction. Firm-level evidence further shows that firms in migrant-dependent regions increased both R&D expenditure and fixed capital per employee after the shock. Heterogeneity analysis reveals that the innovation response is concentrated in counties with already-tight labor markets, where firms could not substitute missing migrants with local workers (Acemoglu and Restrepo, 2018; Danzer et al., 2024) — precisely the conditions under which labor scarcity theory predicts automation investment to be most compelling (Acemoglu, 2010). Importantly, we systematically rule out four alternative explanations: social distancing imperatives, export surges, local government in-

[3] Manufacturing employment is concentrated in coastal and urban industrial counties, far from the rural interior where most workers originate. Agricultural workers, by contrast, tend to work near their place of origin and are therefore less reliant on long-distance mobility.

[4] These patterns confirm that COVID-19 mobility restrictions created a binding labor supply constraint in migrant-dependent counties rather than a broader demand-side shock, supporting the identification strategy in the main analysis.

dustrial policy, and demand-side shocks; each fails to account for the observed automation response.

Finally, we trace the distributional consequences of the pandemic-induced automation episode. Pre-pandemic migrant workers experienced persistent increases in informal employment and income declines relative to non-migrants, bearing most of the adjustment costs (Dix-Carneiro and Kovak, 2019; Ponczek and Ulyssea, 2022). Aggregating these estimates, the income loss among affected workers amounts to approximately 0.8 percent of China's 2020 GDP, comparable in magnitude to the distributional costs of robot adoption in the United States (Acemoglu and Restrepo, 2020) and the "China Shock" (Autor et al., 2013). Importantly, these welfare losses persist well into 2022, after mobility restrictions were lifted, suggesting that the costs reflect not merely the direct disruption to spatial matching but a more structural labor market deterioration consistent with automation displacement. While we cannot fully decompose the two channels, the persistence of effects beyond the restriction period points to automation as a meaningful contributor. Transient mobility frictions, our findings suggest, can generate not only permanent industrial upgrading but also persistent distributional costs concentrated among the most vulnerable workers.

This paper contributes to four strands of literature. First, we provide direct causal evidence for theories of directed technical change. The idea that factor scarcity shapes the direction of innovation dates to Hicks (1932) and was applied to American industrialization by Habakkuk (1962). Acemoglu (2002) formalized these insights, showing that both a price effect and a market size effect govern the direction of technical change.[5] While a broader empirical literature has demonstrated how exogenous shocks can powerfully redirect the volume and focus of firm-level patenting (Azoulay et al., 2019), the effects of sudden factor supply constraints remain heavily debated. Recent work finds that gradual factor supply changes predictably redirect innovation toward labor-saving technologies (Danzer et al., 2024; Hémous et al., 2025). However, sudden shocks have produced mixed evidence: Clemens et al. (2018) document that the sudden Bracero exclusion did not trigger technology adoption, suggesting that binding quantity constraints may be necessary but not sufficient to redirect innovation. Our contribution is to identify the conditions under which they are, exploiting a sudden, economy-wide labor supply shock in a manufacturing context where automation was both technologically feasible and financially accessible, to provide direct evidence that binding quantity constraints can redirect innovation towards automation (Acemoglu, 2010).

Second, we contribute to the literature on migration, labor supply, and firm adjustment. Lewis (2011) shows that abundant low-skilled labor suppresses automation in U.S. manufacturing, and Dustmann and Glitz (2015) demonstrate that labor supply shocks

[5] See also Kennedy (1964), Acemoglu (2010), and Acemoglu and Restrepo (2018) for theoretical extensions.

trigger systematic reorganization of production across the skill distribution. The two most closely related papers are Imbert et al. (2022) and Danzer et al. (2024). Imbert et al. (2022) find that rural-urban migrant inflows into Chinese manufacturing cities make production more labor-intensive. Danzer et al. (2024) exploit a German immigrant allocation policy to show that exogenous increases in low-skilled labor supply reduce automation patenting. Both papers study positive labor supply shocks that suppress automation; we study the causal inverse, identifying how a sudden and binding labor supply collapse triggers it. Peri (2012) provides complementary evidence that exogenous labor supply shifts redirect task specialization among native workers. Studies of internal migration in China further document large positive wage externalities on urban natives (Combes et al., 2015) and substantial mobility frictions that suppress aggregate productivity (Tombe and Zhu, 2019). What distinguishes our setting is that China's dependence on long-distance rural-urban migration, structured by the *hukou* system, created a labor market uniquely vulnerable to mobility restrictions, transforming a public health shock into a binding and geographically concentrated labor supply collapse with no counterpart in the existing migration-and-firms literature.

Third, we speak to the literature on economic crises and structural change. Jaimovich and Siu (2020) showed that jobless recoveries since 1990 stem from the permanent elimination of routine occupations during recessions, as downturns accelerate the displacement of middle-skill workers by technology. Hershbein and Kahn (2018) documented that skill requirements in job postings rose sharply in metropolitan areas hit hardest by the Great Recession, consistent with crisis-induced restructuring.[6] We extend this literature by demonstrating that public health shocks, operating through labor supply rather than product demand, can similarly trigger durable technological upgrading. The pandemic setting is distinctive in this respect: unlike demand-driven recessions, COVID-19 lockdowns constrained labor availability while leaving capital costs and product demand relatively intact, isolating the supply-side mechanism and allowing us to attribute the automation response to factor scarcity rather than demand compression.

Finally, we contribute to a growing literature on robot adoption in China. Previous studies have documented the causes of China's rapid robotization, emphasizing rising labor costs and demographic pressures (Cheng et al., 2019; Fan et al., 2021), as well as its consequences for firms' skill composition (Tang et al., 2021), worker outcomes (Giuntella et al., 2025), and workplace safety (Luo et al., 2025). We complement this literature by identifying a distinct mechanism: China's zero-COVID policies imposed sudden and severe cross-regional mobility restrictions that prevented migrant workers from reaching urban

[6] Related work includes Charles et al. (2016) on manufacturing decline and Autor and Dorn (2013) on job polarization.

manufacturing centers, generating a binding labor supply collapse that the prevailing neoclassical accounts cannot explain. The *hukou* system is central to this story not as a direct constraint, but because it created a labor market structure uniquely dependent on long-distance mobility, amplifying the disruptive impact of travel restrictions. Our findings suggest that firms automated not simply because labor became expensive, but because it became unavailable, reframing China's recent industrial upgrading as a response to a public health shock interacting with deep institutional features of its labor market.

The paper is organized as follows: Section 2 describes detailed background information on COVID-19 and internal migrants in China; Section 3 and Section 4 describe the data and identification strategy; Section 5 presents the baseline results; Section 6 presents additional results that further shed light on the mechanism; Section 7 concludes.

2 Background

2.1 COVID-19 Pandemic and Lockdown Policies in China

The COVID-19 pandemic led to a series of unprecedented public-health interventions in China, including large-scale lockdowns and mobility restrictions that sharply disrupted labor flows. The first and most extensive intervention was the lockdown of Hubei Province, enacted on January 23, 2020, and lasting until April 8, 2020, a total of 76 days. During this period, outbound transportation was suspended and residents were required to remain at home, halting economic activity in one of China's major industrial and transportation hubs.

Subsequent outbreaks triggered additional large-scale restrictions under China's "zero-COVID" strategy. A prominent example is the Shanghai lockdown in 2022. Following a rapid rise in Omicron cases, Shanghai implemented a phased lockdown in late March, followed by a full citywide closure from April 1 to June 1, 2022, lasting roughly 61 days. Although varying in duration and intensity, these lockdowns shared a common feature: they imposed sudden and severe constraints on population mobility, preventing many workers from reaching their jobs.

These physical restrictions were further reinforced by a nationwide digital enforcement infrastructure. As shown in Figure B.2 and Figure B.3, the government implemented a three-color "health code" system, embedded in the ubiquitous WeChat and Alipay applications, which assigned each citizen a color-coded QR code based on their travel history and risk of exposure to COVID-19. A green code was required to access workplaces, public transportation, and commercial venues, while a yellow or red code imposed mandatory quarantine of 7 to 14 days. For rural migrants attempting to return to manufacturing hubs after the Chinese New Year, this system served as a near-complete barrier to the resumption of labor supply. The scale and administrative intensity of these interventions are further reflected in the language of local government policy documents: as Figure B.4 shows, keywords related to epidemic outbreak, epidemic prevention, and quarantine surged sharply after 2020 and remained elevated through 2023, before declining following the end of the zero-COVID policy in 2023. For sectors heavily reliant on low-skilled, on-site labor, these combined constraints produced an immediate labor supply shock and forced firms to reconsider their dependence on physically mobile workers.

2.2 Migrant Workers in China

China's development over the past four decades has been closely intertwined with the large-scale movement of low-skilled rural workers into urban labor markets. Migrant workers are typically defined as individuals with rural household registration (*hukou*) who engage in non-agricultural work outside their home township for at least six months. This group forms the backbone of China's manufacturing, construction, and urban service industries. According to the 2021 Migrant Workers Monitoring Survey Report, the total number of migrant workers reached 292.51 million in 2021. In the same year, China's total employed population stood at 746.52 million, according to the National Bureau of Statistics of China (2021), implying that migrant workers accounted for approximately 39.2% of the national workforce.

The rise of this workforce reflects long-term structural changes. Rapid urbanization, industrial expansion, and ecological land conversion significantly reduced arable land, weakening the viability of agriculture as a primary livelihood. At the same time, improvements in agricultural productivity released surplus labor in rural areas. Migration to cities, therefore, became a dominant strategy for rural households to secure higher and more stable incomes. Over time, this vast pool of low-skilled migrant labor provided China with a sustained comparative advantage in labor-intensive production and facilitated its integration into global supply chains.

Given this heavy reliance on mobile, migrant labor, the outbreak of COVID-19 in early 2020 generated an unprecedented disruption to China's labor mobility. According to the National Bureau of Statistics of China data, the total number of migrant workers declined by approximately 5.17 million in 2020 compared with 2019—the only negative growth year in the statistical record. This contraction reflects both the large-scale return of workers to rural areas during the initial outbreak and the contraction of urban employment opportunities. Consistently, the share of migrant workers in total employment fell to 38% in 2020, highlighting the substantial collapse in inter-regional labor flows.

These dynamics reinforce the relevance of the pandemic-induced mobility shock for understanding firms' production responses. The sudden contraction in migrant labor in 2020, together with ongoing uncertainty regarding mobility restrictions in subsequent years, likely constrained firms' access to low-skilled, on-site workers. In sectors dependent on migrant labor, this scarcity created strong incentives for firms to adjust production processes, potentially accelerating the adoption of automation and other labor-saving technologies.

2.3 Labor Mobility Constraints Beyond Lockdown Policies

Although the nationwide lockdown in early 2020 lasted only several weeks in most regions, the effective disruption to labor mobility and production extended well beyond the formal lockdown period. The pandemic constrained internal labor mobility in China through several reinforcing channels, generating acute labor scarcity in migrant-receiving regions and creating significant uncertainty for firms relying on mobile labor.

First, mobility restrictions persisted even after the lifting of the initial lockdown measures. Following the containment phase, local governments widely adopted digital health code systems to regulate residents' movements. These health codes, typically displayed through smartphone applications, were linked to individuals' nucleic-acid test results and recent travel histories. In many cities during 2020 and 2021, residents were required to undergo frequent nucleic-acid testing—often every 48 to 72 hours—and maintaining a valid negative test result was necessary to retain a "green" health code status that allowed normal mobility. Individuals whose codes turned yellow or red were often unable to leave their residential compounds. Moreover, the detection of positive cases could trigger temporary lockdowns at the neighborhood or residential compound level. These rules substantially increased the uncertainty and cost associated with cross-city and cross-province mobility, discouraging many migrant workers from traveling or returning to urban workplaces (Liu et al., 2023).

Second, these mobility controls generated significant operational uncertainty for firms. Even after formal lockdowns were lifted, the risk of sudden containment measures remained high. If a worker tested positive or had abnormal health status, factories or workshops could be required to suspend production temporarily, and clusters of infections could lead to shutdowns of entire industrial parks or neighborhoods. As a result, many firms did not immediately resume normal production schedules. Instead, they faced difficulties coordinating shifts, maintaining stable production lines, and ensuring the continuous availability of on-site workers.

Third, rural-to-urban migrants were particularly vulnerable to these disruptions due to their weaker access to urban social protection systems and their stronger dependence on wage income (He et al., 2022). Rural-to-urban migrants engaged in non-agricultural employment are often hired under short-term or informal contracts and frequently do not receive wages during periods of production shutdown. At the same time, the cost of maintaining a livelihood in urban areas—particularly housing and daily expenses—remains relatively high. Faced with uncertain employment prospects and the possibility of repeated lockdowns, many migrant workers chose to return to their hometowns rather than remain in cities without stable income. Survey evidence also documents a renewed "returning-home tide" among migrant workers during the pandemic, as deteriorating employment conditions increased incentives to return to rural hometowns (Ma et al., 2024). These dynamics contributed to a temporary contraction in the supply of migrant labor in urban labor markets.

Together, these mechanisms imply that the effective labor supply shock associated with the pandemic extended beyond the initial lockdown period. In sectors heavily dependent on low-skilled migrant workers, the sudden contraction in available labor and the uncertainty surrounding worker mobility posed substantial challenges for production organizations. Under such conditions, firms had incentives to reassess their reliance on physically mobile labor and explore adjustments along the capital–labor margin, potentially accelerating the adoption of automation and other labor-saving technologies.

3 Data

3.1 Migrant Labor Data

3.1.1 County-level Migration Exposure

To capture both the regional exposure to labor shortages and the individual-level labor supply dynamics, we construct our migrant variables using two distinct data sources. First, to measure the spatial variation in pre-pandemic reliance on migrant labor, we construct a county-level measure of migrant exposure using the 2015 China 1% Population Survey (mini-census), following Heblich et al. (2022); Guo et al. (2024). By observing both the registered *hukou* location (origin) and the current place of residence (destination) for each surveyed individual, we aggregate these records and scale them by survey sampling weights to recover population-level bilateral migration flows. This procedure allows us to calculate the migrant share of each county's total population in 2015, which serves as our primary treatment variable capturing local structural dependence on mobile labor prior to the COVID-19 shock. Since this measure is constructed from pre-pandemic data, it is predetermined with respect to the COVID-19 shock, making it suitable as a measure of structural exposure rather than an endogenous response to the pandemic. We report the most migrant-intensive counties based on this distribution in Table C.4.

3.1.2 Individual-level Migration Decision

Second, to independently identify the impact of the COVID-19 pandemic on individual labor supply decisions, we employ data from the China Family Panel Studies (CFPS). Administered by Peking University, this nationally representative longitudinal survey has been conducted biennially since 2010, covering approximately 16,000 households across 25 provinces and collecting rich information on demographics, education, employment, income, health, migration history, and family relations. Utilizing the 2018, 2020, and 2022 waves, we define migrant status based on the survey question: "In the past 12 months, have you worked away from your hometown?". The data reveal a structural collapse in mobility: the prevalence of migrant workers declines sharply across waves, from 26.7% in 2018 to 12.2% in 2020 and 13.8% in 2022, representing declines of 54.3% and 48.3% relative to the 2018 baseline, as shown in Figure 2.

Table C.3 presents summary statistics for the full CFPS sample, stratified by pre-pandemic employment sector. On average, 18.1% of the full sample reported out-of-hometown work, with the share substantially higher among non-agricultural workers (25.1%) than agricultural workers (11.4%). The non-agricultural group is systematically more likely to be migrants: they are younger, more educated, more likely to hold non-agricultural *hukou*, and have a lower female share.[7] The final sample comprises approximately 18,200 individuals in the treatment group and 19,100 in the control group.

3.2 Automation Patents

We obtain patent data from the China National Intellectual Property Administration (CNIPA), covering all patent applications from 2015 to 2024, as a measure of automation innovation following an established literature that uses patent applications to capture the direction of technological change (Danzer et al., 2024; Hémous et al., 2025).[8] To identify automation patents, we apply a keyword-based classification targeting robotics, manipulation-related terms, and automated guided vehicles (AGVs) in both English and Chinese, supplemented by IPC code B25J (manipulators and chambers with manipulation devices). Table C.1 and Table C.2 show the examples of keywords in the patent applications.

[7] Specifically, the non-agricultural group is younger (41.1 vs. 51.9 years), more educated (3.51 vs. 2.29 on an eight-level scale), more likely to hold non-agricultural *hukou* (35.3% vs. 9.7%), and has a lower female share (38.2% vs. 49.2%).

[8] The CNIPA database contains over 40 million records with detailed information on application and grant dates, assignee identity, inventor location, IPC classifications, and citations. All design patents are excluded.

We extract county-level assignee locations to construct annual county-level counts of automation patent applications, covering 2,200 counties over the 10-year sample period.

Table 1 presents summary statistics by migration status and period, where high-migration counties are defined as those with above-median migrant shares in 2015. Three patterns emerge. First, automation patenting increased substantially after COVID-19 in both groups: mean log robot patent counts rose from 1.105 to 1.409 in high-migration counties and from 0.538 to 0.781 in low-migration counties. Second, and most importantly, the gap between high- and low-migration counties widened post-pandemic, with the difference in log robot counts growing from 0.567 to 0.628. Critically, this divergence is specific to automation patents: the gap in log non-automation patent counts remained virtually unchanged (0.530 pre-COVID versus 0.526 post-COVID), suggesting that COVID-19 differentially accelerated automation-directed innovation in migrant-dependent regions rather than spurring broad inventive activity. Figure 7 reinforces this finding, showing a post-COVID decline in the share of counties with zero automation patents, indicating that the pandemic drew new entrants into automation patenting rather than merely intensifying effort among existing innovators. Figure 8 further maps this geographic expansion, showing that the post-COVID surge in robot patent activity spread across a substantially larger set of Chinese counties, with new entrants concentrated in manufacturing provinces historically dependent on migrant labor.

