The Economic and Labour Relations Review (2026), **37**, 143–165
doi:10.1017/elr.2025.10045

CAMBRIDGE UNIVERSITY PRESS

ORIGINAL ARTICLE

How China's digital economy amplifies migrant workers' inequality through demand-supply mismatch

Lei Che[1], Qiaozheng Liu[1] and Jiali Lu[2]

[1]Xi'an University of Architecture and Technology, Xi'an, China and [2]Tsinghua University, Beijing, China

Corresponding author: Lei Che; Email: chelei@xauat.edu.cn

(Received 14 March 2025; revised 19 September 2025; accepted 30 September 2025; first published online 05 December 2025)

Abstract

Unlike existing studies on labour and income in the digital era, this paper argues not only that the impact of the digital economy's intervention in the labour process is fragmented rather than comprehensive, but also that the transformation of job demand and labour supply behaviours is simultaneous and related to the attributes of the industries in which they operate. Drawing on the conventional biased technological progress hypothesis and labour process theory, we argue that the digital economy has generally increased the labour income inequality for migrant workers in China. Using geospatially matched China Labour Dynamics Survey 2018 microdata and provincial digitalisation indices, we uncover a digital 'upgrading trap': the development of the digital economy hides the process of inequality formation in the hedging relationship between objective labour demand 'upgrading' and subjective labour supply 'expanding'. The former can be summarised as the risk of 'no job' and the latter as the risk of 'no way back'. Counterintuitively, consumer Internet development demonstrates a greater role in both reducing workers' inequality in secondary labour markets and promoting a fair primary distribution. These findings reconceptualise digital inequality as coevolutionary outcomes, and offer a tripartite governance way for inclusive growth through portable skill certification, algorithmic accountability mechanisms, and interoperable social security systems.

Keywords: digital economy; income inequality; labour process theory; migrant workers; routine-biased technological change hypothesis

Introduction

Techno-optimists predict a Utopian future where the urban and rural disparity has been reduced, knowledge acquisition costs are decreasing (Kim 2012). Due to machines remaining in control, we all can share the gains from technological progress with less work time and more money to enjoy leisure. In contrast, techno-pessimists envision a dystopian future where industrial robots displace workers from assembly lines and destroy the livelihoods of the 'information have-nots' (Schwabe and Castellacci 2020). Once the discontent is rife in the unions, the capital will use more machines to replace work labours (Davids and Martin 1992).

In recent years, income distribution polarisation among residents – predominantly driven by the GDP growth slowdown – has exerted profound systemic influence. Empirical evidence reveals that while mainland China's GDP growth peaked at 14% (2003–2022) and subsequently stabilised around 5%, indicating steady economic development, the Gini

© The Author(s), 2025. Published by Cambridge University Press on behalf of The University of New South Wales. This is an Open Access article, distributed under the terms of the Creative Commons Attribution licence (https://creativecommons.org/licenses/by/4.0/), which permits unrestricted re-use, distribution and reproduction, provided the original article is properly cited.

https://doi.org/10.1017/elr.2025.10045 Published online by Cambridge University Press

coefficient persistently remained above 0.45 throughout this period, consistently exceeding the international alert threshold of 0.4. (see Appendix A). A considerable body of research has examined how technological advancements impact income inequality in developing countries, focusing on industrial sectors, human capital, family socioeconomic status, and urban characteristics (Shah and Krishnan 2024; Seemab et al 2022). Referring to the division of skilled labour force in existing studies (Acemoglu 2002), we map the changes in the proportion of high-skilled and low-skilled labour force in China's urban employed (2005–2022) and unemployed groups (2005–2015). The high-skilled labour force (main axis) shows an upward trend in its share of the employed and unemployed groups, and the low-skilled labour force (secondary axis) shows a dual tailwind (see Appendix B). Employment upgrading and labour degrading coexist in modern China and become visible chances and challenges for labour inequality with different levels of skill. These intertwined issues of structural production and labour distribution highlight the ongoing challenges of income distribution and social inequality, which remain critical areas for policy intervention.

It is worth noting that the construction of information infrastructure is generating a new revolution in China's urban and rural areas, the economy will flourish (People.cn 2024), and has reshaped the people's livelihood. The impact of the digital revolution driven by 5G, artificial intelligence, big data, and cloud computing on labour market outcomes, particularly the income of low-skilled workers, has garnered attention from economists and policymakers alike. In the past two decades, the scale of China's digital economy has grown rapidly. According to The Boao Forum for Asia's Digital Economy in Asia Report, China's digital economy reached $7.47 trillion in 2022, ranking first in Asia. The development momentum of the digital economy, as represented by the number of patent applications and R&D investment funds, is very strong. The 14th Five-Year Plan of the digital economy (2021–2025) rolled out by China's State Council aims to raise the proportion of the added value of core digital economy industries in its GDP to 10% in 2025, up from 7.8% in 2020 (The State Council of The People's Republic of China 2021). China's economy has transitioned from rapid growth to a new phase of high-quality development. The digital economy is, and will continue to be, a core driver of economic growth in the future of China.

While efficiency has been central to the upgrading of the ICT industry and the digital consumption system, the realisation of equity remains questionable. Scholars argue that such technological advancements often exacerbate, rather than alleviate, existing inequalities (Van 2020). Numerous studies have explored the digital revolution and the socioeconomic consequences in different countries, including theories (Chen et al 2023), measurements of inequality in the digital revolution, policy impacts (Ghosh 2017), and threshold effect on household income diversification (Matsuura-Kannari et al 2024; Wu et al 2024). Some studies suggest that the use of the internet in individual work and business activities increases the chances of employment, entrepreneurship, and part-time work for lower-income groups. The digital economy can promote migrants' household income to improve their economic integration and then contribute to the goal of common prosperity (Hjort and Poulsen 2019; Leng et al 2018; Hou and Huo 2018; Zou and Deng 2022). As digital technologies penetrate and spread across all economic and social sectors, they are transforming labour market supply and demand. A key unanswered question is whether this transformation will deepen or alleviate labour income inequality.

Technical rationalists believe that there may be a digital divide that will widen the gap between rich and poor and lead to polarisation (Seemab et al 2022; Van 2020). Some scholars argue that, with the expansion of China's digital economy and higher labour quality requirements in the labour market, the mismatch between supply and demand in the existing labour market has further widened income inequality (Moll et al 2022;

https://doi.org/10.1017/elr.2025.10045 Published online by Cambridge University Press

Chen et al 2022). Farmers often use ICT and machinery to boost their agricultural income. In contrast, migrant workers, who are typically low-skilled, face a different reality. They are often excluded from the opportunities of rural digital revitalisation and are instead vulnerable to having their jobs replaced by machines. At the same time, they must endure the high costs and culture shock of the urban digital economy. It is expected that with the adjustment of the employment structure, many jobs of low-skilled workers will be replaced (Graetz and Michaels 2018). Migrant workers have become an important group with significant negative impacts on their income and well-being (Gao et al 2023). How to eliminate rural-urban migration workers' income inequality through the development of the digital economy is related to the overall realisation of inclusive growth and ultimately promotes the optimisation of common prosperity and social division of labour. There is limited evidence regarding this impact on migrant workers in developing countries. This paper will first set up a theoretical framework to clarify the association between the digital economy and rural-urban migrant workers' income inequality. Furthermore, based on the nationwide micro-level data from the 2017 China Labour-force Dynamics Survey (CLDS), we use the Kakwani index to measure income inequality and empirically test the association between the digital economy and income inequality.

This paper seeks to make three contributions to the literature. First, this study provides attempts to examine the effect of the digital economy on rural-urban migrants' income inequality. Previous studies have largely focused on the income attainment affected by ICT adoption or technological substitution (Leng et al 2020), while the issue of how the digital economy used by capital to maximise profit margins affects the income distribution of migrant workers, has been overlooked. We focused on migrant workers because the globalisation of capital accumulation and the labour process have created the phenomenon of large-scale migrant workers and their unstable employment status in China. Second, a credible framework will be set up to explain the relationship between the digital economy and rural-urban migrant workers' income situation. The theoretical framework will be composed of directed technological change and labour process theory. We focus on the underlying mechanism of the digital economy on the urban migrant income gap. Previous studies have constructed the production function with the technical characteristics or human capital of the digital economy to indicate that the digital economy expands the skill and gender wage gap or focuses on the directed technological change in structural transformation and income gap (Du and Wei 2020). However, these frameworks fail to address the interplay between technology-induced routinisation, corporate-controlled labour processes, and labour income changes, which are central to the demand-supply mismatch phenomenon. Third, we investigate the heterogeneous effects of information technology penetration at the industry level on income disparities among individual workers, shedding light on how varying degrees of technological adoption create mismatches in labour demand and supply across industries.

The remainder of this paper is organised as follows. The next section introduces the analytical framework and estimation strategy, while the following section presents data, key variable measurements, and descriptive statistics. The empirical results are then presented and discussed, while the final section concludes with policy implications.

Literature review and analytical framework

Digital economy and individual income inequality

Correlations between whether or not a person is poor and whether or not their country, community, or organisation is poor, are weakening. Going beyond the framework of the State, we should consider the individual as the object to address the problems posed by

https://doi.org/10.1017/elr.2025.10045 Published online by Cambridge University Press

inequality (*Chinese Social Sciences Today* 2019). The digital economy development has led to the dissolution of urban-rural inequalities. The Chinese government released the Policy Implementation Plan for Promoting Common Prosperity through the Digital Economy in 2022. It aims to systematically narrow the urban-rural development gap using digital economy tools such as digital supply, network-based sharing, and intelligent services. Existing research confirms that digital finance (DF) helps reduce urban-rural wealth disparities by enabling rural households to engage in opportunity-based agricultural entrepreneurship, thereby increasing their wealth (Wu et al 2024). Emerging labour participation patterns, such as flexible employment, make it possible to address gender equality, but at the same time can create paradoxes. In the digital economy era, employment will not only raise the collective income of workers but only intensify the competition within the group (*Chinese Social Sciences Today* 2019). Existing studies substantiate this perspective. The digital economy expands income inequality through its skill-biased nature, placing low-skilled labourers under greater competitive pressure due to insufficient skills (Zhao and Peng 2022). The benefits of the digital economy, such as economic integration, citizenship, and consumption upgrading, tend not to reach groups below the middle class.

For the backbone of certain low-skill job categories, inequality of ability exists before labour enters the market. This is largely a structural rather than an individual problem. The essence of this phenomenon is the intrusion of the market into the sphere of life. The lack of investment in human capital by the disadvantaged group results in inadequate capacity of the group. In the absence of intervention, this phenomenon solidifies into a social and cultural problem. For example, while the digital economy can narrow income gaps by enhancing human capital (e.g., skill training), low-skilled groups struggle to benefit due to limited access to educational resources (Wang et al 2025). Human capital interventions for migrant workers are generally neglected in public policies, mainly in terms of short durations of education and a lack of vocational training. Upon entering the labour market, it is primarily the market's mechanism of operation that affects the equity of income. More importantly, it is the opportunities for labour development that need to be more equitably distributed. The digital economy can either inhibit or promote income inequality, depending on which disadvantaged group we choose to investigate and the analysis path. Demonstrating inequality at the individual level requires framing the vulnerable groups and focusing on the specific labour processes that will generate their incomes.

Labour market dynamics of migrant workers amid the digital economy

Migrant workers, particularly in developing economies, occupy a distinct niche within the labour market (Bauder 2006). Predominantly employed in basic manufacturing or low-end tertiary industries, these workers constitute the backbone of certain low-skill job categories (Kalleberg 2017). In the context of artificial intelligence, the repetitive tasks undertaken by most migrant workers, which primarily depend on physical strength and are governed by easily mastered rules, are particularly vulnerable to automation (Wisskirchen et al 2017). Consequently, low-skilled labour groups are more likely to experience employment substitution effects (Wolcott 2021). The employment challenges faced by migrant workers not only affect their development and that of their families but also raise broader issues related to urban-rural integration, social welfare, and social stability (Tao and Xu 2007). Therefore, amidst technological progress and economic transformation, it is essential to conduct a comprehensive examination of the dynamic factors and primary manifestations that influence the labour process of migrant workers, as well as the substitution effects induced by technological advancements.

https://doi.org/10.1017/elr.2025.10045 Published online by Cambridge University Press

Research hypothesis and analytical framework

The control of labour is a central issue in labour process theory. While technological development is not inherently neutral and its effects are continually shaped by class dynamics (Kranzberg 1985), the differential 'spill-over' effects of technological progress remain a complex issue. The digital economy exerts a dual impact on employment incomes: it redistributes and recombines labour, creating both de-skilling and up-skilling opportunities (Hall 2010). Technological advancements have bifurcated the labour market into high-skill and low-skill segments, often relegating migrant workers to low-skill tasks (Ra et al 2019). This has led to a cycle of low investment in skill development for migrant workers, while technical personnel experience skill enhancement and income growth (Acemoglu and Autor 2011). Middle and low-skilled labours are often substitutes, and employers prioritise cost-efficiency, maximising output with minimal wages and training for low-skill workers (Reijnders and Ye 2021). Human-robot collaboration reshapes job tasks, exposing migrant workers to substitution risks that heighten income volatility (Acemoglu and Restrepo 2019). Consequently, the digital economy increases demand for high-skilled talent, widening income inequality (Chusseau and Dumont 2013; Xin and Ye 2024). We thus propose:

H1: The digital economy increases income inequality among migrant workers.