4 Empirical Strategy

This paper examines whether COVID-19-induced labor supply disruptions accelerated automation in China. Our primary analysis exploits within-China variation in industrial structure to identify the effect on automation patenting. We complement this with individual-level migration analysis to document the labor supply shock.

4.1 Main Specification: COVID-19 and Automation Patents

Our identification strategy exploits cross-county variation in pre-pandemic migrant reliance as a measure of differential exposure to COVID-19-induced labor supply disruptions. We estimate the following specification:

$$\text{AutoPatent}_{pt} = \alpha + \beta(\text{Migrant Share}_p \times \text{PostCOVID-19}_t) + \gamma_p + \delta_t + \mathbf{X}'_{p,2015} \times \delta_t + \varepsilon_{pt}, \tag{1}$$

where AutoPatent_{pt} measures automation innovation in county p at time t, using both patent shares (direction of innovation) and counts (volume). Migrant Share_p is the share of migrants in county p's population in 2015, capturing pre-pandemic reliance on migrant labor. Figure 3 presents the spatial distribution of treatment intensity. PostCOVID-19$_t$ is an indicator for the post-2020 period. County fixed effects (γ_p) absorb time-invariant local characteristics, and year fixed effects (δ_t) capture aggregate shocks common to all counties. We further include interactions $\mathbf{X}'_{p,2015} \times \delta_t$, where $\mathbf{X}_{p,2015}$ comprises initial GDP per capita, to control for differential trends in wealthy areas. Standard errors are clustered at the county level.

The coefficient of interest, β, captures the differential post-COVID change in automation patenting for counties more exposed to the migrant labor supply disruption. We validate the parallel trends assumption via event study specifications, and conduct placebo tests using non-automation patent counts to confirm that results reflect directed technical change rather than a broad increase in inventive activity.

4.2 Labor Supply Shock

To establish that COVID-19 disrupted labor mobility, we estimate a difference-in-differences model using CFPS panel data:

$$Y_{it} = \alpha + \beta(\text{NonAgri}_{i,2018} \times \text{PostCOVID-19}_t) + \gamma_i + \delta_t + \phi_{pt} + \varepsilon_{ipt}, \tag{2}$$

where Y_{it} indicates individual's out-of-hometown work decision over year. We define the treatment group based on pre-pandemic non-agricultural employment status rather than baseline migrant status, for two reasons. First, non-agricultural workers are structurally more dependent on cross-regional migration than their agricultural counterparts (Krugman, 1991; Au and Henderson, 2006), making pre-pandemic sector of employment a natural intent-to-treat variable. Second, using baseline migrant status directly as the treatment variable mechanically yields negative post-treatment coefficients, as individuals who were migrants before the pandemic are more likely to have reduced their mobility after the shock, confounding the estimated treatment effect with mean reversion. We alternatively include individual, household, year, and province-by-year fixed effects.

5 Results

5.1 COVID-19 and Labor Mobility Restriction: Manufacturing vs. Agricultural Workers

We examine whether workers in migrant-intensive sectors experienced a differential reduction in cross-regional mobility following the onset of COVID-19, relative to those in sectors with low migration dependence. The outcome variable is a binary indicator, *Out-of-Hometown Work*, equal to one if the individual worked outside their registered *hukou* location. Table 2 presents the baseline results. Across all specifications—controlling for individual, household, and province-by-year fixed effects—the coefficient for the interaction term Non-Agricultural Worker$_{\text{pre-COVID}}$ $\times$ PostCOVID-19 is negative and statistically significant at the 1 percent level. The estimate in Column (3) indicates that relative to agricultural workers, non-agricultural workers were approximately 11 percentage points less likely to work outside their hometowns after the onset of the pandemic. This confirms that the COVID-19 shock and associated travel restrictions disproportionately disrupted the labor supply of non-agricultural workers.

A key premise of our mechanism is that the labor supply shock was concentrated among low-skilled workers, who are less able to work remotely and more vulnerable to physical mobility restrictions. Figure B.5 illustrates this pattern descriptively: the share of migrant workers is highest among low-educated workers and declines monotonically with education level, confirming that the migrant labor force is disproportionately composed of low-skilled workers. To test this formally, we examine heterogeneity by education level in Table C.9. The results provide strong support for the low-skill hypothesis. The main interaction coefficient (representing the base group: illiterate or primary education) is large and negative. However, the triple-interaction terms with higher education levels are consistently positive and significant. For individuals with middle school education or above, the positive interaction coefficients largely offset the negative baseline effect. This implies that the reduction in cross-regional labor mobility was driven almost entirely by low-skilled workers, while high-skilled professionals remained relatively shielded from these disruptions. Additional heterogeneity analyses by *hukou* status, gender, and age are reported in Appendix A.3.

5.2 Correlation between Migrants and Automation before COVID-19

We verify the spatial sorting of migrants prior to the shock. Figure 4 illustrates the relationship between the migrant share and local industrial characteristics before 2020. Panel (a) shows that migrants are heavily concentrated in counties with high manufacturing value-added. Panels (b) and (c) reveal that, consistent with the directed technical change mechanism (Danzer et al., 2024), migrant-receiving counties exhibit lower pre-pandemic automation patenting—abundant cheap labor reduced firms' incentive to invest in labor-saving technologies, which is consistent with the literature Danzer et al. (2024). This pattern confirms that the COVID-19 shock hit precisely the regions where labor scarcity was most acute and the scope for automation-driven adjustment was greatest.

5.3 Correlation between Migrant Dependence and Firm-level Labor Shortage During COVID-19

To further validate that migrant-dependent regions experienced more severe labor supply disruptions during the pandemic, we draw on the Enterprise Survey on Innovation and Entrepreneurship in China (ESIEC), a firm-level survey conducted in early 2020 that is widely used in the literature (Barwick et al., 2025). As reported in Table 3, firms in regions with higher migrant shares were significantly less likely to have resumed operations: a one standard deviation increase in the regional migrant share (4.58 percentage points) is associated with a 10.5 percentage point reduction in the probability of resuming operations, consistent with acute labor shortages preventing factories from restarting production lines. These firms also reported a significantly higher share of absent workers and were more likely to have raised wages to attract or retain labor, suggesting that the scarcity of migrant workers generated upward pressure on local wages precisely where labor constraints were most binding. In contrast, supply chain disruption and logistics indicators are uncorrelated with migrant share, ruling out the interpretation that these regions faced broader demand-side or input supply disruptions. Taken together, these patterns confirm that COVID-19 mobility restrictions created a binding labor supply constraint specifically in migrant-dependent counties, rather than a generalized economic disruption, directly supporting the identification strategy in the main analysis.

5.4 Baseline: COVID-19 and Automation Patents

Table 4 reports the effect of COVID-19-induced labor supply disruptions on automation patenting.

5.4.1 Main Findings

Across all specifications, counties with higher pre-pandemic migrant reliance experienced significantly greater post-COVID growth in automation patenting. Under the most demanding specification (Panel B), a one standard deviation increase in the migrant share (1.229 percentage points) is associated with a 0.077 percentage point increase in the robot patent share (relative to total patents), a 4.3% increase in log robot counts, a 6.7 patent increase in the raw robot patent count, and a 10.4% increase in the per capita measure.[9] All estimates are significant at the 1 percent level and robust to alternative functional forms, including IHS-transformed counts (columns 9–10).

[9] Estimates are stable across Panels A and B, with coefficients ranging from 0.049–0.063 for patent share, 5.457–6.814 for raw robot patent counts, and 0.035–0.051 for log counts, suggesting results are not driven by differential trends in wealthy or historically high-migration areas.

These findings are consistent with the canonical directed technical change framework (Acemoglu, 2002), in which a reduction in the relative supply of a factor of production induces innovation complementary to the scarce factor's substitute. In our setting, the sudden curtailment of migration reduced the effective labor supply in manufacturing counties, raising the price of routine labor and tilting the returns to innovation toward automation technologies. This mechanism echoes the historical evidence on skill-biased technical change (Autor et al., 2003), the response of automation investment to labor cost pressures (Acemoglu and Restrepo, 2020). Complementary evidence from cross-country robot installation data further corroborates this interpretation: Chinese robot installations nearly doubled between 2019 and 2022 while the rest of the world stagnated, with the surge concentrated in migrant-intensive sectors such as construction, electrical machinery, and electronic components (Appendix A.1).

Placebo Test Columns (11) and (12) use total patent counts and non-automation patent counts as placebo outcomes. Both coefficients are small in magnitude and statistically indistinguishable from zero (-0.004 and -0.005, respectively), a sharp contrast with the large, precisely estimated effects for automation outcomes. This asymmetry is theoretically informative: it implies that the pandemic did not broadly stimulate inventive activity in affected counties, ruling out explanations based on general increases in R&D investment or government-directed innovation subsidies during the pandemic period. Rather, the evidence points to a reallocation of innovation effort within the firm, away from product innovation and toward process automation, consistent with the substitution mechanism in the directed technical change literature (Acemoglu, 2002) and the task-based framework of Autor et al. (2003).

Robustness: Shift Share Framework To address the concern that pre-pandemic migrant share may be correlated with unobserved county-level trends in automation demand, we construct a shift share variable Z_{pt}. The instrument interacts each destination county's historical migration network composition (Figure B.1) with idiosyncratic COVID-19 outflow disruptions at each origin city, measured by the AR(1) residual of the Baidu Map Migration outflow index. The construction and identifying assumptions are detailed in Appendix A.2. Table C.5 reports the reduced-form estimates. Since Z_{pt} is constructed from the residual of a mobility index, the coefficients are not directly comparable in magnitude to the baseline estimates, but the signs and significance are informative. The coefficient on Z_{pt} is negative and statistically significant across three of the four automation outcomes, consistent with the baseline DiD results. We note that the Baidu Migration data are only available from 2019 onwards, restricting the sample relative to the baseline. Nonetheless, the results suggest that the automation response is driven by exogenous variation in COVID-19 severity at origin regions propagated through pre-existing migration networks, rather than by the endogenous sorting of migrants to high-automation counties.

5.5 Event-study

Figure 5 presents event study estimates for robot and manipulator patent shares, estimated from the following specification:

$$\text{AutoPatent}_{pt} = \alpha + \sum_{\tau \neq 0} \beta_\tau \left(\text{MigrantShare}_p \times \mathbf{1}[t = \tau] \right) + \gamma_p + \delta_t + X'_{p,2015} \times \delta_t + \varepsilon_{pt}, \quad (3)$$

where τ indexes years relative to the onset of COVID-19 in 2020, which serves as the omitted reference year. The coefficients β_τ capture the differential change in automation patenting for counties with higher pre-pandemic migrant shares in each year relative to 2020. All specifications include county fixed effects γ_p, province $\times$ year fixed effects δ_t, and interactions between initial GDP per capita and year fixed effects $X'_{p,2015} \times \delta_t$. Standard errors are clustered at the county level.

As illustrated in Figure 5, pre-2020 coefficients are statistically indistinguishable from zero, providing direct support for the parallel trends assumption and confirming that high-migration counties were not already on a differential automation trajectory prior to the pandemic. This is a nontrivial finding: one might have expected that counties more reliant on migrant labor would systematically differ in their innovation trajectories due to industrial composition or access to capital. The flat pre-trends mitigate this concern.

Following the 2020 outbreak, the automation response builds gradually and persistently. The effect is modest in 2021, as firms were still adjusting to the labor supply disruption and resuming operations, but expands substantially in 2022 and remains large through the end of the sample period. This temporal pattern is informative in two respects. First, it is inconsistent with the interpretation that the patent surge reflects idle engineers filing patents during shutdowns: if that were the case, we would expect the effect to be concentrated in 2020 and fade as firms reopened. Instead, the response accelerates precisely as firms resumed production and confronted the structural reality of a persistently tighter labor supply. Second, the gradual buildup suggests that automation patenting reflects a deliberate, medium-run technological response to a sustained shift in labor availability, rather than a transitory adjustment (Hershbein and Kahn, 2018; Jaimovich and Siu, 2020). The persistence of effects beyond the immediate shock period further suggests that the automation investments embodied in patents are durable and unlikely to be reversed as labor market conditions normalize, consistent with the irreversibility of automation capital documented in Autor (2015) and Acemoglu and Restrepo (2020).

6 Mechanisms and Additional Analyses

The baseline results establish that COVID-19-induced labor supply disruptions accelerated automation patenting in migrant-dependent counties. We now test the mechanism underlying this response, rule out alternative explanations, and present additional evidence on firm-level investment and worker outcomes.

6.1 Mechanism: Labor Market Tightness

The central premise of our identification strategy is that the COVID-19 pandemic acted as a negative labor supply shock that rendered quantity constraints binding. Economic theory predicts that firms should only substitute capital for labor when local labor reserves are insufficient to absorb the migrant shortfall (Acemoglu, 2010; Acemoglu and Restrepo, 2018). We test this prediction through two complementary proxies for labor market tightness: the employment-to-population ratio and the pre-pandemic unemployment rate. If the automation response is driven by binding labor scarcity rather than a general pandemic shock, it should be concentrated precisely in counties where firms could not replace missing migrants with local workers.

We first define a tight labor market as a county with an employment-to-population ratio above the national median in 2015. Figure 6 presents dynamic treatment effects from an event study specification, comparing counties with tight versus slack labor markets. Prior to 2020, both groups exhibit similar trends, with coefficients fluctuating around zero, validating the parallel trends assumption. A sharp divergence emerges after the onset of COVID-19: in tight labor market counties, the treatment effect rises substantially and persists through 2023, reaching a 0.20 percentage point increase in robot-related patent share, while slack labor market counties show no discernible response throughout the post-pandemic period. The absence of any automation response in slack markets is as informative as the positive result in tight markets: it rules out the interpretation that the surge reflects a general pandemic shock rather than a binding labor supply constraint. Panel A of Table 5 confirms this in a regression framework, showing that the automation patent response is concentrated in tight labor markets while the effect in slack markets and for non-automation patents is negligible.

6.2 Mechanism: County Unemployment Rate

Panel B of Table 5 splits the sample by pre-pandemic unemployment level, defining low- and high-unemployment counties by the national median. Figure 6 presents the corresponding event study estimates. As with the labor market tightness results, pre-2020 coefficients are indistinguishable from zero for both groups, supporting parallel trends. A sharp divergence emerges after 2020: low-unemployment counties exhibit a sustained increase in automation patenting, while high-unemployment counties show no discernible response. The regression results confirm this pattern: a one standard deviation increase in the migrant share (1.229 percentage points) is associated with a 0.123 percentage point increase in the robot patent share in low-unemployment counties, while the effect in high-unemployment counties is small and statistically insignificant. Non-automation patents show no significant response in either subsample.

Taken together, these two sets of results provide direct and mutually reinforcing evidence that the COVID-19 shock operated through a labor scarcity channel. Where local labor markets were already tight and unemployment low, firms faced a binding quantity constraint when migrants became unavailable, compelling them to substitute capital for labor. Where local labor reserves were ample, the automation incentive was dampened. This pattern is precisely what directed technical change theory predicts (Acemoglu, 2010; Acemoglu and Restrepo, 2018), and it rules out broader pandemic-driven explanations for the observed automation surge.

6.3 Alternative Explanations

We address four alternative explanations for the observed automation response: social distancing imperatives, export demand surges, local government industrial policy, and demand-side shocks. Each predicts a distinct pattern of results that is inconsistent with the data. We address them in turn.

6.3.1 Alternative Explanation: Health Risk and Social Distancing

A potential concern is that firms adopted automation not because migrant labor became unavailable, but to minimize physical contact and reduce viral transmission risk. Under this alternative interpretation, our estimates would reflect pandemic severity and social distancing imperatives rather than labor supply disruptions.

To distinguish between the labor scarcity channel and the health risk channel, we introduce two proxies for pandemic-related health concerns. First, we use an industry in-person intensity index that captures the structural necessity of physical presence in the workplace. Following Dingel and Neiman (2020), we compute the employment-weighted average share of jobs that cannot be performed remotely, applying their industry-level measures to each county's pre-pandemic industry employment distribution. Counties with a higher concentration of on-site work might face stronger pressure to automate production processes to reduce contact intensity. Second, we use population density in

2015 as a proxy for viral transmission risk and lockdown severity, as densely populated areas faced higher infection rates and more stringent mobility restrictions.[10]

If automation were primarily driven by health concerns, we would expect these variables to absorb or attenuate our main treatment effect. Conversely, if labor scarcity is the dominant mechanism, the migrant share interaction should remain significant even after controlling for pandemic severity and contact-intensity proxies. We estimate the following horse-race specification:

$$\begin{aligned}\text{AutoPatent}_{pt} = \alpha &+ \beta_1(\text{MigrantShare}_p \times \text{PostCOVID-19}_t) \\ &+ \beta_2(\text{InPerson}_p \times \text{PostCOVID-19}_t) \\ &+ \beta_3(\text{PopDensity}_p \times \text{PostCOVID-19}_t) + \gamma_p + \delta_t + X'_{p,2015} \times \delta_t + \varepsilon_{pt},\end{aligned} \tag{4}$$

Columns (1) through (3) of Table 6 report these results. Across all specifications, the coefficient on the interaction between migrant share and the COVID-19 indicator remains positive, statistically significant, and remarkably stable, ranging from 0.062 to 0.067. In contrast, the health risk proxies, both the in-person intensity interaction in Column (2) and the population density interaction in Column (3), are consistently small and statistically insignificant. Column (6) confirms this pattern holds when both proxies are included simultaneously alongside the export controls.

These findings rule out the social distancing hypothesis. If firms automated primarily to reduce workplace contact, we would observe stronger responses in denser areas or those with a higher structural necessity for in-person work. We observe neither. Instead, the data point to labor scarcity as the operative mechanism: automation was a structural response to the sudden unavailability of migrant workers rather than a precautionary measure against viral transmission.

6.3.2 Alternative Explanation: Export-oriented Automation

A second alternative explanation is that the COVID-19 pandemic reshaped global demand patterns, disrupting supply chains and generating export surges in certain sectors and countries, which may have independently induced automation investment in export-oriented counties. As shown in Figure B.7, China's export performance during the pandemic was striking. After a modest contraction in 2019, total exports of goods and services rebounded from \$2.73 trillion in 2020 to \$3.55 trillion in 2021, a year-on-year surge of approximately 30 percent, the sharpest single-year acceleration in the sample period. Exports continued to climb to \$3.72 trillion in 2022 before moderating slightly in 2023 and recovering again in

[10] Population density is calculated as the total population divided by the county's land area in square kilometers.

2024.[11] If firms in export-intensive counties responded to this demand surge by investing in automation to expand capacity, our estimates could partly reflect demand-side pressures from international markets rather than domestic labor supply constraints. Since migrant-dependent counties may also be more integrated into global value chains, failing to account for export exposure could confound our estimates.

To evaluate this hypothesis, we construct two measures of county-level export exposure using China's customs transaction data from 2014, which records export values at the product level for each county. We collapse this data to the county level to obtain pre-pandemic export exposure measures that are plausibly exogenous to the COVID-19 shock. The first measure is a binary indicator for whether a county had positive export activity (*Exporting County*), capturing the extensive margin of trade participation. The second is the county's total export value as a share of county GDP (*Export Share of GDP*), capturing the intensive margin of export dependence. If export-driven demand were responsible for the automation response, counties more exposed to international trade should exhibit disproportionately stronger automation investment during the pandemic.

Columns (4) and (5) of Table 6 introduce each export measure separately alongside the baseline migrant share interaction. The coefficients on both the exporting county dummy (0.094, Column 4) and the export share of GDP (-0.686, Column 5) are small and statistically insignificant at conventional levels. Crucially, the migrant share interaction remains positive and significant in both specifications, with point estimates of 0.066 and 0.068 respectively, virtually unchanged from the baseline. Columns (6) and (7) further include the social distancing proxies alongside each export measure, and the pattern is unchanged: export exposure absorbs no meaningful variation in automation patenting, while the labor scarcity channel remains robust.

These results suggest that, within our sample period and using pre-pandemic export exposure as a proxy, the export-demand channel does not account for the observed automation response. Although China experienced an unprecedented export boom during the pandemic, the automation response documented in this paper was concentrated in counties that experienced the greatest disruption to their migrant labor supply, not those most exposed to international trade fluctuations. This is consistent with a supply-side mechanism in which binding labor constraints rather than demand-side incentives drove

[11] This boom was concentrated in medical supplies, electronics, and work-from-home goods, propelling China's global export market share from 12 percent at the end of 2019 to a record 15 percent by early 2021. Net exports contributed roughly 25 percent of China's real GDP growth in 2020 and 2021, the largest such contribution since the late 1990s.

the accelerated adoption of automation technologies during the pandemic.[12]

6.3.3 Alternative Explanation: Local Industrial Policy

A further concern is that local governments in migrant-receiving counties may have responded to labor shortages by prioritizing automation-related industrial policies, such that our estimates capture government-directed investment rather than decentralized firm responses to labor scarcity. To test this, we text-mine county-level government work reports and construct keyword frequency measures for six automation-related policy dimensions: robot substitution, industrial robots, automation equipment, smart manufacturing, industry upgrading, and unmanned factories.

As shown in Table C.7 in the Appendix, the interaction between migrant share and the COVID-19 indicator is small and statistically insignificant across all six dimensions and the composite total, indicating that counties facing greater migrant labor disruption did not systematically intensify their policy emphasis on automation. The automation response documented in this paper therefore reflects firm/plant-level adaptation to labor scarcity rather than top-down industrial policy.

6.3.4 Alternative Explanation: Demand Shock

A natural concern is that COVID-19 lockdowns simultaneously reduced labor supply and product demand, potentially confounding the labor scarcity interpretation. We address this concern through four pieces of evidence. First, ESIEC firm survey data show that firms in high-migrant counties faced severe labor shortages and raised wages to attract workers, while supply chain and logistics disruption indicators are uncorrelated with migrant share (Table 3). The wage-raising behavior is particularly informative: firms actively competing for scarce workers would only do so if they wanted to produce but could not find labor, which is inconsistent with a demand collapse narrative (Lazear and Spletzer, 2012). Second, the automation response is uncorrelated with pre-pandemic export exposure (Table C.16), ruling out demand fluctuations as a confound. Third, the automation response is concentrated exclusively in counties with tight labor markets and low unemployment, where firms faced binding quantity constraints (Table 5, Figure 6). If demand collapse were the operative mechanism, automation responses should be broadly uniform across labor market conditions rather than concentrated precisely where local labor reserves were insufficient to replace missing migrants (Acemoglu, 2010; Acemoglu

[12] Our proxy captures pre-existing export exposure and cannot fully account for dynamic reallocation of export demand across counties during the pandemic. Whether trade-induced demand surges independently accelerated automation remains an open question for future research as richer time-varying county-level trade data become available.

and Restrepo, 2018). Fourth, cross-country robot installation data show that China's automation surge diverged sharply from identical sectors in the rest of the world during the same period (Appendix A.1). If a global demand shock were the operative mechanism, we would expect similar automation patterns across all major manufacturing economies facing the same pandemic. The country-specific nature of China's automation acceleration is most naturally explained by a labor supply shock specific to China's institutional context rather than by global demand fluctuations.

6.4 Demand Side: Upstream Regional Firm Investment in Automation

To shed light on the investment inputs underlying the automation patenting response, we draw on listed firm data from the China Stock Market and Accounting Research (CSMAR) database, collapsing firm-year balance sheet and R&D records to the county level.[13]

Table C.6 presents the results. Counties with higher pre-pandemic migrant dependence experienced significant post-COVID increases across all investment margins. A one standard deviation increase in the migrant share (1.23 percentage points) is associated with a 15.8% rise in R&D spending, an 8.9% rise in R&D personnel, a 19.5% increase in the R&D personnel ratio, and an approximate 11,730 yuan increase in fixed assets per employee. These patterns are consistent with the literature demonstrating that labor scarcity induces firms to substitute capital for labor and redirect innovation toward labor-saving technologies (Acemoglu and Restrepo, 2018; Danzer et al., 2024; Hémous et al., 2025).

Complementary evidence from our baseline patenting results sharpens this interpretation. While automation patents respond strongly to migrant-dependent labor shortages, non-automation patenting shows no such response (Table 4). This asymmetry suggests that the post-COVID innovation response was not a broad increase in inventive activity, but was specifically directed toward labor-saving technologies—consistent with rising labor costs shifting the direction rather than the overall level of innovation (Acemoglu and Restrepo, 2018; Hémous et al., 2025). Although the CSMAR data cannot separate automation from non-automation R&D expenditures, this joint pattern suggests that labor-saving technologies were the primary target of marginal R&D spending under a tightening labor supply.[14]

[13] We construct annual county-level measures of R&D expenditure, R&D personnel, R&D intensity, and fixed assets per employee. The estimating equation mirrors our main specification, using the 2015 migrant population share as the treatment measure.

[14] CSMAR covers only publicly listed firms, which skew toward larger establishments in major urban counties. The investment response among smaller unlisted firms—which employ the bulk of migrants—remains unobserved, so these results should be interpreted as suggestive given potential selection concerns in the listed-firm sample.

6.5 Supply Side Consequences: Worker Reallocation, Informality, and Income

Having established that COVID-19 mobility frictions accelerated automation, we turn to the micro-level welfare incidence. To examine how displaced workers adjusted—via informality, unemployment, sectoral reallocation, and lost income—we estimate the following specification:

$$Y_{it} = \alpha + \beta(\text{MigrantWorker}_{i,\text{pre-COVID}} \times \text{COVID-19}_t) + \gamma_i + \delta_t + \phi_{pt} + \varepsilon_{it} \tag{5}$$

where Y_{it} is the outcome for individual i in year t. The treatment group comprises pre-pandemic migrant workers, compared against a control group of non-migrants. We control for individual fixed effects and province-year fixed effects.

Unlike our mobility analysis, which relied on non-agricultural employment as an intent-to-treat variable to avoid mechanical mean reversion, we define treatment here strictly by baseline migrant status. Because the dependent variables in this section are distinct from the treatment indicator, mechanical bounds are not a concern. More importantly, this tighter definition isolates the specific population exposed to the spatial lock-out. Using the broader non-agricultural category for welfare outcomes would introduce severe attenuation bias by confounding locked-out rural migrants with local urban workers, who faced no spatial barriers and potentially benefited from localized labor shortages.

Table 7 reports the results. Columns (1) and (2) show that COVID-19 significantly raised the probability of informal employment among pre-pandemic migrant workers by 4.1–4.3 percentage points. This suggests that workers disrupted by migration restrictions did not smoothly transition into unemployment or alternative formal employment, but were instead pushed into the informal sector. This pattern is consistent with a well-established finding in the literature: the informal sector serves as a residual absorber of workers displaced by shocks to labor markets, technological change, and aggregate disruptions (Dix-Carneiro and Kovak, 2019; Ponczek and Ulyssea, 2022).

Turning to unemployment, columns (3) and (4) reveal a modest but statistically significant increase of 1.0–1.3 percentage points. While the magnitude is small, the result is consistent with the informality findings: workers displaced from formal employment largely sought income-generating activity in the informal sector rather than registering as unemployed. The sharp rise in informality thus accounts for the muted unemployment response, as the informal sector absorbed the bulk of displaced workers.

Columns (5) and (6) document the income consequences of the migration shock. Across specifications, the interaction between pre-pandemic migrant worker status and the post-2020 COVID-19 indicator is negative and statistically significant, implying that pre-pandemic migrant workers experienced a decline in annual income of approximately 8–9 percent following the outbreak of COVID-19 relative to workers who did not engage in cross-regional migration prior to the pandemic. These earnings losses are consistent with the disruption of the spatial matching process that underpins migrant labor markets: when migration is curtailed, workers are forced into lower-productivity local employment, depressing wages.

Finally, columns (7) and (8) examine sectoral reallocation out of manufacturing, restricting the sample to workers employed in manufacturing prior to the pandemic. The results suggest that the reallocation out of manufacturing was not concentrated among pre-pandemic migrant workers relative to non-migrants. This pattern is consistent with a broad-based disruption to manufacturing employment during the pandemic rather than one specifically mediated by migration status.

Figure B.8 plots the dynamic treatment effects by year and reveals a pattern: the welfare effects persist and strengthen into 2022, well after mobility restrictions were lifted. If income losses and informality were purely mechanical consequences of being locked out, we would expect attenuation as restrictions eased. Instead, the persistence of effects beyond the restriction period suggests a more structural labor market deterioration, consistent with returning migrants encountering a more automated production environment, and points to automation as a meaningful contributor to the distributional costs documented here.

Taken together, these findings show a picture of labor market adjustment in the wake of the pandemic-induced migration shock. Migrant workers faced meaningful income losses and were disproportionately pushed into informal employment, while unemployment rose modestly. The earnings consequences were sustained through the informal absorption of displaced workers rather than open unemployment, reflecting the income-smoothing role of informal work in the absence of adequate social insurance (Dix-Carneiro and Kovak, 2019).

6.6 Back-of-the-Envelope: Aggregate Welfare Costs

The estimates of income losses among displaced migrant workers, rising informality, and firm-level investment responses can be aggregated to provide a rough sense of the macroeconomic stakes. We stress that the following calculations are illustrative: they combine our regression estimates with aggregate statistics under strong assumptions, and should be interpreted as order-of-magnitude benchmarks rather than precise welfare decompositions.

6.6.1 Income Losses Among Displaced Migrant Workers

China's 2020 census counts approximately 376 million internal migrants. Of these, roughly 170 million were employed in manufacturing-intensive, migrant-dependent counties that constitute our treatment group. Our estimates in columns (5)–(6) of Table 7 imply that pre-pandemic migrant workers in these counties experienced an 8–9 percent decline in annual income following COVID-19. Taking the midpoint (8.5 percent) and applying it to average migrant annual earnings of approximately 52,000 yuan in 2020 National Bureau of Statistics of China (2021), the per-worker income loss amounts to roughly 4,420 yuan per year.[15]

Multiplying across the affected migrant population:

$$\underbrace{\text{170 million workers}}_{\text{treated migrants}} \times \underbrace{\text{4,420 yuan}}_{\text{per-worker loss}} \approx \text{751 billion yuan} \approx \text{USD 105 billion.} \tag{6}$$

At China's 2020 nominal GDP of approximately 101.6 trillion yuan, this represents roughly 0.74 percent of GDP, an aggregate income loss concentrated entirely among workers at the lower end of the income distribution.

6.6.2 Informality Wage Penalty

The income loss estimate above captures the total earnings decline, which conflates the direct disruption to spatial matching with a composition effect: workers pushed into informality typically earn substantially less than their formal-sector counterparts. To isolate the informality channel, we apply a standard informal-sector wage penalty of 15–20 percent, consistent with estimates for China in Dix-Carneiro and Kovak (2019) and the broader development literature. Our estimates in columns (1)–(2) of Table 7 indicate that pre-pandemic migrant workers experienced a 4.1–4.3 percentage point increase in informal employment probability. Applied to 170 million affected workers, this implies approximately 7 million additional workers displaced into informality. At an average formal-sector wage of 52,000 yuan and a 17.5 percent informal penalty, each newly informal worker faces an annual earnings shortfall of around 9,100 yuan, implying an informality-channel aggregate loss of approximately:

$$\text{7 million workers} \times \text{9,100 yuan} \approx \text{64 billion yuan} \approx \text{USD 9 billion,} \tag{7}$$

[15] The number of 4,420 yuan is similar to the point estimate of migrant worker income loss in levels (e.g., 4,540 yuan per year).

or roughly 0.06 percent of GDP. This is a partial lower bound: it captures only the wage penalty from formal-to-informal transitions, not the broader welfare costs of reduced job security, foregone benefits, or occupational downgrading.

6.6.3 Capital Reallocation on the Firm Side

Our estimates in Table C.6 imply that a one standard deviation increase in migrant dependence (1.23 percentage points) was associated with an 11,730 yuan increase in fixed assets per employee. China's listed manufacturing firms employed approximately 12 million workers in the counties covered by our CSMAR sample. Scaling up, the aggregate increase in fixed asset investment attributable to the automation response amounts to roughly:

$$\text{12 million employees} \times \text{11,730 yuan} \approx \text{141 billion yuan} \approx \text{0.14 percent of GDP.} \tag{8}$$

This capital reallocation represents a directed technical change response that substituted capital for labor (Acemoglu and Restrepo, 2018). While this investment may raise long-run productivity, in the short run it crowds out employment and depresses wages among low-skill workers, consistent with the labor market evidence above.

6.6.4 Aggregate Welfare Costs

Table 8 consolidates these estimates. The dominant welfare cost is the aggregate income loss among displaced migrant workers (approximately 0.74 percent of GDP), with an additional contribution from the informality wage penalty (0.06 percent). Taken together, the aggregate labor market disruption attributable to the COVID-induced automation episode amounts to approximately 0.80 percent of China's 2020 GDP, a figure comparable in magnitude to estimates of the distributional costs of robot adoption in the United States (Acemoglu and Restrepo, 2020) and the labor market dislocations associated with "China Shock" (Autor et al., 2013). For reference, the memo row reports the aggregate increase in fixed asset investment among listed manufacturing firms (141 billion yuan, 0.14 percent of GDP), which represents the firm-side counterpart to the worker-side losses. Whether this capital deepening generates productivity gains sufficient to offset the distributional costs depends on the long-run returns to automation, which we cannot estimate from our data.

Three caveats bear emphasis. First, these estimates capture short-run transition costs and do not net out any long-run productivity gains from automation. Second, our CSMAR investment estimates cover only listed firms; if smaller unlisted firms, which employ the bulk of migrants, responded similarly, the capital reallocation figure would be substantially larger. Third, and most importantly, the income loss estimates capture the *total* welfare costs of the pandemic-induced automation episode rather than isolating the automation channel specifically. The observed income losses and informality transitions reflect a combination of two distinct mechanisms: the immediate disruption to spatial matching caused by mobility restrictions, which prevented workers from reaching their jobs, and the longer-run displacement effects of the subsequent automation investment, which rendered some of those jobs permanently obsolete. While our event study evidence suggests that the automation response is durable and persistent well beyond the mobility restriction period, implying that returning migrants would face a more automated production environment, we cannot cleanly decompose the welfare costs between these two channels with the available data. The estimates should therefore be interpreted as upper bounds on the total welfare costs of the pandemic-induced automation episode rather than as precise measures of automation-attributable displacement, and we encourage future work with comprehensive employer-employee matched data to refine these figures.

7 Conclusion

This paper provides causal evidence that labor scarcity induces directed technical change. Exploiting the unprecedented disruption to internal migration in China during the COVID-19 pandemic, we document a clear chain linking labor supply shocks to automation innovation.