Substitution effects faced by migrant workers

The coexistence of digitisation and labour is well-documented, with the creation effect often outweighing the substitution effect (Liu et al 2023). However, for migrant workers, industrial robots attract skilled labour while displacing routine labour, intensifying employment polarisation (Ernst et al 2019). Routine-biased technological change suggests that unstable labour relations are more likely in routine cognitive and operational tasks (Autor et al 2003; Du and Wei 2020). Migrant workers, confined to industries like manufacturing and construction, face heightened vulnerability to economic fluctuations (Farrer 2016). Digital technology accelerates the replacement of low- and medium-skilled labour, particularly in labour-intensive industries (Manning 2004; Balsmeier and Woerter 2019). Furthermore, the digital divide limits migrant workers' access to digital resources, exacerbating their challenges. Employers often prioritise laying off low-skill labours due to economic cost considerations, reinforcing structural inequalities. We hypothesise that:

H2: The digital economy increases income inequality among migrant workers through the substitution effect on routine-task jobs.

Labour control and income inequality

Career plateauing, characterised by excessive work and inadequate protection, is prevalent in China (Huo and Jiang 2023). During China's economic reform, not only have production relations and property ownership changed, but also young rural workers' perceptions of 'work' and its social significance have also evolved (Tai 2010). Power imbalances between labour and capital lead companies to dominate pricing and product delivery schedules, creating intense pressures and resulting in illegal overtime for workers (Chan et al 2013). Digital workers dependent on platform-based income face job instability, excessive working hours, sleep deprivation, and overwork (Schor et al 2020). In the digital era, algorithmic management on labour platforms has reached unprecedented levels of control over migrant workers. Labour process theory (LPT) highlights that while technological advancements do not inherently result in increased control, mechanisation can cause workers to lose control over their work's pace and process (Edwards 1979). Workers are typically excluded from decisions about automation and robot integration, weakening their bargaining power and leading to self-

https://doi.org/10.1017/elr.2025.10045 Published online by Cambridge University Press

exploitation (Burawoy 1979). This dynamic results in stagnant or deteriorating labour conditions for migrant workers, as they endure longer working hours and other sacrifices in exchange for higher wages. Furthermore, labour control mechanisms such as algorithmic supervision and performance monitoring may inadvertently moderate certain aspects of income inequality by compelling extended working hours, which temporarily elevate earnings among low-skilled workers. However, this apparent mitigation conceals significant hidden costs. Under the guise of autonomy, low-skilled workers often intensify their self-exploitation, for example, by voluntarily prolonging working shifts or accepting heightened workloads, to compensate for job precarity and income fluctuation, a phenomenon observed in global gig economy contexts (Wood et al 2019). This heightened self-investment not only exacerbates physical and mental health deterioration but also reinforces a cycle of overwork without substantially improving long-term economic security (Kellogg et al 2020). Thus, while such strategies may partially offset immediate income risks, they encounter physiological limits and ultimately undermine subjective well-being (Wood et al 2019). Thus, we propose that:

H3: The digital economy intensifies labour control by increasing work hours and task loads to decrease migrant workers' income inequality.

Based on the main hypothesis we discussed above, the core research framework of this paper is shown in Figure 1. At the centre of the framework is H1, which posits a positive association between digital economy development and income inequality among migrant workers. As digital technologies become increasingly embedded in both consumer and industrial sectors, the resulting skill-biased transformations tend to marginalise low-skilled workers who are concentrated in routine-intensive, vulnerable jobs. These changes fragment the labour market and exacerbate structural disparities in skill development, employment stability, and income distribution.

The upper pathway reflects H2, which highlights the substitution effect: digital technologies disproportionately replace routine cognitive and manual tasks typically held by migrant workers. This leads to rising job insecurity and further exclusion from digitally upgraded production sectors. Due to limited access to reskilling opportunities and persistent digital divides, many migrant workers are unable to transition into high-skill roles, to achieve the same productivity, deepening inequality. The lower pathway aligns with H3, which addresses heightened labour control and the intensification of work. Digital technologies exert tighter control over work pace, hours, and conditions. The migrant workers intend to mitigate inequality through clearer links between effort, productivity, and reward. These forms of self-exploitation are often accepted in exchange for limited or unstable wage gains, creating a paradox in which labour conditions worsen even as digital participation increases. Together, these pathways reflect how migrant workers are structurally constrained in both upward mobility and fall-back options: they are 'at risk of no job' yet also face 'no way back' to traditional rural livelihoods.

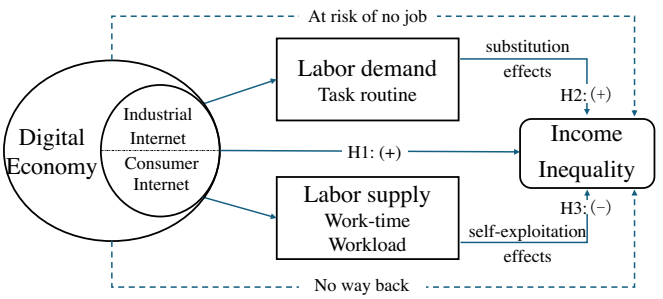


Fig 1. The analytical framework of digital economy and migrants' income inequality.

https://doi.org/10.1017/elr.2025.10045 Published online by Cambridge University Press

Changes in different industries

Furthermore, based on the main research framework, we propose a heterogeneity analysis hypothesis. The advancement of information technology and artificial intelligence has accelerated the replacement of human labour with machines and intensified hustle culture among migrant workers, thereby propelling the emergence of new industries and the adoption of novel forms of employment (Ning et al 2023). The digital economy has a positive spillover effect on employment in the tertiary sector by enhancing the correlation between manufacturing and tertiary industries and promoting deeper integration (Hu et al 2023). The expansion of the consumer internet, driven by the digital economy, offers a key avenue for migrant workers to reduce income inequality through occupational mobility. The digital economy is conducive to the promotion of employment in the tertiary industry, reduces employment in the primary and manufacturing industries, and transfers the labour force from the primary and manufacturing industries to the tertiary industry. This transformation enhances information acquisition in job searching, providing opportunities for flexible employment (Xiong and Sui 2025). It reduces the search and matching costs for migrant workers seeking jobs or part-time jobs in the search friction market and strengthens their willingness to supply labour and the quality of supply. Jobs related to the consumer internet have a greater demand for routine operations and routine cognitive executive tasks, attenuating the employment substitution effect of the digital economy on low-skilled migrant workers. We thus hypothesise that:

H1a: The digital economy is negatively associated with income inequality among tertiary industry migrant workers.