Our analysis yields three main findings. First, the pandemic disproportionately displaced low-skilled, non-agricultural workers, reducing their cross-regional mobility relative to agricultural workers, with the disruption concentrated among those least able to work remotely and most dependent on physical mobility. Second, counties with greater pre-pandemic dependence on migrant labor experienced significant post-COVID increases in automation-related patents, with null effects on total patenting, confirming directed technical change toward labor-saving technologies rather than a generalized innovation boom (Acemoglu, 2002). The automation response is concentrated in counties with tight labor markets, where firms could not substitute missing migrants with local workers, providing direct evidence that quantity constraints rather than price changes are the operative mechanism (Acemoglu, 2010). Third, we trace the distributional consequences of this technological transition: displaced migrant workers experienced significant increases in informal employment and income losses, bearing the bulk of the adjustment costs. A back-of-the-envelope calculation suggests these welfare losses are comparable in magnitude to the distributional costs of robot adoption in the United States (Acemoglu and Restrepo, 2020) and China's trade liberalization (Autor et al., 2013).

Several alternative explanations are ruled out. The automation response is not driven by social distancing imperatives, export demand surges, or local government industrial policy, but reflects firm-level adaptation to binding labor supply constraints.

Our findings suggest that transient mobility frictions can trigger permanent industrial upgrading. More broadly, we demonstrate that sudden, high-frequency shocks can redirect the direction of innovation when labor constraints become acute, with lasting consequences for both technological trajectories and the distribution of gains and losses across workers.

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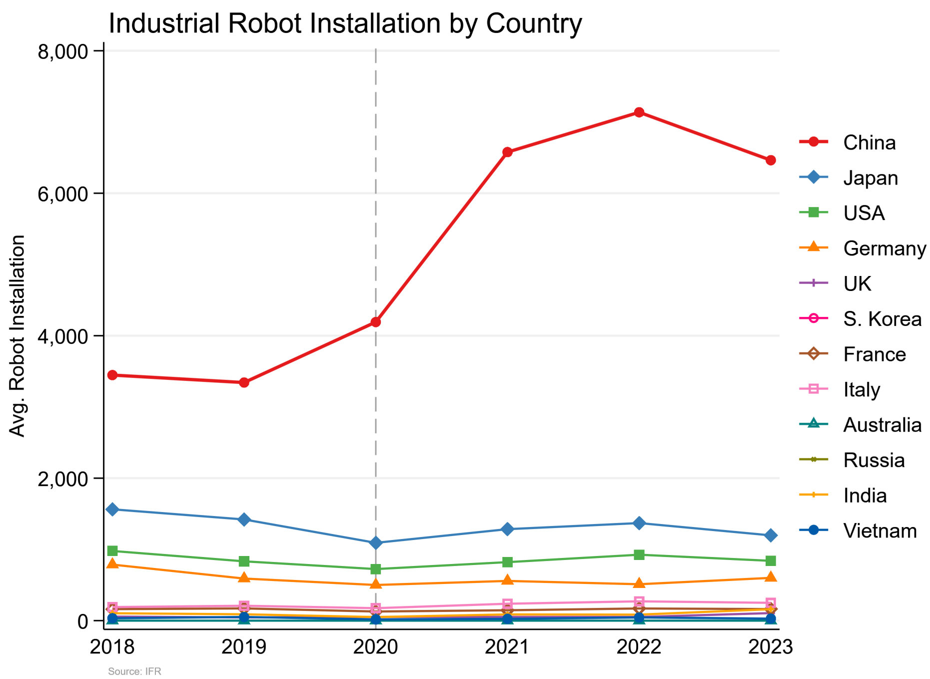
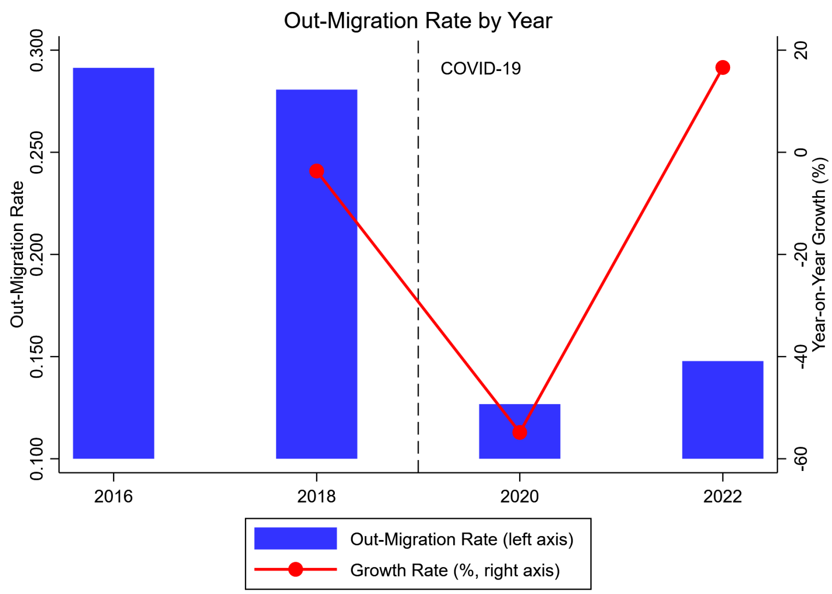
8 Figures

Figure 1: Robotics Installation by Country Before and After COVID-19



Notes: Sourced from International Federation of Robotics Reports https://ifr.org/worldrobotics

Figure 2: Out-migration Rate by Year: Before and After COVID-19

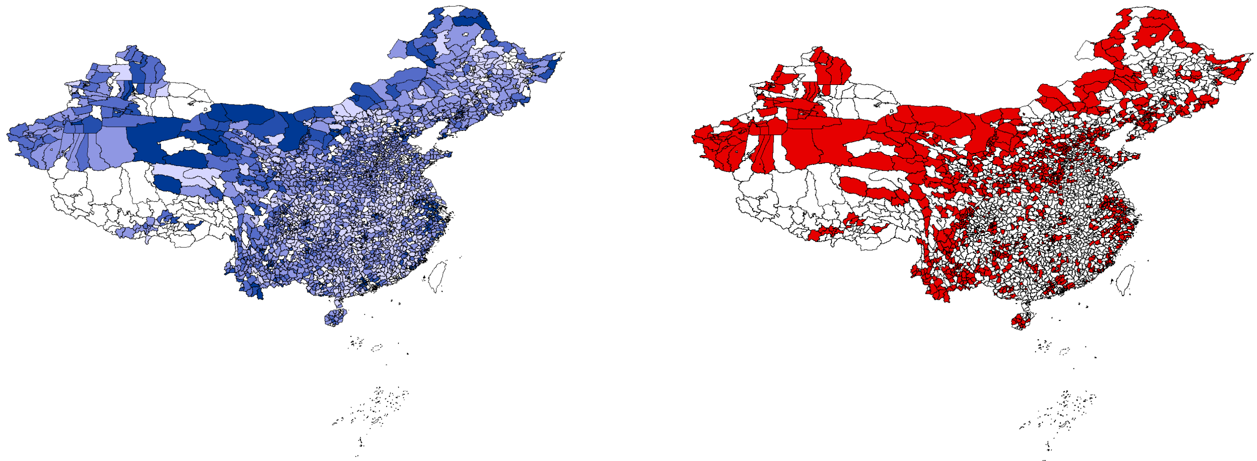


Notes: This figure displays the average out-migration/migrant worker rate by year using individual survey data (CFPS).

Figure 3: Regional Treatment Intensity and Treatment Indicator in 2015

(a) Migrant Share %

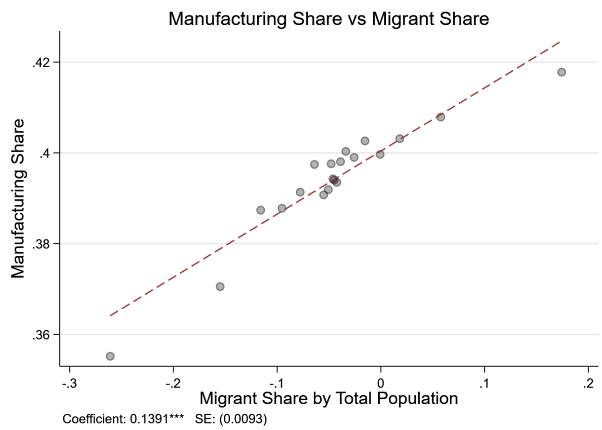
(b) Migrant Share Above the Median Value



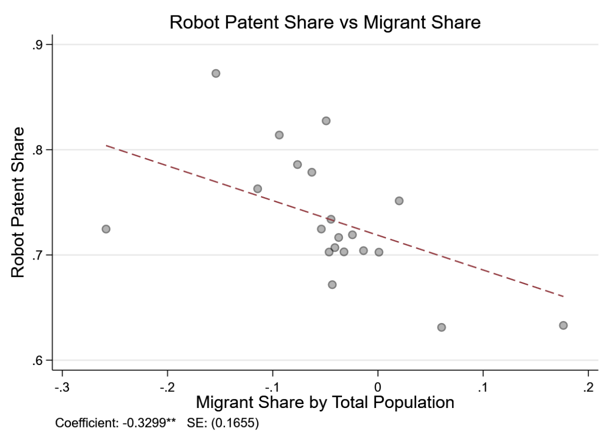
Notes: This figure displays regional treatment intensity and treatment status across Chinese counties in 2015. Panel (a) shows the continuous migrant share, defined as the number of migrants relative to the total population in each county. Panel (b) shows the binary treatment indicator, which equals one if a county's migrant share exceeds the sample median. Data are drawn from the 2015 China 1% Population Survey (mini-census).

Figure 4: Migrant Share and Manufacturing/Automation Before COVID-19

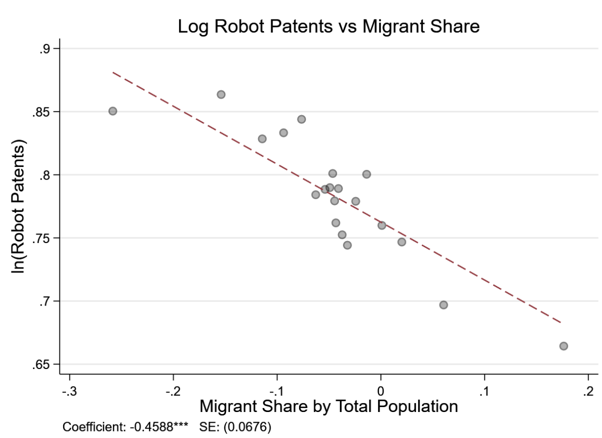
(a) Manufacturing Output Share by GDP



(b) Robot Patent Share

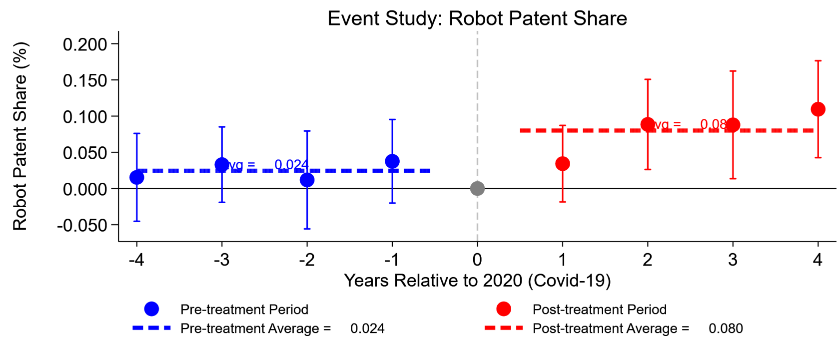


(c) Robot Patent Count



Notes: Each panel shows the binscatter plot with county fixed effects absorbed. The sample period is 2015-2019 (prior to COVID-19). Coefficients and standard errors are from reghdfe regressions with county fixed effects and clustered standard errors at the county level. *** p<0.01, ** p<0.05, * p<0.10.

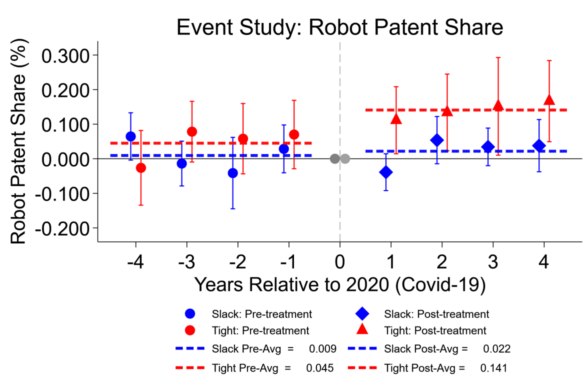
Figure 5: Event Study for County Robotics Patent %



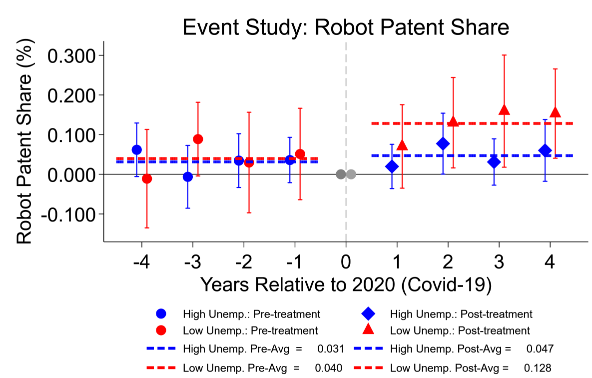
Notes: This figure plots dynamic treatment effects from an event study specification. The dependent variables are the share of robotics patents. The treatment variable is the pre-pandemic number of migrants relative to the total population in each county. The omitted reference year is 2020. All specifications include county fixed effects and interactions between initial conditions (GDP per capita in 2015) and province-year fixed effects. Vertical bars represent 95% confidence intervals based on standard errors clustered at the county level. The vertical dashed line indicates the onset of COVID-19 in 2020.

Figure 6: Tight vs. Slack Market Response: Event Study for County Robotics Patent %

(a) Counties with Tight Market vs. Slack Market Before COVID-19

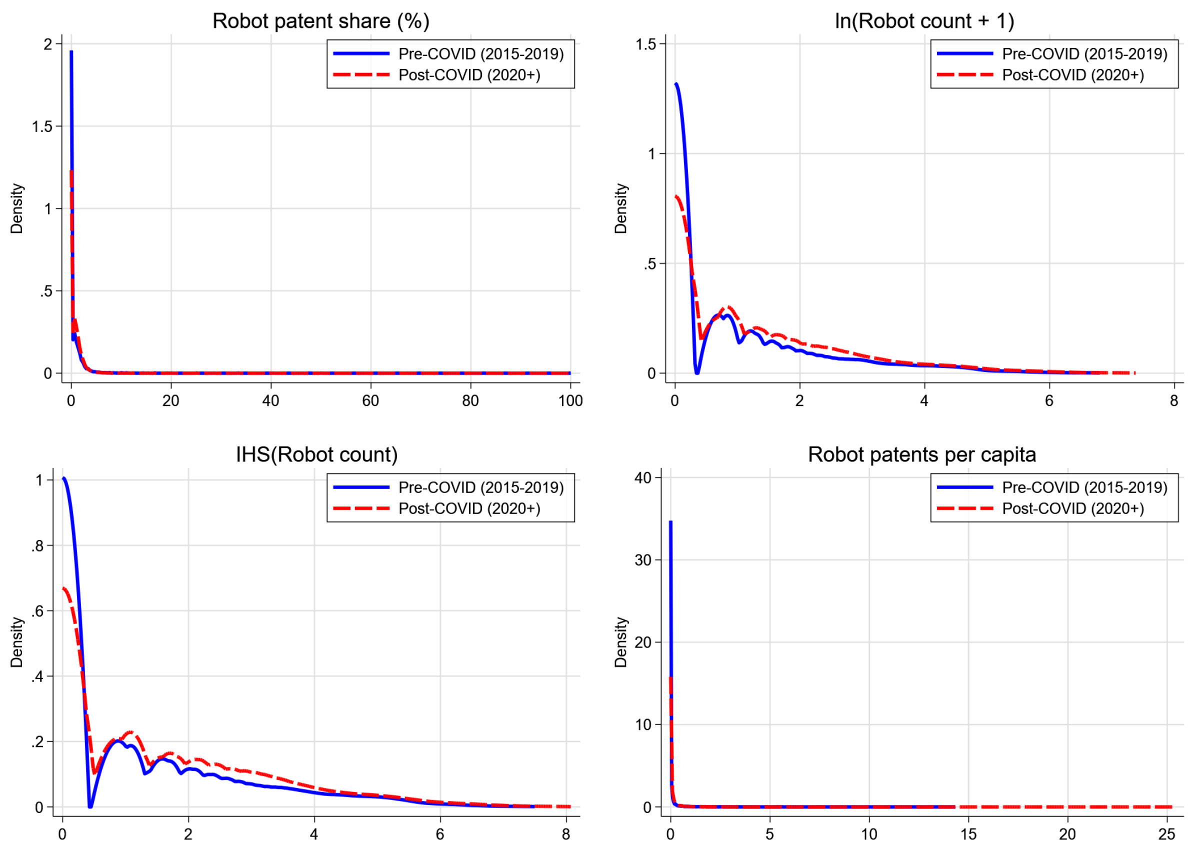


(b) Counties with Low Unemployment Rate vs. High Unemployment Rate Before COVID-19



Notes: This figure plots dynamic treatment effects from an event study specification, examining heterogeneous responses by local labor market conditions. The dependent variable is the share of robotics patents among total patents in each county. Panel (a) compares counties with tight labor markets versus slack labor markets prior to COVID-19. Panel (b) compares counties with low unemployment rates versus high unemployment rates prior to COVID-19. The omitted reference year is 2020. All specifications include county fixed effects and interactions between initial conditions (GDP per capita in 2015) and province-year fixed effects. Vertical bars represent 95% confidence intervals based on standard errors clustered at the county level. The vertical dashed line indicates the onset of COVID-19 in 2020. Horizontal dashed lines show the average post-treatment effects for each group. Points are horizontally offset for visual clarity.