Data and method

This study draws on employment and income data of migrant workers from the 2018 China Labour Dynamics Survey (CLDS). Supplementary data on the consumer internet were obtained from Peking University's Digital Financial Inclusion Index, the China Urban Statistical Yearbook, and the Statistical Bulletin of National Economic and Social Development. The penetration of industrial robot data was sourced from the International Federation of Robotics (IFR) and the China Labour Statistics Yearbook. The CLDS covers 29 provinces, municipalities, and autonomous regions, excluding Hong Kong, Macao, Taiwan, Tibet, Hainan, and Xinjiang. Conducted biennially, the survey tracks urban and rural village residents, establishing a comprehensive database focused on the labour force. It includes individual, household, and community-level data, providing a robust foundation for empirical research. To ensure sample balance and comparability, we restricted the analysis to workers aged 16 to 68, retaining 3922 valid samples after excluding observations with missing key data.

Peking University's Digital Financial Inclusion Index, spanning 2011 to 2021, measures digital financial development across 31 provinces, 337 prefecture-level cities, and approximately 2800 counties. It comprises three dimensions and 33 indicators, offering granular insights into regional disparities. The IFR provides annual data on industrial robot installations and stocks globally since 1993, enabling detailed analysis of their application in manufacturing. These datasets collectively support a rigorous examination of the digital economy's impact on migrant workers' income inequality.

Variable selection and measurement

As the focus of this study is whether digital technology will increase the income inequality among migrant workers in general, the dependent variable is set as the 'Kakwani index' based on the relative income of migrant workers and the unemployment risk of migrant workers in 2016 and 2018 (the value is between 0 and 1, when the index is close to 0, the

https://doi.org/10.1017/elr.2025.10045 Published online by Cambridge University Press

income distribution is more average; when the index approaches 1, the income distribution is unbalanced).

Dependent variable

The calculation of income disparity has predominantly involved the computation of aggregate or grouped income disparities. Since the mid-1990s, the use of decomposable inequality measures has become widespread in analysing income disparity, verifying income inequality theories. The Kakwani index, derived from the Yitzhaki index, serves as the primary measure in this study for calculating income disparity among individuals. The Kakwani index is characterised by its decomposability and adherence to desirable normalisation properties, making it a preferred metric.

The formula for the Kakwani index is:

$$RD(x, x_k) = \frac{1}{n\mu_X} \sum_{i=k+1}^{n} (x_i - x_k) = \gamma_{x_k^+} \left[\left(\mu_{x_k^+} - x_k \right) / \mu_X \right]$$

where $RD(x, x_k)$ denotes the deviation experienced by individual x_k in group x, $\mu_{x_k^+}$ represents the average yearly income of the sample that exceeds x_k within sample X. $\gamma_{x_k^+}$ represents the percentage of the sample that exceeds x_k within sample X, and μ_X is the average income within sample X.

Independent variable

This study employs two independent variables: the consumer internet, measured by DF, and the industrial internet, represented by robot penetration (RP). On the consumer internet, DF effectively captures the nature of the consumer internet because it reflects how technological advances are driven by, and in turn reshape, consumer preferences and behaviours. As Guo et al (2022) suggest, DF plays a crucial role in demand-driven technological innovation. The rapid growth of mobile payment applications, digital wallets, and various fintech services further illustrates this pattern, directly responding to consumer demand for convenience, speed, and accessibility in financial transactions (Yamin and Abdalatif 2024; Akhtar et al 2024). Therefore, DF is not only an outcome of digital transformation but also a barometer of consumer internet penetration, indicating how users increasingly engage in seamless, instant, and personalised digital interactions.

On the industrial internet, RP serves as a robust proxy for the industrial internet and broader production-side digitalisation. A large body of literature supports this perspective: the penetration of industrial robots – typically measured as the number of robots per 10,000 manufacturing employees – is widely recognised as an indicator of industrial upgrading and automation (Dauth et al 2017; Fu et al 2021; Klenert et al 2023; Czarnitzki et al 2023; Ye and Zhang 2025). Robot penetration reflects the integration of advanced technologies into manufacturing systems, the shift toward smart production, and the evolution of supply-side capabilities. It enables industries to reduce labour costs, enhance flexibility, and respond more efficiently to market demands. Consequently, the penetration of robots captures the depth of industrial digital transformation and serves as a meaningful representation of the industrial internet.

Taken together, these two variables – DF and RP – offer a theoretically grounded and empirically supported lens through which to measure the dual structure of the digital economy from both consumer and industrial perspectives.

To quantify the development level of the urban digital economy, we adopt Zhao Tao's methodology. Based on five third-level indicators from the Digital Inclusive Financial Index, we construct a digital economy index (Score) using the entropy method (Guo et al 2020). This index serves as a proxy for the consumer internet. For the industrial internet,

https://doi.org/10.1017/elr.2025.10045 Published online by Cambridge University Press

we use RP (RP), with raw data sourced from the IFR. Following Dauth et al (2017), we focus on panel data from 30 provincial administrative units (excluding Tibet, Xinjiang, and Hainan) from 2017, as IFR's sub-industry robot inventory data for China became reliable only after 2006.

Job routine tasks, mapped to industries following Acemoglu and Restrepo (2019), are measured by averaging standardised routine task demands across micro-workers within each industry. As information technology penetration increases, routine task demands decline, displacing workers who must transition to other industries for re-employment. Concurrently, non-routine task demands rise, reflecting their complementary relationship with routine tasks. We use occupation as a proxy variable to measure work tasks and explore whether workers with different types of tasks are shifted across industries due to the impact of information technology. We categorise tasks using criteria from the CLDS occupational classifications. This approach draws on methods from both the U.S. Occupational Information Network (OIN) and Dohse and Ott (2015). The specific classification criteria are as follows: conventional occupations include clerical and related personnel, operators of production and transportation equipment, and related personnel; nonconventional cognitive occupations include heads of state organs, party organisations, enterprises, institutions, professional and technical personnel; and nonconventional operational occupations include personnel in commerce and service industries.

Migrant workers with low incomes are more likely to suffer from overload worktime and task contents (Zhang et al 2024). According to the labour law of the People's Republic of China, we included overtime workers in the sample who worked more than 44 hours per week (Marcolin et al 2019). Utilising individuals' own judgements about their task contents can help account for latent unobserved phenomena, specifically unobserved task contents, thus yielding a relatively more accurate proxy for routine intensity grouping (Du and Wei 2020). Following Marcolin et al (2019) and adopting the measurement approach of Du and Wei (2020), this study uses similar questions from the CLDS survey to derive the Routine Intensity Indicator (RII). In the CLDS, workers were asked to report their degree of autonomy in determining workload, work schedule, and task contents, based on three questions using a 3-point scale. The total score was further trichotomised to indicate job task intensity.

Control variable

The control variables encompass several categories. Industry type distinguishes between secondary and tertiary sectors. Task routine includes both routine and non-routine cognitive and operational tasks. Work conditions cover overtime and workload levels. Demographics include age, education, marital status, gender, language skills, and skill certificates. We also control for geographic region, health status, and seniority (work experience).

Analytical method

In this section, we employ the regression method below to estimate the impact of the digital economy on migrant workers' income inequality:

$$Kakwani_t = \alpha + \beta DE + \Gamma X_t + \varepsilon_t$$

Here, $Kakwani_t$ represents the Kakwani index at time t, which measures income inequality among migrant workers. α is the constant term, DE stands for the digital economy variable, Γ represents the coefficient vector for control variables X_t, and ε_t is the error term.

https://doi.org/10.1017/elr.2025.10045 Published online by Cambridge University Press

Empirical findings

The attributes of the digital economy and migrants' income inequality

Table 1 lists the descriptive statistics of variables used in this study, which mainly includes the mean value of each variable and their proportion in the manufacturing industry and the tertiary sector. The table shows that there is significant income inequality among migrant workers, evidenced by a Kakwani index of 0.483. This aligns with established literature indicating that welfare improvements for migrant workers consistently lag behind those who are urban residents. That phenomenon is attributed to institutional gaps in social protection, human capital deficits, and inadequate financial inclusion (Cai et al 2010; Gradín and Wu 2020). The average penetration rate of robots and DF is 2.576 and 0.305, respectively, and their density in the manufacturing industry is relatively high. This reflects that manufacturing, as the traditional focal area for automation applications, has production processes that are more easily substitutable by robots and greater demand for investment in physical equipment. In the types of industries, the tertiary sector accounts for about 56%, indicating that respondents are mainly engaged in the tertiary industry. This aligns with the trend of China's overall economic structure transitioning towards the service sector, which has become the main domain for absorbing labour. 51% of the respondents had non-routine operations, which were mainly concentrated in the tertiary industry. The proportion of non-routine cognition is 35%, which is mainly concentrated in the secondary industry.

About 59% of respondents have experienced overtime work in both sectors, with a relatively high number in the secondary industry. Possible reasons include the manufacturing sector being more affected by order-driven demands and requirements for continuous production line operation, leading to a more prevalent overtime culture. Meanwhile, the proportion of middle load and high load in work overload is about 34% and 30%, respectively. This indicates that migrant workers are generally suffering from overtime work, sleep deprivation, or overwork. This may potentially stem from factors such as enterprises' pursuit of efficiency maximisation, labour cost control, and labour supply-demand dynamics. The proportion of respondents aged 33–54 and 55–69 is about 52% and 17%, respectively, and the average education level in high school and college or above is 19% and 17%, respectively, among which the number of people engaged in the tertiary industry is relatively large. It indicates that the conventional task attributes of work in the secondary industry are relatively high, and with the increase of age and educational background, respondents gradually withdraw from the labour industry.

The proportion of married respondents is about 87%, and the proportion of female respondents is about 42%. Female respondents are mainly engaged in the tertiary industry, accounting for 52%. In the presence of service industries, occupational segregation seems to increase as both female labour force participation and the level of educational inequality rise. Despite high female participation rates in the service sector, women may be more concentrated in specific 'gender-typed' occupations such as clerical work, customer service, and low-end care work, while highly educated women entering high-end services like finance and technology may still face barriers, thereby contributing to occupational gender segregation. About 41% of the respondents mainly use Mandarin in their work, while only about 19% of the respondents have one or more skill certificates, and they are mainly engaged in the tertiary industry, indicating that the tertiary industry job has relatively high language and skill requirements. Service jobs, involving direct customer interaction or handling complex information, indeed place generally higher demands on communication skills, professional knowledge, and certified skills compared to many traditional manufacturing positions. The average values of respondents in the central, western, and northern regions were 16.22, 22.27, and 2.16, respectively, and the

https://doi.org/10.1017/elr.2025.10045 Published online by Cambridge University Press

number of western respondents engaged in the tertiary industry was relatively large. This may stem from the Western Development Strategy of China, promoting the development of local service industries, such as tourism and logistics.

Among the respondents' evaluation of their physical status, 23% respondents are in average level and 69% are in good health, respectively, which proves that most respondents are generally healthy. The average seniority of respondents is about 11, and that of the secondary industry is about 11.8, about 1.5 years longer than that of the tertiary industry, indicating relatively high stability in the secondary industry. Manufacturing positions, particularly in large factories, often provide longer-term, stable contracts and relatively clearer promotion paths, including mechanisms like seniority accumulation. These roles typically exhibit stronger skill specificity, which reduces turnover. Conversely, service sector jobs frequently take diverse forms, such as flexible employment, involve more intense competition, or require more frequent career transitions, ultimately resulting in marginally shorter average job tenure.

Table 1. Descriptive statistics of variables

	Mean (S.D.)	Secondary industry	Tertiary industry
Kakwani index	0.483(0.246)	0.459(0.217)	0.478(0.248)
RP	2.576(2.253)	2.892(2.328)	2.348(2.179)
DF	0.305(0.161)	0.310(0.149)	0.301(0.169)
The types of industries (ref. secondary)			
Tertiary industry	56.17	–	–
Task routine (ref. Regular task routine)			
Non-routine operation	50.91	31.72	65.98
Non-routine cognition	35.11	61.45	14.44
Work overtime (ref. have not)			
Overtime worked	58.98	53.41	75.52
Work overload (ref. have not)			
Middle load	34.40	35.08	33.86
High load	29.78	22.51	35.45
Age group (ref. 16-34)			
35-54	51.94	55.15	49.43
55-69	16.80	16.40	17.11
Education level (ref. junior high school and below)			
High school	19.33	17.10	21.06
Collage and above	16.78	10.24	21.88
Marriage status (ref. single)			
Married	86.61	88.31	85.29
Gender (ref. male)			
Female	42.12	29.44	52.02

(*Continued*)

https://doi.org/10.1017/elr.2025.10045 Published online by Cambridge University Press

Table 1. (*Continued*)

	Mean (S.D.)	Secondary industry	Tertiary industry
Language skill (ref. dialect)			
Mandarin	41.15	36.71	44.62
Skill certificate (ref. no)			
One or more	19.45	16.11	22.06
Region (ref. Eastern)			
Middle	16.22	16.67	15.87
Western	22.27	18.35	25.33
Northeast	2.16	1.26	2.86
physical status (ref. in bad health)			
About average	23.18	25.01	21.74
In good health	69.48	67.83	70.77
Seniority (Year)	10.969(10.632)	11.767(11.140)	10.347(10.410)

Baseline regression results

The regression results presented in Table 2 illustrate the impact of digital economy on the income inequality of migrant workers. The four models use Ordinary Least Squares (OLS) estimation methods, incorporating different sets of variables to capture the effects comprehensively.