Figure 7: Distribution of Automation Patents by Periods: Changes in Extensive Margin

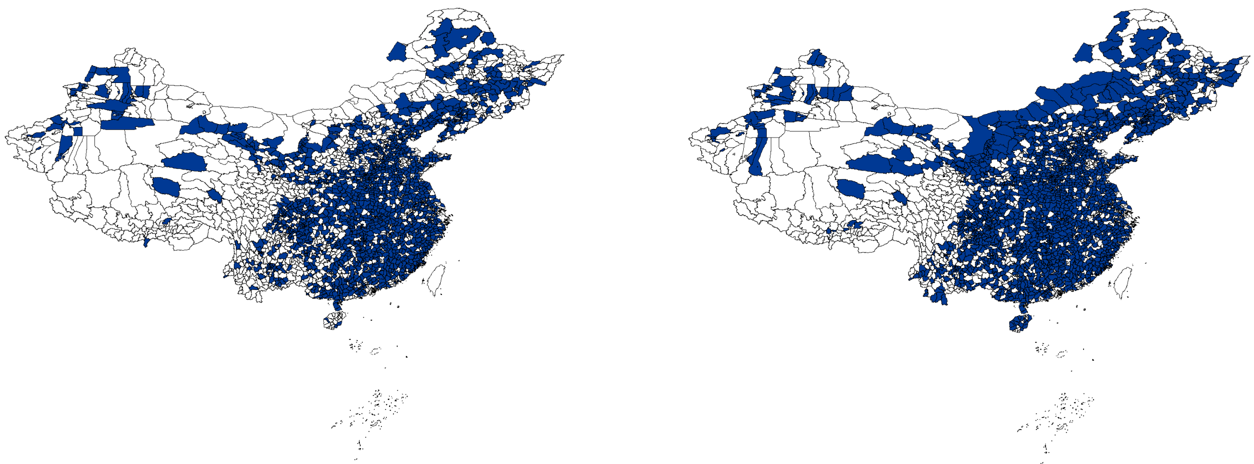


Notes: This figure plots the kernel density distributions of automation patent variables before and after COVID-19. The top panels show log counts of robot patents (left) and manipulator patents (right). The bottom panels show the share of robot patents (left) and manipulator patents (right) among total patents. Pre-COVID period: 2015–2019; Post-COVID period: 2020–2024. Data sourced from the China National Intellectual Property Administration (CNIPA).

Figure 8: Robot Patent Activity Before and After COVID-19

(a) Pre-COVID (2019)

(b) Post-COVID (2020)



Notes: This figure displays the extensive margin of robot patent activity across Chinese counties before and after the COVID-19 shock. Panel (a) shows counties with at least one robot-related patent application in 2019, and Panel (b) shows counties with at least one robot-related patent application after 2020. A county is defined as having robot patent activity if it filed at least one patent related to robots, manipulators, or automated guided vehicles (AGVs) in the given year. Data are drawn from the China National Intellectual Property Administration (CNIPA).

9 Tables

Table 1: Summary Statistics of Patent Variables by Migration Status and Period

	High Migration County				Low Migration County			
	Mean	SD	Min	Max	Mean	SD	Min	Max
Panel A: Pre-COVID								
Robot patent share (%)	0.845	2.390	0	82.609	0.683	2.257	0	100
ln(Robot count + 1)	1.105	1.483	0	6.807	0.538	0.871	0	5.529
IHS(Robot count)	1.344	1.742	0	7.499	0.681	1.077	0	6.219
Robot patents per capita	0.204	0.663	0	14.333	0.036	0.151	0	4.841
ln(Total patents + 1)	4.972	2.062	0.693	10.547	4.441	1.467	0.693	9.657
ln(Non-auto patents + 1)	4.937	2.057	0	10.508	4.407	1.465	0	9.618
Panel B: Post-COVID								
Robot patent share (%)	0.904	1.296	0	20	0.750	2.391	0	100
ln(Robot count + 1)	1.409	1.608	0	7.377	0.781	0.987	0	5.204
IHS(Robot count)	1.706	1.870	0	8.070	0.985	1.215	0	5.892
Robot patents per capita	0.331	1.057	0	25.365	0.054	0.155	0	4.583
ln(Total patents + 1)	5.398	2.024	0.693	10.838	4.871	1.487	0.693	9.433
ln(Non-auto patents + 1)	5.367	2.018	0	10.770	4.840	1.486	0	9.409

Notes: This table reports summary statistics for patent variables by migration status and time period. Panel A covers the pre-COVID period and Panel B covers the post-COVID period. High and Low migration groups are defined by the median net migrant share in 2015.

Table 2: Impact of COVID-19 on Migration by Pre-Pandemic Employment Sector

	Out-of-Hometown Work		
VARIABLES	(1)	(2)	(3)
Non-Agricultural Worker$_{\text{pre-COVID}}$ × COVID-19	-0.095***	-0.111***	-0.110***
	(0.007)	(0.008)	(0.008)
Observations	37,377	36,880	37,239
R-squared	0.635	0.457	0.640
Individual FEs	✓		✓
Household FEs		✓	
Year FEs	✓	✓	
Province × Year FEs			✓

Notes: The dependent variable is an indicator for out-of-hometown migrant work. The key coefficient captures the interaction between pre-pandemic non-agricultural employment status and a post-2020 indicator (COVID-19 period). Columns differ in the fixed effects included: Column (1) includes individual and year fixed effects; Column (2) includes household and year fixed effects; Column (3) includes individual and province-by-year fixed effects. Standard errors clustered at the individual level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Table 3: Correlation between Migrant Labor Dependence and Firm-level Disruptions During COVID-19 (in 2020)

VARIABLES	1(Resumed Operations) (1)	1(Absent Workers Share Index) (2)	1(Wage Increase for Labor) (3)	1(No Delivered Orders) (4)	1(Protection Shortage) (5)	1(Supply Chain Disruption) (6)	1(Logistics Disruption) (7)	1(Labor Cost Pressure) (8)
Migrant Share %	−0.023***	0.050***	0.007***	0.007*	−0.003	0.002	−0.003	−0.006
	(0.005)	(0.017)	(0.002)	(0.004)	(0.007)	(0.003)	(0.005)	(0.004)
Employment in 2019	−0.009	0.219**	0.037*	0.049*	0.056**	−0.006	0.027	0.022
	(0.024)	(0.106)	(0.022)	(0.025)	(0.023)	(0.023)	(0.017)	(0.041)
Revenue in 2019	0.068***	−0.077	−0.021	−0.052**	−0.023	−0.007	0.028	0.002
	(0.020)	(0.062)	(0.018)	(0.024)	(0.026)	(0.020)	(0.020)	(0.030)
Observations (# Firms)	348	314	348	348	348	348	348	348
R-squared	0.148	0.121	0.147	0.091	0.108	0.038	0.083	0.095
Province FEs	✓	✓	✓	✓	✓	✓	✓	✓
Industry FEs	✓	✓	✓	✓	✓	✓	✓	✓

Notes: This table examines the relationship between migrant labor dependence and firm-level operational disruptions during the COVID-19 pandemic, using firm survey data collected in early 2020 (ESIEC). Each column reports an OLS regression where the dependent variable captures a distinct dimension of firm disruption: whether the firm had resumed operations (Column 1), the share of workers absent due to mobility restrictions (Column 2), whether the firm reported wage increases (Column 3), inability to fulfill existing orders (Column 4), shortages of personal protective equipment (Column 5), supply chain disruptions (Column 6), logistics disruptions (Column 7), and labor cost pressures (Column 8). Migrant Share is the county-level net migration rate from the 2015 census. All specifications include province fixed effects. Standard errors clustered at the province level in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table 4: Baseline: Effect of Migration Restrictions on Automation Adoption

	Automation-Related Patent										Placebo	
	Robot Patent Share %		Robot Patent Count		ln(Robot Count+1)		Robot per Capita		IHS(Robot Count)		ln(Total Patent+1)	ln(Non-Auto Patent+1)
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: County FEs + Year FEs												
Migrant Share % × COVID-19	0.049***		6.814***		0.051***		0.093***		0.051***			
	(0.015)		(1.395)		(0.010)		(0.016)		(0.011)			
Panel B: + Province × Year FEs + Initial GDP × Year FEs												
Migrant Share % × COVID-19		0.063***		5.457***		0.035***		0.081***		0.034***	-0.004	-0.005
		(0.021)		(1.231)		(0.010)		(0.015)		(0.012)	(0.010)	(0.010)
Dep. Var. Mean	0.792	0.792	10.211	10.211	0.944	0.944	0.151	0.151	1.163	1.163	4.910	4.877
No. of Counties	2,165	2,165	2,165	2,165	2,165	2,165	2,165	2,165	2,165	2,165	2,165	2,165
Observations	21,568	21,568	21,568	21,568	21,568	21,568	21,568	21,568	21,568	21,568	21,568	21,568
R-squared	0.194	0.219	0.789	0.826	0.841	0.863	0.791	0.822	0.829	0.850	0.943	0.942
County FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FEs	✓		✓		✓		✓		✓			
Province × Year FEs		✓		✓		✓		✓		✓	✓	✓
Initial GDP × Year FEs		✓		✓		✓		✓		✓	✓	✓

Notes: This table reports the effect of labor mobility restrictions on automation adoption across alternative fixed effect specifications. The key independent variable is the interaction between county-level migrant share and COVID-19 onset. Columns (1)–(2), (3)–(4), (5)–(6), (7)–(8), and (9)–(10) report results for robot patent share, robot patent count, log robot count, robots per capita, and IHS-transformed robot count, respectively. Columns (11) and (12) use total patents and non-automation patents as placebo dependent variables. Panel A includes county and year fixed effects only; Panel B adds Province × Year and Initial GDP × Year fixed effects. Standard errors clustered at the county level in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Table 5: Heterogeneity Analyses: Labor Market Tightness and Unemployment

	Robot Patent Share		ln(Non-Auto Patent+1)		Robot Patent Share		ln(Non-Auto Patent+1)	
	Tight	Slack	Tight	Slack	Low Unemp.	High Unemp.	Low Unemp.	High Unemp.
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Migrant Share × COVID-19	0.103***	0.015	−0.010	−0.004	0.100***	0.025	−0.017	0.005
	(0.036)	(0.023)	(0.015)	(0.014)	(0.034)	(0.023)	(0.015)	(0.012)
Observations	11,266	10,265	11,266	10,265	10,445	10,427	10,445	10,427
R-squared	0.228	0.216	0.945	0.940	0.214	0.296	0.920	0.954
County FEs	✓	✓	✓	✓	✓	✓	✓	✓
Province × Year FEs	✓	✓	✓	✓	✓	✓	✓	✓
Initial GDP × Year FEs	✓	✓	✓	✓	✓	✓	✓	✓

Notes: This table reports split-sample heterogeneity analyses for the effect of COVID-19 on automation patents. Columns 1–4 split the sample by labor market tightness (tight vs. slack markets); Columns 5–8 split by unemployment level (low vs. high unemployment). The dependent variables are the robot patent share (Columns 1–2 and 5–6) and log non-automation patents (Columns 3–4 and 7–8). All specifications include county fixed effects, province × year fixed effects, and initial GDP × year fixed effects. Standard errors clustered at the county level in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table 6: Alternative Explanations: Industry In-Person Intensity, Population Density, and Export Exposure

	Robot Patent Share						
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Migrant Share % × COVID-19	0.063***	0.062**	0.067***	0.066***	0.068***	0.061**	0.062**
	(0.021)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.025)
Industry In-Person Intensity × COVID-19		0.003				0.002	0.002
		(0.004)				(0.004)	(0.004)
Population Density × COVID-19			0.252			0.214	0.243
			(0.249)			(0.262)	(0.253)
Exporting County × COVID-19				0.094		0.092	
				(0.089)		(0.088)	
Export Share of GDP × COVID-19					−0.686		−0.700
					(1.167)		(1.169)
Observations	21,568	18,723	18,723	18,723	18,723	18,723	18,723
R-squared	0.219	0.234	0.234	0.234	0.233	0.234	0.233
County FEs	✓	✓	✓	✓	✓	✓	✓
Province × Year FEs	✓	✓	✓	✓	✓	✓	✓
Initial GDP × Year FEs	✓	✓	✓	✓		✓	

Notes: This table tests whether the COVID-19-induced automation response was driven by industry in-person intensity, population density, or export exposure rather than labor scarcity. The dependent variable is robot patent share. Migrant Share is net migration as a share of total population in 2015. Industry In-Person Intensity is the employment-weighted average of industry-level inability-to-work-from-home shares from Dingel and Neiman (2020), computed using each county's pre-period industry employment distribution; higher values indicate a county's workforce is more concentrated in industries requiring on-site presence. Population Density is population per square kilometer in 2015. Exporting County is a binary indicator for counties with positive export activity in the pre-period. Export Share of GDP is the value of exports as a share of county GDP in the pre-period. COVID-19 indicates years 2020–2023. Column (1) uses the full baseline sample; Columns (2)–(7) are restricted to the common sample across all alternative control specifications. All specifications include county fixed effects, province × year fixed effects, and interactions of initial GDP per capita with year fixed effects. Standard errors clustered at county level in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table 7: Effect of Migration Restrictions on Labor Market Reallocation and Occupational Adjustment

	Informal Employment		Unemployment		ln(Income)		Switch from Mfg	
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Migrant Worker$_{\text{pre-COVID}}$ $\times$ COVID-19	0.043***	0.041***	0.010	0.013**	-0.079*	-0.090*	-0.010	-0.012
	(0.009)	(0.009)	(0.006)	(0.006)	(0.045)	(0.049)	(0.013)	(0.013)
Observations	38,298	38,298	38,298	38,298	16,878	16,876	13,770	13,766
R-squared	0.843	0.844	0.578	0.581	0.604	0.608	0.384	0.389
Individual FEs	✓	✓	✓	✓	✓	✓	✓	✓
Year FEs	✓		✓		✓		✓	
Province $\times$ Year FEs		✓		✓		✓		✓

Notes: This table reports the effect of COVID-19-induced migration restrictions on labor market reallocation and occupational adjustment. The key independent variable is the interaction between pre-pandemic migrant worker status and COVID-19 onset. Columns (1) and (2) report results for informal employment; columns (3) and (4) for unemployment; columns (5) and (6) for migrant worker's income; and columns (7) and (8) for switching out of manufacturing. All specifications include individual fixed effects. Odd-numbered columns include year fixed effects; even-numbered columns replace year fixed effects with Province $\times$ Year fixed effects. Standard errors clustered at the county level in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table 8: Back-of-the-Envelope Aggregate Welfare Costs of the Automation Response

Channel	Affected workers	Annual loss (bn yuan)	% of GDP
Migrant income loss (8.5%)	170 million	751	0.74%
Informality wage penalty (17.5%)	7 million	64	0.06%
Total labor market cost		**815**	**0.80%**
Memo: Capital deepening	*12 million*	*141*	*0.14%*

Notes: Back-of-the-envelope estimates combining regression coefficients from Tables 7 and C.6 with aggregate population and earnings statistics. The income loss row applies the midpoint estimate of 8.5 percent (from columns 5 and 6 of Table 7) to 170 million migrant workers in treatment counties earning an average of 52,000 yuan annually (NBS Migrant Workers Monitoring Survey, 2020). The informality row applies a 17.5 percent informal-sector wage penalty to the 4.2 percentage point increase in informality probability, implying approximately 7 million newly informal workers. The capital deepening row scales the fixed-asset-per-employee estimate from Table C.6 to the 12 million employees covered by the CSMAR listed-firm sample and is reported as a memo item because it reflects firm-level investment rather than a net social loss; whether it offsets the worker-side welfare costs depends on the long-run productivity returns to automation. The GDP denominator is China's 2020 nominal GDP of 101.6 trillion yuan (NBS). All figures are approximate and should be interpreted as order-of-magnitude benchmarks.

Online Appendix

Table of Contents

A Additional Results

A.1 Robotics Installation: China vs. Rest of the World

To distinguish domestic labor supply shocks from global industry trends, we complement our analysis of indigenous innovation with data on physical capital adoption. We obtain industrial robot installation statistics from the International Federation of Robotics (IFR), covering the period from 2014 to 2023. While our patent data captures the development of technology within China, the global scope of the IFR database allows us to construct a necessary counterfactual: tracking how automation evolved in the rest of the world during the same period. This source is widely recognized as the authoritative standard for cross-country comparisons and has been extensively employed in the literature (Graetz and Michaels, 2018; Acemoglu and Restrepo, 2020).

The IFR data report annual robot installations (newly deployed industrial robots) disaggregated by country and industry sector. Industrial robots are defined as automatically controlled, reprogrammable, multipurpose manipulators programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications. The data exclude service robots and focus exclusively on robots used in manufacturing and related industrial activities. Each installation represents a unit deployment, regardless of the robot's capabilities or price.

For our analysis, we focus on several key dimensions of the robot installation data. First, we construct country-level measures of robot adoption, with particular attention to China versus the rest of the world. China has emerged as the world's largest market for industrial robots, accounting for over 50% of global installations since 2016. Second, we disaggregate installations by industry sector, focusing on sectors that employ significant shares of low-skilled internal migrants in China. These sectors include: electronic components manufacturing, automotive parts and components, textiles, and construction. This sectoral focus allows us to test whether COVID-19 had differential effects on automation in labor-intensive industries.