Model 1 focuses on the primary independent variables: RP and DF, and the results show that RP has a statistically significant positive effect on income inequality, with coefficients of 0.003 (significant at the 1% level). This indicates that an increase in RP is associated with an increase in income inequality among migrant workers. This may be attributable to robotic automation preferentially replacing low-skilled positions, thereby widening the wage gap between high-skilled and low-skilled migrant workers. DF exhibits a significant negative effect on income inequality, with coefficients of −0.328 (significant at the 1% level) in Model 1. This suggests that advancements in DF tend to reduce income inequality within the migrant worker population. Model 2 incorporates two moderators, job labour demand and individual labour supply, into the regression. Nonroutine cognitive tasks are associated with lower inequality, while non-routine operational tasks show less significant effects. Cognitive jobs such as technology research and development and management decision-making rely on continuous learning and experience accumulation. Their skill-return curve is relatively flat, and companies prefer investing in employee training, narrowing the income gap caused by initial competency differences. Meanwhile, routine operational tasks like repetitive labour have been partially replaced by automation or feature relatively rigid compensation structures, making it difficult to significantly alter the inequality landscape. Similarly, working overtime shows a significant alleviating effect on income inequality. Both middle and high levels of work overload, relative to no overload, also demonstrate significant mitigating effects on inequality, with coefficients of −0.055 and −0.031, respectively ($p < 0.001$). Working overtime and experiencing high workloads tend to reduce inequality, possibly due to higher earnings compensating for additional work hours. A potential explanation lies in workers being compelled to adapt to extended working hours and intensified task demands to secure higher incomes. While ostensibly reducing income inequality, this effectively comes at the cost of generating overwork and undermining labour autonomy. When considering the application status of

https://doi.org/10.1017/elr.2025.10045 Published online by Cambridge University Press

industrial robots at the provincial level and the development level of DF at the same time, this negative impact of DF remains robust (model 3), and the positive impact of industrial robots' penetration is not remarkable.

Across model 4, the regression analysis highlights the nuanced impact of the digital economy on income inequality among migrant workers. Robot penetration generally increases inequality, especially in cognitive skill-intensive jobs. While DF appears to reduce inequality broadly, it may interact with job characteristics to reveal complexities. The amplifying effect dominates because technological displacement generates irreversible earnings losses, while DF only partially compensates through welfare trade-offs. Moreover, self-exploitation strategies, like prolonging work hours, are physiologically unsustainable, rendering any alleviating effect transient (WHO 2021; Zhang 2025). Service sectors exhibit pronounced wage dispersion, spanning low-wage temporary workers to high-salary professionals, whereas manufacturing wages remain relatively homogeneous. This disparity is further amplified by intensified competition and more diverse skill requirements within service industries. Age, education, marital status, gender, language skills, and regional factors also play significant roles in shaping income inequality. For instance, older workers (aged 55–69) and female workers are subject to higher inequality, likely due to age discrimination, skills misalignment, and gender-based occupational segregation. Conversely, higher education levels and Mandarin proficiency are associated with reduced inequality, as they expand employment opportunities, enhance bargaining power, and facilitate mobility into higher-tier service occupations. Better health and longer job tenure also correlate with lower inequality, underscoring the roles of physical capacity and accumulated experience in stabilising earnings. These findings suggest that policy interventions aimed at leveraging digital economic growth must account for these varied mechanisms to effectively address income disparities among migrant workers.

Table 2. The baseline regression model

	Model 1	Model 2	Model 3	Model 4
RP	0.003***(0.001)		0.002(0.002)	0.006***(0.002)
DF	−0.328***(0.029)		−0.308***(0.029)	−0.363***(0.034)
Task routine (ref. Regular task routine)				
Non-routine operation		0.078***(0.012)	0.074***(0.011)	0.004(0.011)
Non-routine cognition		−0.114***(0.012)	−0.110***(0.012)	−0.049***(0.013)
Work overtime (ref. have not)				
Overtime worked		−0.034***(0.008)	−0.033***(0.007)	−0.027***(0.007)
Work overload (ref. have not)				
Middle load		−0.055***(0.008)	−0.052***(0.008)	−0.031***(0.008)
High load		−0.031***(0.010)	−0.034***(0.009)	−0.045***(0.009)

(*Continued*)

https://doi.org/10.1017/elr.2025.10045 Published online by Cambridge University Press

Table 2. (*Continued*)

	Model 1	Model 2	Model 3	Model 4
The types of industries (ref. secondary)				
Tertiary industry				0.031***(0.008)
Education level (ref. junior high school and below)				
High school				−0.039***(0.009)
Collage and above				−0.128***(0.012)
Language skill (ref. dialect)				
Mandarin				−0.045***(0.008)
Skill certificate (ref. no)				
One or more				−0.038***(0.009)
Physical status (ref. in bad health)				
About average				−0.082***(0.015)
In good health				−0.098***(0.014)
Seniority (Year)				−0.004***(0.000)
Age group (ref. 16-34)				
35-54				−0.034***(0.009)
55-69				0.051***(0.012)
Marriage status (ref. single)				
Married				−0.070***(0.012)
Gender (ref. male)				
Female				0.105***(0.007)
Region (ref. Eastern)				
Middle				0.044***(0.016)
Western				0.071**(0.029)
Northeast				0.228***(0.039)
Constant	0.579***(0.008)	0.444***(0.012)	0.538***(0.014)	0.744***(0.024)
Observations	3,922	3,922	3,922	3,922
R-squared	0.043	0.037	0.075	0.231

Note: Standard errors in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; RP=Robot penetration. DF=Digital finance index.

Alleviation of the endogeneity problem and robustness test

To mitigate potential endogeneity issues such as mutual causation and omitted variables, instrumental variable estimation was chosen for the tests in this paper. Based on two basic conditions of IV, the variable relevant to the digital economy must be determined, which

https://doi.org/10.1017/elr.2025.10045 Published online by Cambridge University Press

does not directly affect migrant workers' income inequality. According to Zhao et al (2020), the Historical data on post and telecommunications in 1984 for each province is normally regarded as an IV for the development of the RP and DF index to correct estimation errors caused by endogeneity. In a sense, the digital economy is a continuation of the development of traditional communication technology, and its technical application will be affected by the traditional telecommunication infrastructure in the region. At the same time, the reduction of the use of traditional telecommunication tools in the work of workers will not affect their wage inequality, so the use of postal and telecommunication historical data as an instrumental variable for the development of the digital economy meets the requirements of relevance and exogeneity. Table 4 shows that the F statistic was 83.979 and 2056.470, which is significantly higher than 10 (Staiger and Stock 1997). As a result, the possibility of a weak IV can be excluded. The DWH result tellingly shows that an endogenous relationship exists between the digital economy and migrant workers' income inequality. The regression results in column 1 and column 3 reveal that the post and telecommunications in 1984 are significantly and positively related to digital economy development. Column 2 and Column 4 in Table 3 also show that the total effect of digital economy on urban migrant income inequality is positive.

For the purpose of the robustness check and comparison regarding the positive effects of the digital economy on migrant workers' income diversity, we also estimate the RP and DF index impact on the Yizhaki and Podder index. The results show that RP tends to affect rural household income inequality positively and significantly, while the DF, by contrast, tends to have strongest positive effects in the equalisation of income, such as takeout platform riders. When we focused on the impact between the digital economy and income equality among old staff and female labourers, the conclusion is robust compared with Model 2 in Table 2. The labour demand substitution effect of the digital economy is more pronounced among the group of older employees and female workers (Wu et al 2024). At the same time, they all tend to increase their labour supply to counteract the risk of falling incomes (Zhang et al 2024). Those findings confirm the results presented in Table 2 above.

Table 3. The IV-SLS regression and robustness test results

Instrument variable regression (IV-SLS)				
	RP	Kakwani	DF	Kakwani
PE84	1.349***(0.147)		0.448***(0.010)	
DE		0.099***(0.015)		0.299***(0.034)
Control *variable*	YES	YES	YES	YES
Constant	1.707***(0.187)	0.720***(0.039)	0.095***(0.013)	0.579***(0.020)
Observations	5845	5845	5845	5845
Centered R2	0.091	0.345	0.359	0.232
Durbin Wu-Hausman		677.376		734.234
CD Wald F	83.979		2056.470	
SW S stat.	75.200		75.200	
Change variable of inequality			*Change sample size*	
	Yizhaki	*Podder*	*Have worked for 10 years*	*Female workers*
RP	0.020**(0.008)	0.021(0.029)	0.009***(0.003)	0.005(0.003)

(*Continued*)

https://doi.org/10.1017/elr.2025.10045 Published online by Cambridge University Press

Table 3. (*Continued*)

Change variable of inequality			*Change sample size*	
	Yizhaki	*Podder*	*Have worked for 10 years*	*Female workers*
DF	−1.387***(0.130)	−1.898***(0.441)	−0.356***(0.049)	−0.368***(0.054)
Task routine (ref. Regular task routine)				
Non-routine operation	0.014(0.043)	−0.029(0.152)	−0.003(0.017)	0.014(0.018)
Non-routine cognition	−0.179***(0.046)	−0.478***(0.175)	−0.037**(0.018)	−0.066***(0.020)
Work overtime (ref. have not)				
Overtime worked	−0.126***(0.027)	−0.485***(0.108)	−0.037***(0.011)	−0.046***(0.011)
Work overload (ref. have not)				
Middle load	−0.124***(0.030)	−0.017(0.115)	−0.030**(0.012)	−0.021*(0.012)
High load	−0.134***(0.034)	0.458***(0.141)	−0.005(0.013)	−0.015(0.014)
Control *variables*	YES	YES	YES	YES
Constant	2.986***(0.089)	2.886***(0.406)	0.679***(0.040)	0.873***(0.036)
Observations	4,108	4,108	1,808	1,761
R2	0.233	0.049	0.228	0.184

Note: PE84= post and telecommunications in 1984; DE= digital economic; Standard errors in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The heterogeneity analysis results

Model 5 and Model 6 introduce interaction terms to explore how the relationship between income inequality and RP or DF varies across different contexts. Specifically, Model 5 includes interactions between RP and various job characteristics, while Model 6 includes interactions between DF and these characteristics. The significant negative interaction between RP and non-routine cognitive tasks (−0.018***) indicates that automation selectively reduces inequality in knowledge-intensive roles. This occurs because industrial robots increase demand for human decision-making in areas like quality control and workflow optimisation. Consequently, it becomes more difficult for low-skilled workers to match the productivity of cognitive workers. The significantly negative interactions between RP and both middle workload (−0.013*), high workload (−0.024*), and overtime (−0.011*) suggest that automation's inequality-reducing effect is amplified in jobs characterised by higher work intensity and overload. This may arise from industrial robots enabling more transparent performance measurement and output-based compensation in demanding roles, thereby the migrated worker intends to mitigating inequality through clearer links between effort, productivity, and reward. In Model 6, the interaction terms reveal how DF's inequality-mitigating effect varies by job context.

The interaction between DF and non-routine cognitive tasks is negative and significant (−0.078, significant at the 1% level), suggesting that DF can decrease inequality in cognitive skill-intensive jobs. DF's interactions with middle and high workloads are negative and significant (−0.090 and −0.088, respectively), indicating that DF mitigates inequality more

https://doi.org/10.1017/elr.2025.10045 Published online by Cambridge University Press

effectively in higher workload jobs. This demonstrates distinct demand-supply mismatch mechanisms in inequality mitigation: industrial internet development critically depends on skill-technological complementarity within labour supply structures, while consumer internet substantially reduces inequality yet remains vulnerable to compensation inefficiencies. These inefficiencies stem from the inherent fragility of workers' compensatory labour supply (extended hours/intensified effort), whose marginal returns diminish under platform-mediated control. Critically, this early signal of compensatory mechanism fragility foreshadows the sectoral divergence empirically confirmed in Models 7–8.

The Model 7 and Model 8 indicate that the RP has a significantly positive impact on the income inequality of both secondary and tertiary industry workers. The DF index has a significantly negative impact on the individual income inequality for workers in secondary and tertiary industries. For the magnitude of coefficients, the development of DF plays a greater role in promoting the economic inequality of secondary workers and hindering their fair primary distribution. Within secondary industries, the penetration of industrial robots synergises with non-routine cognitive tasks, substantially reducing Kakwani inequality coefficients by 0.448 units (Model 7). This aligns with industrial automation, enhancing cognitive labour productivity. Concurrently, the interaction between robot density and high work intensity further lowers inequality by 0.215 units, indicating robust efficiency gains from technology-labour complementarity. Contrastingly, tertiary sectors exhibit a compensatory paradox: while DF development independently reduces inequality by 0.279 units (Model 8), it systematically diminishes overtime work's equalising returns by 12.1%. This suggests algorithmic control in platform economies erodes marginal compensation for labour intensification. Critically, high work intensity shows no significant interaction with DF, revealing structural constraints on compensation mechanisms in service digitisation. Since the majority of the rural migrant workers employed in the tertiary industry are in more routine operational positions, the effects of income enhancement for the middle and low-skilled groups brought about by routine-biased technological progress have not been reflected. And as shown in Table 1, migrant workers employed in the tertiary industry have a higher proportion of overtime and overloaded labour, so the income assimilation effect brought about by self-exploitation is obvious. Hypothesis H1a cannot be rejected.