We construct our primary dependent variable as $\ln(\text{Robot Installations} + 1)$ to account for zero installations in some country-sector-year cells and to facilitate interpretation of coefficients as semi-elasticities. We also use the current stocks of robotics as the secondary outcome variable. Our final dataset includes robot installation data for over 100 countries and 30 detailed sectors.[16]

We employ a difference-in-differences framework augmented with a triple interaction to capture sector-specific heterogeneity. The estimating equation is:

$$Y_{cst} = \alpha + \beta(\text{Sector}_s \times \text{China}_c \times \text{PostCOVID-19}_t) + \gamma_c + \lambda_s + \delta_t + \varepsilon_{cst}, \tag{9}$$

where Y_{cst} denotes the log of new robot installations in country c, industry sector s, and year t. The term Sector_s is a binary indicator for migrant-intensive industries (electronics, textiles, machinery, and construction), which we hypothesize were most exposed to the labor supply shock. China_c identifies the domestic economy, and PostCOVID-19_t takes the value of one for years 2020 and after.

The specification includes a set of fixed effects to absorb invariant heterogeneity: γ_c captures country fixed effects; λ_s accounts for sector fixed effects; and δ_t denotes year fixed effects. The coefficient of interest, β, captures the differential acceleration of robot adoption in China's migrant-intensive sectors—specifically electronics, textiles, machinery, and construction. According to official data, the manufacturing and construction sectors alone absorb nearly half of China's total migrant workforce (National Bureau of Statistics of China, 2021). Furthermore, Cheng et al. (2019) document that the electronics and automotive industries have historically possessed the highest labor intensity, making them the primary targets for robotization as labor costs rise. A positive β would confirm that the automation surge was specific to the Chinese institutional context and concentrated in sectors facing binding labor constraints.

Table C.14 presents difference-in-differences estimates for robot installations on a global sample of countries. Panel A reports the baseline China $\times$ COVID-19 coefficient, capturing

[16] We also use robotics stock as the second outcome variable for robustness.

the aggregate differential increase in robot adoption in China relative to the rest of the world. Panel B reports the triple-interaction terms (China $\times$ COVID-19 $\times$ Sector), isolating the additional surge specific to each sector within China.

The results indicate a substantial and country-specific pivot toward automation. Column (1) shows that the aggregate effect of the pandemic on robot installations in China is large, positive, and highly significant relative to the global baseline, confirming that Chinese manufacturers accelerated automation far more rapidly than their global peers. This acceleration is concentrated in sectors historically reliant on migrant labor. Columns (2) through (8) reveal considerable heterogeneity across sectors. The Construction sector exhibits the largest differential increase, followed by Electrical Machinery and Electric & Auto Parts, all of which faced acute physical labor constraints during the pandemic. Electronic Components and Household Appliances show smaller but still significant additional effects. In contrast, Figure 1 shows that these same sectors in the rest of the world experienced muted or negative investment trends during the pandemic. The divergence confirms that the impetus for automation was not a global shift in final product demand, but a shock to labor availability specific to the Chinese institutional context.

Figure B.6 complements these regression results by displaying the sectoral composition of China's industrial robot stock before and after COVID-19. The post-COVID period is characterized by a notable expansion in the shares of construction, electrical machinery, and electronic components, precisely the sectors most reliant on migrant labor and most exposed to the mobility shock, consistent with the triple-interaction estimates in Table C.14.

To ensure the main results reflect structural capital deepening rather than a temporary investment spike, we replicate the analysis using operational robot stocks as the outcome variable. These results are reported in Table C.15. The coefficients for robot stocks are consistent with the installation data, confirming that the pandemic induced a permanent substitution of capital for labor in China's migrant-intensive industries.

A.2 Shift-Share Variable

We employ the Bartik instrumental variable methodology following Imbert et al. (2022) to construct exogenous COVID-19-induced migrant labor supply shocks at the destination county level, denoted as Z_{pt}.[17] This method involves an interaction between each destination county's historical migration network composition (the share) and the idiosyncratic COVID-19 mobility disruptions at each origin city (the shift) to compute Z_{pt}, which represents the predicted migrant labor supply shock experienced by each destination county. For example, a manufacturing county that historically recruited migrants from

[17] The instrument is constructed at the county level, which is an administrative division ranking below a prefecture city and above the township in China.

Henan — which experienced severe COVID-19 lockdowns due to its proximity to Wuhan — receives a more negative predicted shock than an otherwise identical county that recruited from less-affected provinces. This cross-county variation in predicted exposure, driven purely by origin-level epidemiological conditions, constitutes our identifying variation (Goldsmith-Pinkham et al., 2020). In the subsequent subsections, we provide a more detailed description of the construction of these variables.

Historical Migration Network (Share) The destination county migration network is constructed from bilateral migration flows between origin cities and destination counties.[18] The data on bilateral migration flows are sourced from the 2015 China 1% Population Survey (mini-census). For each individual in the survey, we observe both their registered *hukou* location (origin) and their current place of residence (destination). We aggregate these individual records to construct the bilateral flow f_{op}, defined as the number of surveyed migrants with *hukou* registered in origin city o currently residing in destination county p, scaled by the survey sampling weight to recover population-level counts.[19] The share of destination county p's migrant labor force originating from city o is:

$$s_{op} = \frac{f_{op}}{\sum_{o'} f_{o'p}} \tag{10}$$

where the denominator is the total number of migrants received by destination county p across all origin cities. By construction, $\sum_o s_{op} = 1$ for all p. The shares are fixed at the baseline census year and do not vary over time, ensuring they are predetermined with respect to the COVID-19 shock.

Mobile-Tracking Outflow Index (Shift) We derive the annual outflow mobility index for each origin city using daily city-level migration data from the Baidu Migration platform, which tracks smartphone-based population outflows across Chinese cities at high frequency.[20] The platform provides a daily outflow index q_{od} for each origin city o on day d, measuring the relative intensity of population outflows. We first collapse the daily index to an annual city-level average:

[18] We aggregate origin locations from the county to the city (prefecture) level to avoid the sparse matrix problem arising from the many county-to-county pairs with zero observed flows (Goldsmith-Pinkham et al., 2020).

[19] Migration flows are measured as the number of individuals whose current place of residence differs from their registered *hukou* location.

[20] The Baidu Migration platform (Baidu Qianxi) covers over 95% of China's smartphone users, providing near-universal coverage of population mobility patterns.

$$\bar{q}_{ot} = \frac{1}{|D_t|} \sum_{d \in D_t} q_{od} \tag{11}$$

where D_t denotes the set of days in year t and $|D_t|$ is the number of days. To isolate the idiosyncratic COVID-19 mobility disruption at each origin city, purging autocorrelation and common national mobility trends, we obtain the yearly deviation in each city's outflow index by the following autoregressive process of order 1 (AR(1)) specification:

$$\log(\bar{q}_{ot}) = \beta \log(\bar{q}_{o,t-1}) + \theta_t + \delta_o + \varepsilon_{ot} \tag{12}$$

where $\log(\bar{q}_{ot})$ denotes the log annual outflow index of origin city o in year t; θ_t denotes year fixed effects absorbing common national mobility trends; and δ_o denotes origin city fixed effects absorbing time-invariant city characteristics such as population size and geographic location. We derive the residual $\hat{\varepsilon}_{ot}$ from the above regression, capturing the idiosyncratic deviation in outflow mobility from its predicted level.[21]

Instrument Construction We use s_{op} and $\hat{\varepsilon}_{ot}$ to construct the Bartik instrument Z_{pt}. Specifically, Z_{pt} for a given destination county p in year t is calculated as the share-weighted sum of origin city outflow shocks:

$$Z_{pt} = \sum_{o} s_{op} \cdot \hat{\varepsilon}_{ot} \tag{13}$$

The temporal variation of Z_{pt} arises from the idiosyncratic fluctuations in origin city outflow mobility captured by $\hat{\varepsilon}_{ot}$, with large negative values concentrated in 2020. The spatial variation of Z_{pt} originates from the heterogeneity in historical migration network composition across destination counties. Two counties with identical characteristics but different historical origin city compositions receive different predicted shocks if their respective origin cities were differentially disrupted by COVID-19 mobility restrictions. This cross-county variation in predicted exposure constitutes our identifying variation.[22] The reduced-form specification is:

[21] By construction, $\hat{\varepsilon}_{ot}$ has mean zero. Large negative values in 2020 reflect the unexpected contraction in outmigration induced by COVID-19 lockdowns, over and above any common national trend or city-specific tendency.

[22] The identification assumption requires that the idiosyncratic outflow disruptions at origin cities affect destination county automation only through migrant labor supply. This is plausible because lockdown severity at the origin was determined by local epidemiological conditions — population density, proximity to Wuhan, and local government responses — which are unrelated to automation investment decisions at the destination. The AR(1) residual further strengthens this argument by purging the shift of common national trends and city-specific fixed characteristics that could otherwise confound the instrument.

$$\text{AutoPatent}_{pt} = \alpha Z_{pt} + \mathbf{X}'_{p,2015} \times \delta_t + \gamma_p + \delta_t + \varepsilon_{pt} \tag{14}$$

where AutoPatent_{pt} is an automation outcome for county p in year t; $\mathbf{X}'_{p,2015} \times \delta_t$ includes log 2015 GDP per capita interacted with year fixed effects to flexibly control for pre-existing economic trends; γ_p are county fixed effects; δ_t are year fixed effects; and standard errors are clustered at the county level.

Table C.5 reports the reduced-form estimates. Since Z_{pt} is constructed from the AR(1) residual of a mobility index, the coefficients are not directly comparable in magnitude to the baseline DiD estimates but the signs and significance are informative. The coefficient on Z_{pt} is negative and statistically significant across three of the four automation outcomes, consistent with the baseline results — a more negative predicted shock is associated with higher automation patenting at the destination county. The coefficient on robots per capita is insignificant (column 3), likely reflecting the noisiness of this measure in counties with small populations where a single large patent filer can dominate the per capita count. We note that the Baidu Migration data are only available from 2019 onwards, restricting the sample relative to the baseline. Nonetheless, the results corroborate the baseline findings and suggest that the automation response is driven by exogenous variation in COVID-19 severity at origin cities propagated through pre-existing migration networks, rather than by the endogenous sorting of migrants to high-automation counties.

A.3 Heterogeneity in Migration Effects

Heterogeneity by *hukou* China's *hukou* system classifies individuals into agricultural and non-agricultural registration types, with important implications for labor mobility. Agricultural *hukou* holders face more institutional and economic barriers when working outside their hometowns, including limited access to urban social services and weaker integration into non-local labor markets. These constraints make them more vulnerable to disruptions during periods of restricted mobility.

Table C.8 presents the heterogeneity results by *hukou* type. The baseline interaction term—capturing the effect for agricultural *hukou* workers—is large, negative, and highly significant, indicating a sharp decline in out-of-hometown work for this group during the pandemic. In contrast, the triple-interaction coefficients for non-agricultural *hukou* holders are positive and significant across all specifications. These effects substantially offset the negative baseline impact.

Heterogeneity by Gender We also examine whether the impact of COVID-19 on cross-regional labor mobility differs by gender. In our specification, the baseline group consists of male workers, and the key interaction term captures the effect of COVID-19 on out-of-hometown work for pre-pandemic non-agricultural male workers. As reported in Table C.10, this coefficient is negative and highly significant across all columns (around -0.08), indicating a sizable decline in migration among men employed in non-agricultural jobs before the pandemic.

The triple-interaction terms for women (Female $\times$ Non-Agri $\times$ Post-COVID) are also negative and statistically significant, with magnitudes of roughly -0.03. This implies that the overall reduction in out-of-hometown work is even larger for female workers than for their male counterparts. In other words, conditional on working in non-agricultural sectors prior to COVID-19, women experienced a stronger contraction in migration in the post-pandemic period. This pattern is consistent with the idea that women face additional constraints during crises—such as increased caregiving responsibilities and a higher concentration in service jobs that are more exposed to lockdowns and social distancing measures—which amplify the impact of mobility restrictions on their labor supply.

Heterogeneity by Age To examine life-cycle differences in the impact of COVID-19, individuals are grouped into three age categories: Age Group 1 (ages 35–49), Age Group 2 (ages 16–34), and Age Group 3 (ages 50–60). The prime-age group (35–49) serves as the reference category in the heterogeneity analysis.

Table C.11 presents the results. For the base group (Age 35–49), the interaction between being a pre-pandemic non-agricultural worker and the post-COVID period is negative and highly significant across all specifications (-0.096). This confirms a substantial decline in out-of-hometown work among prime-age migrants following the onset of COVID-19.

The triple-interaction terms reveal clear differences across age groups. For younger workers (Age 16–34), the coefficients are positive but statistically insignificant. This suggests that their reduction in migration was smaller than that of prime-age workers, but the difference is not large enough to be precisely estimated. In contrast, older workers (Age 50–60) show consistently negative and significant triple interactions across all columns, with magnitudes between -0.035 and -0.043. These results imply that older workers experienced a sharper contraction in cross-regional mobility relative to the prime-age reference group.

The results point to a clear life-cycle pattern: older workers reduced their migration the most, prime-age workers experienced substantial but moderate declines, and younger workers were the least affected. This gradient is consistent with heightened health risks and mobility constraints faced by older individuals during the pandemic.

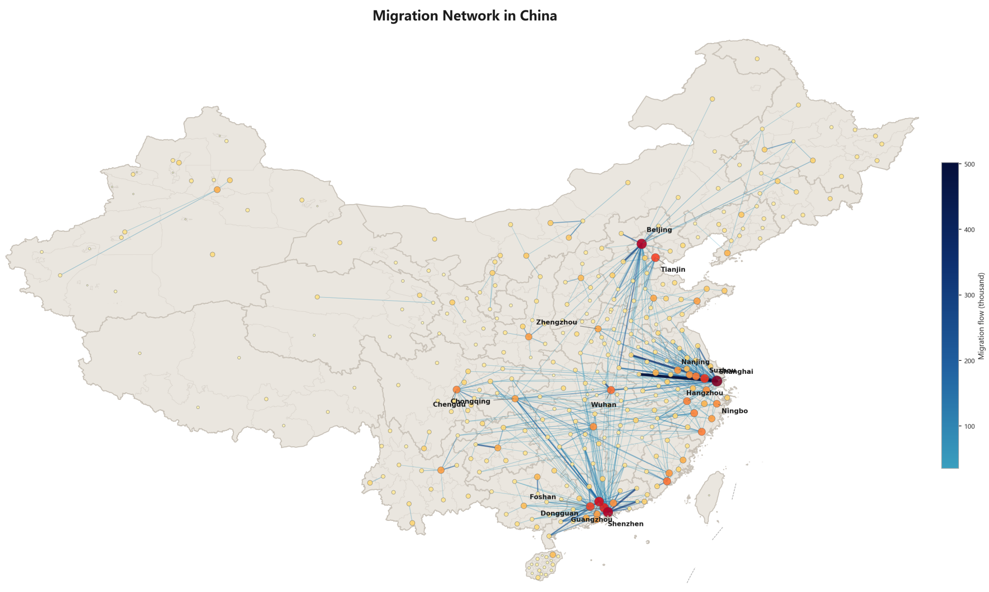
A.4 Additional Robustness Checks Using COVID-19 Cases

Migrants and COVID-19 Cases To assess the sensitivity of the baseline estimates to the definition of the COVID-19 shock, we replace the post-pandemic indicator with a continuous exposure measure constructed from prefecture-level confirmed COVID-19 cases in 2020 and 2022. Specifically, we use the logarithm of one plus the number of confirmed infections in each prefecture-year as an alternative measure of pandemic intensity. The results are reported in Table C.12. Across all specifications, the interaction between pre-pandemic non-agricultural employment and COVID-19 intensity remains negative, highly significant, and similar in magnitude, with coefficients ranging from -0.013 to -0.019. These estimates indicate that the observed decline in cross-regional labor mobility is not driven by the binary timing structure of the baseline DID design but is robust to a more continuous measure of local pandemic severity.

Alternative Measure: COVID-19 Intensity for Patents If the mechanism driving automation is labor supply disruption, the effect should scale with pandemic severity. Regions with higher infection rates faced stricter lockdowns and more acute labor shortages. To test this, we replace the binary post-COVID indicator with a continuous exposure measure, interacting the pre-pandemic migrant share with the log number of confirmed COVID-19 cases at the prefecture level. Table C.13 reports the results. The interaction term is positive and statistically significant across all automation patent outcomes: a one unit increase in log COVID cases is associated with a 0.009 percentage point increase in robot patent share (column 1), a 0.8% increase in log robot counts (column 2), and a 2.8% increase in robots per capita (column 3). Consistent with the baseline placebo tests, the interaction is small and insignificant for total and non-automation patents (columns 5 and 6). This dose-response pattern confirms that the automation response scales with pandemic intensity and is specifically directed toward labor-saving technologies rather than reflecting a general increase in innovative activity.

B Figures

Figure B.1: Migration Networks in China



Notes: This figure displays the bilateral migration networks across Chinese cities, constructed from the 2015 China 1% Population Survey (mini-census). Each node represents a city and each line represents a migration flow between origin and destination cities. The thickness of the lines reflects the intensity of bilateral migration flows. Data are aggregated from individual-level records by observing both the registered *hukou* location (origin) and current place of residence (destination) of each surveyed individual.

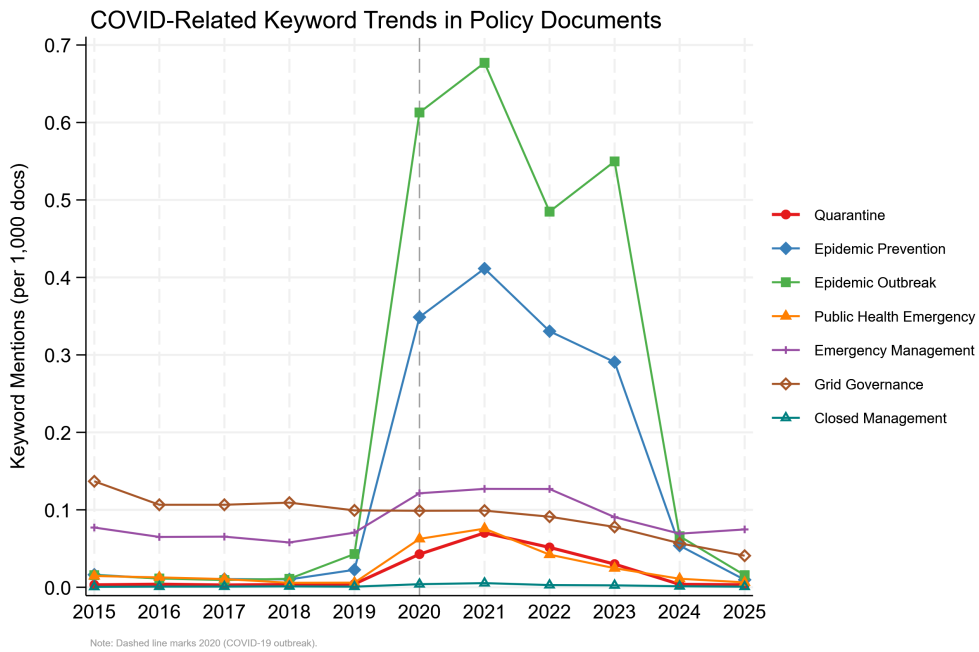
Figure B.2: Enforcement of Digital Health Codes for Inter-Regional Travel

Notes: This figure illustrates a typical digital checkpoint at a railway transit hub during the post-lockdown pandemic period. The blue sign requires passengers to present a valid "green" code via the local municipal health application (in this case, the Beijing Health Kit) before being permitted to board. These widespread digital checkpoints served as binding constraints on the cross-regional mobility of migrant workers.

Figure B.3: The Three-Tier Color-Coded Health Classification System

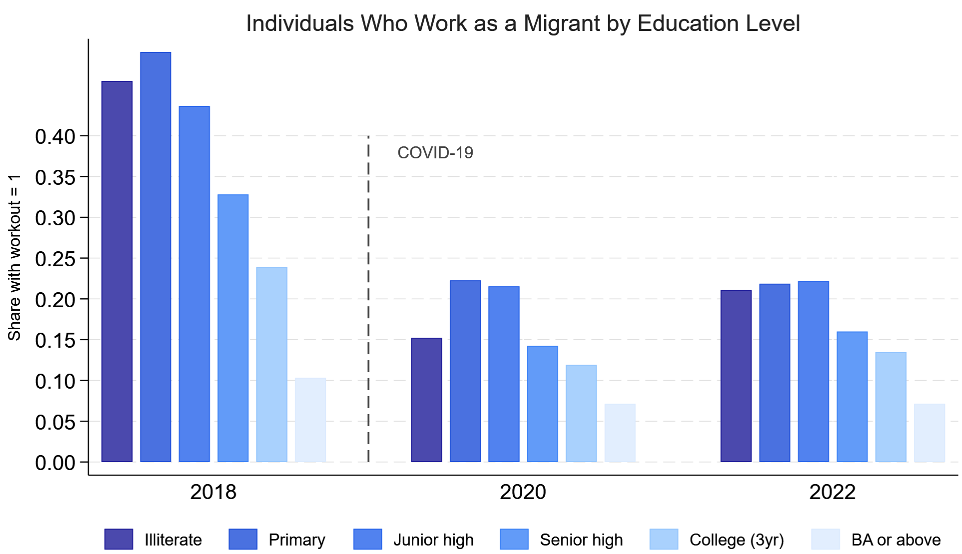
Notes: This figure displays a representative municipal health code interface (the Hangzhou Health Code), which dynamically classified individuals based on nucleic acid test results and travel history. A Green code permitted normal mobility, a Yellow code mandated a 7-day quarantine, and a Red code mandated a 14-day quarantine. For migrant workers, losing green code status effectively halted their ability to travel for work or access urban labor markets, creating severe, high-frequency labor supply shocks for manufacturing and construction firms.

Figure B.4: COVID-Related Keyword Trends in Chinese Local Government Policy Documents



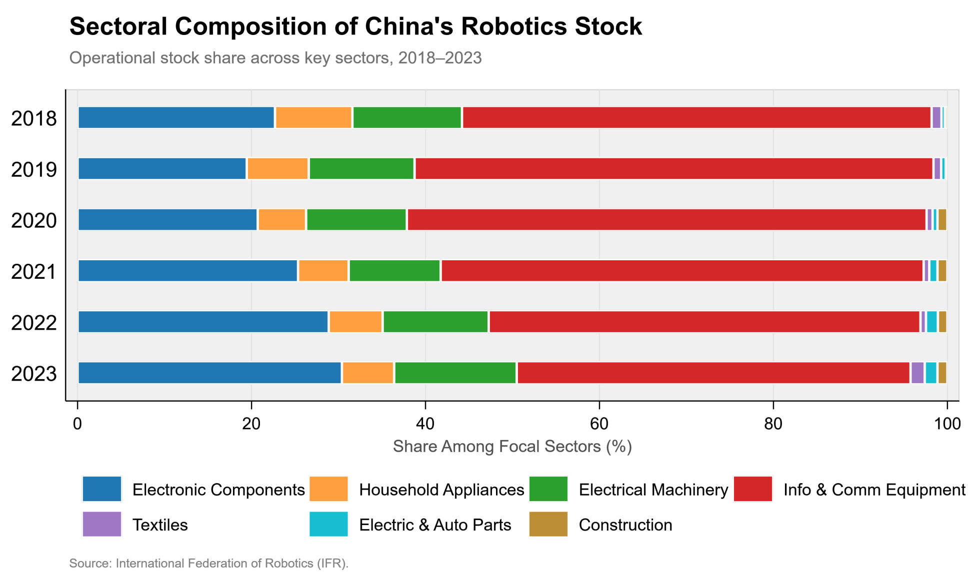
Notes: Each series shows the average number of keyword mentions per 1,000 words across county-level government policy documents. The dashed vertical line marks 2020, the onset of the COVID-19 pandemic. Keywords are extracted from Chinese local government work reports.

Figure B.5: Presence of Migrant Workers by Education Level



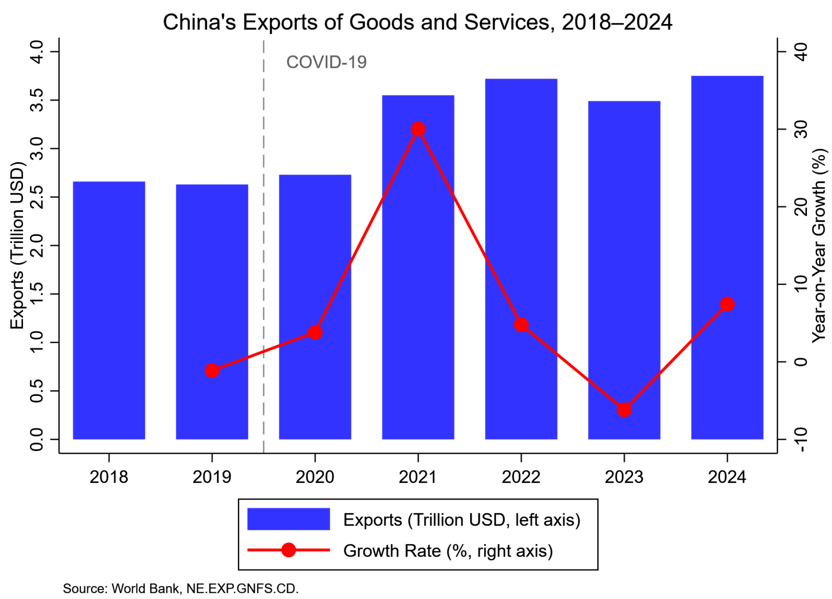
Notes: This figure displays the share of migrant workers by education level using CFPS data. Education categories range from no schooling to college and above.

Figure B.6: Decomposition of Robotics by Industries in China Before and After COVID-19



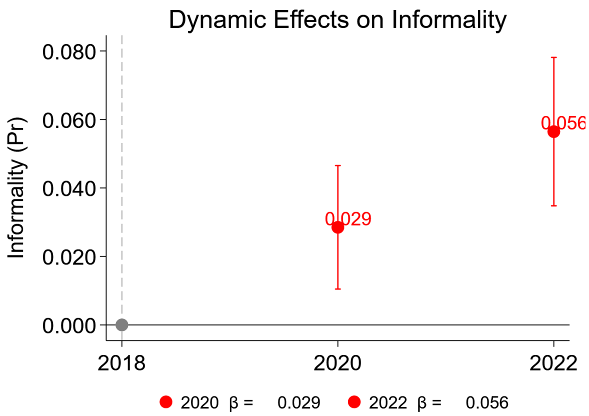
Notes: This figure displays the sectoral composition of industrial robot stock in China, comparing the pre-COVID and post-COVID periods. Each bar shows the share of total robot stock attributed to each industry. Data are drawn from the International Federation of Robotics (IFR).

Figure B.7: China's Exports of Goods and Services, 2018–2024

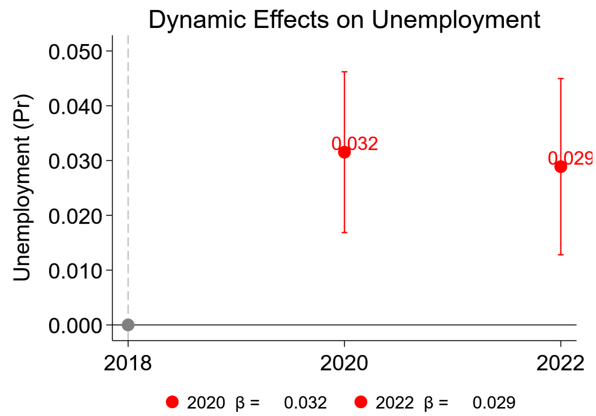


Notes: This figure plots China's total exports of goods and services in trillion USD (bars, left axis) and the year-on-year growth rate (line, right axis) from 2018 to 2024. The dashed vertical line marks the onset of the COVID-19 pandemic in 2020. Data are from the World Bank National Accounts.

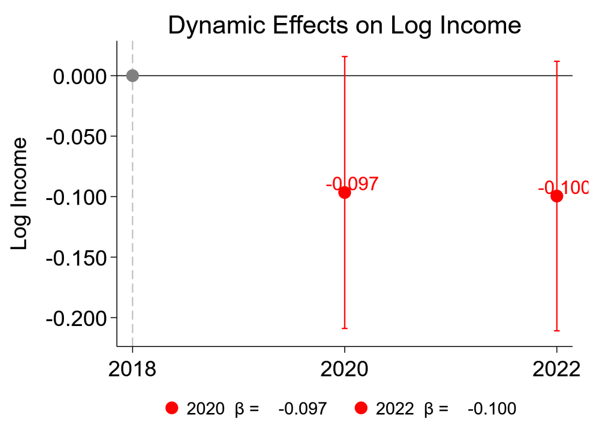
Figure B.8: Dynamic Effects of Migrant-Work Exposure on Labor Market Outcomes



(a) Informality



(b) Unemployment



(c) Log Income

Notes: Each panel plots the coefficients from interacting an indicator for working outside one's hometown in 2018 with year dummies, relative to the 2018 baseline (normalized to zero). The sample covers CFPS waves 2018, 2020, and 2022. All regressions include individual fixed effects and province $\times$ year fixed effects. Standard errors are clustered at the individual level. The 95% confidence intervals are shown as vertical bars.

C Tables

Table C.1: Sample Automation Patent from the CNIPA Database

Example Patent Record: Automation Technology	
Title (Original)	一种汽车零件 自动化焊接用机器人
Title (Translated)	A **Robot** for **Automated** Welding of Automotive Parts
Patent ID	CN202120476704.1
Application Date	2021-03-05 (Post-COVID)
Applicant	Shanghai Aocen Automation Technology Co., Ltd.
Location	Jiading District, Shanghai
IPC Code	B23K37/00 (Auxiliary devices for welding)
Abstract (Translated)	The utility model discloses a **robot for automated welding** of automotive parts. It belongs to the technical field of welding robots. The device includes a base, a rotating arm, a fan, and an exhaust system. Through the coordination of the suction hood and pipes, it effectively diverts gas generated during the welding process, improving visibility for the operator and reducing environmental interference.

Note: This patent illustrates a labor-saving technology (welding robot) filed in a manufacturing hub (Shanghai) after the pandemic outbreak. Our text analysis algorithm identifies this as an automation patent based on the keywords “Robot”.

Table C.2: Sample Manipulator Patent from the CNIPA Database

Example Patent Record: Automation Technology	
Title (Original)	一种加工定位方法及柔性工装系统
Title (Translated)	A Processing Positioning Method and **Flexible** Tooling System
Patent ID	CN202110165235.6
Application Date	2021-02-06 (Post-COVID)
Applicant	Shanghai University
Location	Baoshan District, Shanghai
IPC Code	B23Q3/00 (Devices for holding workpieces)
Abstract (Translated)	The invention discloses a positioning method and flexible tooling system. By utilizing a **robotic arm** (mechanical arm) to drive a six-degree-of-freedom platform, the system significantly improves automation. It is designed for processing workpieces with similar structures but varying positioning requirements, effectively reducing tooling design time and production cycles while enhancing positioning accuracy and efficiency.

Note: This patent illustrates the adoption of "flexible" manufacturing technology filed in Shanghai immediately following the first pandemic wave. Our text analysis identifies this as a relevant outcome based on the keywords "Robotic Arm" in the abstract.

Table C.3: Descriptive Statistics: Individual Characteristics and Intent to Treatment (Migration)

	Full Sample		Treatment = 1 (Non-agri Worker)		Treatment = 0 (Agricultural Worker)	
	Mean	SD	Mean	SD	Mean	SD
Migrant worker	0.181	0.385	0.251	0.433	0.114	0.318
Female	0.438	0.496	0.382	0.486	0.492	0.500
Age	46.640	13.640	41.138	11.610	51.882	13.363
Non-agric *hukou*	0.221	0.415	0.353	0.478	0.097	0.296
Education level	2.885	1.425	3.509	1.370	2.290	1.205
N	37,377		18,237		19,140	

Notes: This table reports summary statistics for individual characteristics from the China Family Panel Studies (CFPS). Treatment is defined as individuals engaged in non-agricultural work prior to the pandemic (Treat = 1) versus those in agricultural work (Treat = 0). Education level is measured on an eight-level scale.

Table C.4: Counties Most and Least Exposed to Migrants

Most Exposed Counties			Least Exposed Counties		
County	City	Province	County	City	Province
Nanhai	Foshan	Guangdong	Dongyuan	Heyuan	Guangdong
Yiwu	Yiwu	Zhejiang	Ji	Linfen	Shanxi
Shunde	Foshan	Guangdong	Zhuozi	Ulanqab	Inner Mongolia
Ruili	Ruili	Yunnan	Liangzihu	Ezhou	Hubei
Aksay Kazakh A.C.	Jiuquan	Gansu	Pengan	Nanchong	Sichuan
Jimei	Xiamen	Fujian	Yingshang	Fuyang	Anhui
Huiyang	Huizhou	Guangdong	Huaiji	Zhaoqing	Guangdong
Chenggong	Kunming	Yunnan	Taipusi Banner	Xilin Gol	Inner Mongolia
Shishi	Shishi	Fujian	Qinghemen	Fuxin	Liaoning
Kunshan	Kunshan	Jiangsu	Anju	Suining	Sichuan
Huolinguole	Huolinguole	Inner Mongolia	Guyang	Baotou	Inner Mongolia
Erenhot	Erenhot	Inner Mongolia	Huoqiu	Lu'an	Anhui
Bayan Obo Mining	Baotou	Inner Mongolia	Qingjian	Yulin	Shaanxi
Furong	Changsha	Hunan	Yantan	Zigong	Sichuan
Suifenhe	Suifenhe	Heilongjiang	Kangbao	Zhangjiakou	Hebei
Hainan District	Wuhai	Inner Mongolia	Xinghai	Hainan Tibetan	Qinghai
Sanshui	Foshan	Guangdong	Urumqi County	Urumqi	Xinjiang
Haicang	Xiamen	Fujian	Lixin	Bozhou	Anhui
Gangkou	Fangchenggang	Guangxi	Liangcheng	Ulanqab	Inner Mongolia
Simao	Pu'er	Yunnan	Shangdu	Ulanqab	Inner Mongolia
Gongshan D.N. A.C.	Nujiang Lisu	Yunnan	Xiuyu	Putian	Fujian
Xishan	Wuxi	Jiangsu	Zizhou	Yulin	Shaanxi
Dongsheng	Ordos	Inner Mongolia	Zhaohua	Guangyuan	Sichuan
Wujin	Changzhou	Jiangsu	Anyi	Nanchang	Jiangxi
Beichen	Tianjin	Tianjin	Fengzhen	Fengzhen	Inner Mongolia

Notes – This table lists the top and bottom 25 counties by migrant share, defined as net migration divided by 2015 total population. A.C. = Autonomous County. D.N. = Dulong-Nu. Counties with missing population in 2015 are excluded.

Table C.5: Alternative Specification: Bartik Instrumental Variable

	Robot Patent Share %	ln(Robot Count+1)	Robot per Capita	IHS(Robot Count)
VARIABLES	(1)	(2)	(3)	(4)
$Z_{p,t}$ (Shift Share Variable)	-0.640*	-0.562***	0.074	-0.721***
	(0.383)	(0.150)	(0.061)	(0.189)
Observations	13,124	13,124	13,124	13,124
R-squared	0.246	0.890	0.875	0.877
County FEs	✓	✓	✓	✓
Province × Year FEs	✓	✓	✓	✓
Initial Econ. Condition × Year FEs	✓	✓	✓	✓

Notes: This table reports the estimates of the Bartik instrumental variable specification. The key independent variable $Z_{p,t}$ is the shift-share variable, constructed as the share-weighted sum of idiosyncratic COVID-19 outflow disruptions at each origin region. The shift is derived from the AR(1) residual of the log annual outflow index from the Baidu Migration platform, purging autocorrelation and common national mobility trends. The share is constructed from Chinese Population Census bilateral migration flows, aggregated to the city-origin by county-destination level. All specifications include county fixed effects, Province × Year fixed effects, and Initial GDP × Year fixed effects. Standard errors clustered at the county level in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Table C.6: Effect of COVID-19 on Upstream Automation Investment of Firms

VARIABLES	ln(R&D Spending+1) (1)	ln(R&D Personnel+1) (2)	R&D Spending Ratio (3)	R&D Personnel Ratio (4)	Fixed Assets per Employee (5)
Migrant Share % $\times$ COVID-19	0.119**	0.069***	1.155	0.159**	9,541.632*
	(0.057)	(0.020)	(0.883)	(0.064)	(5,524.748)
Observations	21,568	21,568	21,568	21,568	21,568
R-squared	0.936	0.937	0.180	0.857	0.818
County FEs	✓	✓	✓	✓	✓
Province $\times$ Year FEs	✓	✓	✓	✓	✓
Initial GDP $\times$ Year FEs	✓	✓	✓	✓	✓

Notes: This table reports the effect of pandemic-induced labor mobility restrictions on firm-level upstream automation investment, collapsed to the county level using listed firm data from CSMAR. The key independent variable is the interaction between county-level migrant share (2015) and COVID-19 onset. All specifications include county fixed effects and interactions of initial GDP per capita and migrant share with year fixed effects. Standard errors clustered at the county level in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table C.7: Alternative Explanation: Local Government Industrial Policy Priority and Migrant Labor Scarcity

	Automation-related Keyword Frequency in County Government Work Reports (per 1,000 words)						
	Robot Substitution	Industrial Robot	Automation Equipment	Smart Manufacturing	Industry Upgrading	Unmanned Factory	Total Keywords
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Migrant Share % × COVID-19	−0.000	−0.001	−0.000	−0.002	−0.000	0.000	0.001
	(0.000)	(0.002)	(0.000)	(0.001)	(0.000)	(0.000)	(0.005)
Observations	15,159	15,159	15,159	15,159	15,159	15,159	15,159
R-squared	0.143	0.249	0.155	0.216	0.221	0.170	0.304
County FEs	✓	✓	✓	✓	✓	✓	✓
Province × Year FEs	✓	✓	✓	✓	✓	✓	✓
Initial GDP × Year FEs	✓	✓	✓	✓	✓	✓	✓

Notes: This table tests whether the observed automation response was driven by local government industrial policy rather than firm-level responses to labor scarcity. Dependent variables measure the frequency of automation-related keywords per 1,000 words in county-level government work reports, a standard proxy for local policy priority. The keyword categories are: robot substitution (Column 1), industrial robots (Column 2), automation equipment (Column 3), smart manufacturing (Column 4), industry upgrading (Column 5), unmanned factories (Column 6), and a composite total across all categories (Column 7). If counties facing greater migrant labor disruption simultaneously intensified local automation policy, the main estimates could reflect government-directed investment rather than decentralized firm-level responses. The uniformly small and statistically insignificant coefficients across all seven columns rule out this interpretation: counties with larger migrant shares did not experience systematically greater government emphasis on automation during the COVID-19 period. The automation response is therefore unlikely to be an artifact of local industrial policy. Migrant Share is net migration as a share of total population in 2015. COVID-19 indicates years 2020–2023. All specifications include county fixed effects, province × year fixed effects, and interactions of initial GDP per capita with year fixed effects. Standard errors clustered at county level in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table C.8: Heterogeneity: The Effect of COVID-19 by *hukou*

	Out-of-Hometown Work		
VARIABLES	(1)	(2)	(3)
Base Effect (Agricultural hukou)			
Non-Agri $\times$ COVID-19	-0.153***	-0.159***	-0.165***
	(0.009)	(0.011)	(0.010)
Interactions (Relative to Agricultural hukou)			
$\times$ Non-agric *hukou*	0.167***	0.154***	0.170***
	(0.022)	(0.025)	(0.022)
Observations	34,785	34,351	34,785
R-squared	0.631	0.464	0.638
Individual FEs	✓		✓
Household FEs		✓	
Year FEs	✓	✓	
Province $\times$ Year FEs			✓

Notes: This table reports heterogeneity in the COVID-19 effect by *hukou* status. The dependent variable is an indicator for out-of-hometown migrant work. The base category is agricultural *hukou* holders, so the coefficient on Non-Agri $\times$ COVID-19 reflects the effect for this group. The interaction term captures the differential effect for non-agricultural *hukou* holders. Column (1) includes individual and year fixed effects; Column (2) includes household and year fixed effects; Column (3) includes individual and province-by-year fixed effects. Standard errors clustered at the individual level in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table C.9: Heterogeneity: The Effect of COVID-19 by Skill Level (Proxy by Education)

	Out-of-Hometown Work		
VARIABLES	(1)	(2)	(3)
Base Effect (Illiterate or semi-literate)			
Non-Agri × COVID-19	-0.228***	-0.233***	-0.227***
	(0.024)	(0.027)	(0.024)
Interactions (Relative to Illiterate or semi-literate)			
× Primary School	0.047	0.045	0.035
	(0.030)	(0.033)	(0.030)
× Middle School	0.147***	0.140***	0.134***
	(0.028)	(0.031)	(0.028)
× High School	0.191***	0.176***	0.176***
	(0.032)	(0.036)	(0.032)
× 3-Year College / Vocational	0.219***	0.175***	0.220***
	(0.054)	(0.056)	(0.054)
× BA or above	0.260***	0.213***	0.250***
	(0.043)	(0.057)	(0.043)
Observations	37,336	36,838	37,200
R-squared	0.640	0.469	0.644
Individual FEs	✓		✓
Household FEs		✓	
Year FEs	✓	✓	
Province × Year FEs			✓

Notes: The dependent variable is an indicator for out-of-hometown migrant work. The base education category is "Illiterate or semi-literate", and the coefficient on Non-Agri × COVID-19 therefore reflects the COVID-19 period effect for the lowest-education group. The interaction terms show how this effect differs for individuals with higher schooling levels. Column (1) includes individual and year fixed effects; Column (2) includes household and year fixed effects; Column (3) includes individual and province-by-year fixed effects. Standard errors clustered at the individual level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Table C.10: Heterogeneity: The Effect of COVID-19 by Gender

	Out-of-Hometown Work		
VARIABLES	(1)	(2)	(3)
Base Effect (Male)			
Non-Agri × COVID-19	-0.075***	-0.091***	-0.087***
	(0.010)	(0.012)	(0.011)
Interactions (Relative to Male)			
× Female	-0.029**	-0.027*	-0.034**
	(0.014)	(0.016)	(0.014)
Observations	37,377	36,880	37,239
R-squared	0.637	0.468	0.642
Individual FEs	✓		✓
Household FEs		✓	
Year FEs	✓	✓	
Province × Year FEs			✓

Notes: This table reports heterogeneity in the COVID-19 effect by gender. The dependent variable is an indicator for out-of-hometown migrant work. The base category is male workers, so the coefficient on Non-Agri × COVID-19 reflects the effect for men. The interaction term captures the differential effect for women. Column (1) includes individual and year fixed effects; Column (2) includes household and year fixed effects; Column (3) includes individual and province-by-year fixed effects. Standard errors clustered at the individual level in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Table C.11: Heterogeneity: The Effect of COVID-19 by Age Group

	Out-of-Hometown Work		
VARIABLES	(1)	(2)	(3)
Base Effect (Age 35–49)			
Non-Agri × COVID-19	-0.082***	-0.084***	-0.096***
	(0.013)	(0.014)	(0.013)
Interactions (Relative to Age 35–49)			
× Age 16–34	0.036	0.035	0.039
	(0.024)	(0.027)	(0.024)
× Age 50–60	-0.040**	-0.035*	-0.043**
	(0.019)	(0.021)	(0.018)
Observations	33,152	32,666	33,014
R-squared	0.630	0.478	0.636
Individual FEs	✓		✓
Household FEs		✓	
Year FEs	✓	✓	
Province × Year FEs			✓

Notes: This table reports heterogeneity in the COVID-19 effect by age group. The dependent variable is an indicator for out-of-hometown migrant work. The base category is prime-age workers (ages 35–49), so the coefficient on Non-Agri × COVID-19 reflects the effect for this group. Interaction terms capture the differential effects for younger workers (ages 16–34) and older workers (ages 50–60). Column (1) includes individual and year fixed effects; Column (2) includes household and year fixed effects; Column (3) includes individual and province-by-year fixed effects. Standard errors clustered at the individual level in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Table C.12: Robustness: Using Prefecture-Level COVID-19 Cases

	Out-of-Hometown Work		
VARIABLES	(1)	(2)	(3)
Non-Agri × ln(COVID cases + 1)	-0.013***	-0.019***	-0.018***
	(0.002)	(0.002)	(0.002)
Observations	33,986	33,510	33,856
R-squared	0.631	0.454	0.636
Individual FEs	✓		✓
Household FEs		✓	
Year FEs	✓	✓	
Province × Year FEs			✓

Notes: This table reports robustness checks using a continuous measure of COVID-19 intensity. The dependent variable is an indicator for out-of-hometown migrant work. The shock variable is the natural logarithm of one plus the number of confirmed COVID-19 cases at the prefecture-year level. Column (1) includes individual and year fixed effects; Column (2) includes household and year fixed effects; Column (3) includes individual and province-by-year fixed effects. Standard errors clustered at the individual level in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table C.13: Effect of COVID-19 Cases on Automation Innovation

VARIABLES	Robot Patent % (1)	Robot Count (2)	ln(Robot Count+1) (3)	Robot per Capita (4)	IHS(Robot Count) (5)	ln(Total Patent+1) (6)	ln(Non-Auto Patent+1) (7)
Migrant Share %	0.009**	2.059***	0.008***	0.028***	0.007**	0.002	0.002
× ln(COVID Cases+1)	(0.004)	(0.418)	(0.003)	(0.005)	(0.003)	(0.002)	(0.002)
Observations	21,568	21,568	21,568	21,568	21,568	21,568	21,568
R-squared	0.219	0.830	0.863	0.826	0.850	0.943	0.942
County FEs	✓	✓	✓	✓	✓	✓	✓
Province × Year FEs	✓	✓	✓	✓	✓	✓	✓
Initial GDP × Year FEs	✓	✓	✓	✓	✓	✓	✓

Notes: This table reports heterogeneous effects of COVID-19 intensity on automation patent innovation by county-level migrant share. The interaction term captures how counties with higher pre-period migrant shares respond differentially to COVID-19 exposure (measured as the natural logarithm of one plus confirmed 2020 prefecture-level cases). Columns 1–5 report outcomes related to robot/automation patents; Columns 6–7 report broader patent counts as placebo checks. All specifications include county fixed effects, province × year fixed effects, and interactions between initial GDP per capita and year fixed effects. Standard errors clustered at the county level in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table C.14: COVID-19 Effect on Robot Installations: China vs. Rest of World

VARIABLES	Overall (1)	Electronic Components (2)	Household Appliances (3)	Electrical Machinery (4)	Info Comm. (5)	Textiles (6)	Electric & Auto Parts (7)	Construction (8)
Panel A: China's Trend								
China × COVID-19	2.949***	2.914***	2.918***	2.886***	2.895***	2.925***	2.888***	2.869***
	(0.057)	(0.056)	(0.057)	(0.057)	(0.057)	(0.058)	(0.057)	(0.058)
Panel B:Sector Specific								
× Sector		1.105***	0.969***	1.952***	1.692***	0.763***	1.917***	2.479***
		(0.120)	(0.080)	(0.073)	(0.075)	(0.050)	(0.085)	(0.062)
Observations	55,800	55,800	55,800	55,800	55,800	55,800	55,800	55,800
R-squared	0.668	0.668	0.668	0.668	0.668	0.668	0.668	0.668
Country FEs	✓	✓	✓	✓	✓	✓	✓	✓
Industry FEs	✓	✓	✓	✓	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓	✓	✓	✓	✓

Notes: This table reports difference-in-differences estimates for robot installations comparing China to the rest of the world. Panel A reports the baseline China × COVID-19 coefficient from each regression. Panel B reports the triple-interaction term (China × COVID-19 × Sector), capturing the additional effect in each sector relative to other industries. Column (1) reports the overall effect without a sector interaction. Columns (2)–(8) correspond to sector-specific regressions. All specifications include country, industry, and year fixed effects. Robot installation data are from the International Federation of Robotics (IFR), 2014–2023. Standard errors clustered by country in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table C.15: COVID-19 Effect on Robot Stocks: China vs. Rest of World

VARIABLES	Overall (1)	Electronic Components (2)	Household Appliances (3)	Electrical Machinery (4)	Info Comm. (5)	Textiles (6)	Electric & Auto Parts (7)	Construction (8)
Panel A: China's Trend								
China × COVID-19	2.862***	2.853***	2.826***	2.822***	2.788***	2.840***	2.850***	2.842***
	(0.072)	(0.070)	(0.072)	(0.071)	(0.071)	(0.073)	(0.071)	(0.073)
Panel B:Sector Specific								
× Sector		0.283**	1.143***	1.241***	2.298***	0.698***	0.378***	0.641***
		(0.114)	(0.108)	(0.091)	(0.102)	(0.075)	(0.110)	(0.067)
Observations	55,800	55,800	55,800	55,800	55,800	55,800	55,800	55,800
R-squared	0.765	0.765	0.765	0.765	0.765	0.765	0.765	0.765
Country FEs	✓	✓	✓	✓	✓	✓	✓	✓
Industry FEs	✓	✓	✓	✓	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓	✓	✓	✓	✓

Notes: This table reports difference-in-differences estimates for robot stocks comparing China to the rest of the world. Panel A reports the baseline China × COVID-19 coefficient from each regression. Panel B reports the triple-interaction term (China × COVID-19 × Sector), capturing the additional effect in each sector relative to other industries. Column (1) reports the overall effect without a sector interaction. Columns (2)–(8) correspond to sector-specific regressions. All specifications include country, industry, and year fixed effects. Robot installation data are from the International Federation of Robotics (IFR), 2014–2023. Standard errors clustered by country in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table C.16: More Robustness Checks

VARIABLES	Robot Patent Share % (1)	Robot Count (2)	ln(Robot Count+1) (3)	Robot per Capita (4)	IHS(Robot Count) (5)
Panel A: Weighted by Population Size					
Migrant Share % × COVID-19	0.039**	11.676***	0.033***	0.143***	0.027*
	(0.019)	(2.819)	(0.013)	(0.028)	(0.015)
Observations	21,568	21,568	21,568	21,568	21,568
R-squared	0.255	0.836	0.879	0.835	0.865
Panel B: Excluding Provincial Capital Cities					
Migrant Share % × COVID-19	0.051**	11.374***	0.035**	0.136***	0.032*
	(0.021)	(3.587)	(0.014)	(0.035)	(0.016)
Observations	19,166	19,166	19,166	19,166	19,166
R-squared	0.235	0.838	0.837	0.842	0.821
Panel C: Excluding Deputy Provincial-Level Cities					
Migrant Share % × COVID-19	0.040**	10.763***	0.032**	0.128***	0.027*
	(0.020)	(3.248)	(0.014)	(0.032)	(0.016)
Observations	20,632	20,632	20,632	20,632	20,632
R-squared	0.247	0.848	0.864	0.843	0.849
Panel D: Excluding Provincial Capitals and Deputy Provincial-Level Cities					
Migrant Share % × COVID-19	0.047**	11.425***	0.030**	0.133***	0.027
	(0.023)	(3.988)	(0.014)	(0.038)	(0.017)
Observations	18,935	18,935	18,935	18,935	18,935
R-squared	0.234	0.836	0.826	0.841	0.810
Panel E: Alternative Clustering at Province-Year Level					
Migrant Share % × COVID-19	0.063***	5.457***	0.035***	0.081***	0.034***
	(0.018)	(1.309)	(0.009)	(0.018)	(0.010)
Observations	21,568	21,568	21,568	21,568	21,568
R-squared	0.219	0.826	0.863	0.822	0.850
Panel F: Controlling for County Non-Agricultural Value Added × Year FEs					
Migrant Share % × COVID-19	0.056***	5.578***	0.025**	0.078***	0.023*
	(0.021)	(1.384)	(0.011)	(0.016)	(0.013)
Observations	21,242	21,242	21,242	21,242	21,242
R-squared	0.218	0.829	0.861	0.829	0.847
County FEs	✓	✓	✓	✓	✓
Province × Year FEs	✓	✓	✓	✓	✓
Initial GDP × Year FEs	✓	✓	✓	✓	✓

Notes: This table presents robustness checks for the baseline estimates of the effect of labor mobility restrictions on automation patent innovation, interacted with county-level migrant share. COVID-19 is a binary indicator equal to one in the post-onset period. The interaction term captures how counties with higher pre-period migrant shares differentially increase automation adoption following COVID-19 onset. All panels use the fully saturated specification (county FEs, province × year FEs, and initial economic conditions × year FEs). Panel A reweights observations by county population size. Panel B excludes counties belonging to provincial capital cities. Panel C excludes counties belonging to deputy provincial-level cities. Panel D applies both exclusions simultaneously. Panel E re-estimates the baseline using standard errors clustered at the province-year level rather than the county level. Panel F adds interactions between county-level non-agricultural value added (2015) and year fixed effects to control for differential trends in industrial composition. Standard errors clustered at the county level in parentheses (except Panel E). *** $p<0.01$, ** $p<0.05$, * $p<0.10$.