Table 4. The moderating effect of digital economy on income inequality by different sectors

	Full sample		Secondary industry migrant workers	Tertiary industry migrant workers
	Model 5	Model 6	Model 7	Model 8
DE	−0.014***(0.005)	−0.338***(0.076)	−0.009(0.006)	−0.279***(0.090)
Task routine (ref. Regular task routine)				
Non-routine operation	−0.003(0.012)	−0.001(0.012)	−0.046(0.038)	0.001(0.014)
Non-routine cognition	−0.038***(0.014)	−0.044***(0.014)	−0.003(0.037)	−0.036*(0.018)
Work overtime (ref. have not)				
Overtime worked	−0.030***(0.008)	−0.030***(0.007)	−0.031***(0.010)	−0.029***(0.010)

(*Continued*)

https://doi.org/10.1017/elr.2025.10045 Published online by Cambridge University Press

Table 4. (*Continued*)

	Full sample		Secondary industry migrant workers	Tertiary industry migrant workers
	Model 5	Model 6	Model 7	Model 8
Work overload (ref. have not)				
Middle load	−0.029***(0.009)	−0.027***(0.008)	−0.038***(0.011)	−0.018(0.012)
High load	−0.042***(0.010)	−0.041***(0.009)	−0.031**(0.014)	−0.043***(0.013)
The types of industries (ref. secondary)				
Tertiary industry	0.030***(0.008)	0.027***(0.008)		
Non-routine operation # DE	0.005(0.005)	0.008(0.068)	0.394*(0.209)	0.027(0.077)
Non-routine cognition # DE	−0.018***(0.005)	−0.078***(0.024)	−0.448**(0.208)	−0.003(0.105)
Overtime worked # DE	−0.011*(0.005)	0.063(0.045)	−0.032(0.065)	−0.121**(0.060)
Middle load # DE	−0.013***(0.003)	−0.090*(0.049)	0.009(0.070)	−0.170**(0.067)
High load # DE	−0.024***(0.004)	−0.088***(0.018)	−0.215**(0.088)	−0.057(0.078)
Constant	0.684***(0.025)	0.670***(0.024)	0.705***(0.047)	0.705***(0.030)
Observations	3,922		1,719	2,203
R-squared	0.211	0.231	0.278	0.213

Note: Standard errors in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; RP=Robot penetration. DF=Digital finance index. We used the robot penetration to represent industrial internet in model 5, model 8; For model 6 and tertiary industry migrant workers, we used digital finance index to represent the consumer internet.

Discussion and conclusion

The canonical task-based model of inequality, while effectively capturing skill substitution effects through its two-sector framework (Autor et al 2003), fails to explain China's migrant worker inequality paradox under digital transformation – where simultaneous labour demand contraction in manufacturing and supply-side overwork in services coalesce into structural mismatches. In this study, we argue that despite its notable successes, the classical model is largely silent on labourers' self-exploitation during labour supply in the last decades. The labour substitution effect causes some workers to be displaced and trapped in a low-income cycle. The 'consent manufacturing' of employers regarding the length and intensity of work mitigates the risk of income declines for some groups. Still, it also leaves them with no other path to offset the income gap than to make concessions in the labour supply afterward.

In 2023, China's digital economy exceeded 55 trillion yuan ($7.6 trillion), as the digital economy is playing an important role in the national economy. But economists said those figures did not amount to a genuine rebalancing of the economy. The widespread application of digital technology development in various industries has a significant impact on the employment of labour (Xin and Ye 2024). In this process, we need to pay particular attention to whether migrant workers are replaced or autonomously increase their labour supplies, who are impacted by the application of digital technology in manufacturing and services, and ultimately, how the income inequality situation of this group is formed.

https://doi.org/10.1017/elr.2025.10045 Published online by Cambridge University Press

The improvement of the industrial RP rate significantly increases the probability of income inequality among migrant workers. The underlying logic lies in: automation technologies systematically replace low-skilled positions, leading to a widening wage gap between high-skilled and low-skilled labourers. The DF index reduces income inequality, but this apparent equality may stem from workers being compelled to extend working hours and intensify labour efforts to achieve income growth (Jiang et al 2016; Lopes et al 2023). This model essentially achieves superficial equality at the cost of sacrificing labour autonomy and health rights. Nonroutine cognitive positions demonstrate more equitable income distribution characteristics. Such roles rely on knowledge accumulation and continuous learning, where skill returns exhibit long-term gradualism; simultaneously, enterprises tend to provide systematic training, weakening the impact of initial capability differences on ultimate earnings. The influence of routine operational tasks on income distribution is relatively weak. These positions face dual pressures: displacement by automation technologies and constraints from rigid compensation systems, making it difficult to generate significant momentum for altering the income landscape. Heterogeneity analysis indicates that the digital economy plays a more substantial role in exacerbating economic inequality among female and older migrant workers. The reasons include that older labourers face age discrimination and skill devaluation constraints, forcing them into precarious employment; women remain persistently confined to low-wage positions due to occupational segregation and family responsibilities.

Our analysis reveals divergent adjustment mechanisms between secondary and tertiary sector migrant workers. Industrial automation, driven by robotic adoption in manufacturing, systematically displaces routine-task workers through technological substitution, simultaneously increasing demand for non-routine cognitive skills. This dual demand shift forces substantial cross-sector mobility while exacerbating unemployment risks for those lacking adaptive capacities. Conversely, service-sector digitalisation enables capital-driven labour process restructuring, characterised by algorithmic management of workloads and extended working hours. Low-skilled workers face compounded vulnerabilities: manufacturing displacement creates re-employment barriers due to skill mismatches, while service sector intensification generates income instability despite prolonged labour inputs. Structural deficiencies in social protection systems – particularly inadequate unemployment coverage and portable benefits – amplify these disparities, locking disadvantaged groups into cyclical inequality patterns across economic transitions.

In China, the advancement of intelligent manufacturing continues to place a strong emphasis on comprehensive support for enterprises and technological transformation. In the workplace, the digital economy could increase productivity and promote shared prosperity although, the benefits and costs will likely be distributed unevenly across industries, sectors, and worker demographics. To leverage the digital economy's potential for common prosperity, three policy priorities emerge. First, implementing workforce digital upskilling initiatives that enhance low-skilled workers' digital literacy and technical adaptability is critical to mitigate skill mismatch risks induced by the industrial internet. Second, enforcing labour regulations through algorithmic governance frameworks becomes imperative, particularly for monitoring working hours and intensity in platform-based service sectors, establishing a balanced labour-capital relationship mechanism in the digital era. Third, constructing a demand-responsive public service system that elevates migrant workers' health insurance coverage and vocational training accessibility to align with permanent residents' levels can buffer digital transformation shocks through social security safeguards. These systemic reforms collectively address the 'digital divide' in technological dividend distribution, providing institutional foundations for shared prosperity.

https://doi.org/10.1017/elr.2025.10045 Published online by Cambridge University Press

This study contributes theoretically by deconstructing the disparate impact mechanisms of demand-side and supply-side digitalisation on labour markets. Integrating task substitution models with labour process theory, we reveal complementary inequality generation pathways between manufacturing routine job disappearance and service sector work intensification, offering a novel analytical framework for labour market polarisation in the digital economy. Methodologically, developing provincial-level bidirectional moderation effect models using RP rates and DF indices provides the first empirical verification of cross-industry transmission channels through which digital technologies affect migrant income gaps. These findings deliver micro-evidence supporting optimised digital economy policies and vulnerable group labour protections. It should be noted that although we do our best to reduce possible analytical bias, there are still some limitations in this paper in terms of data collection, variable measurement, and causality identification, which may lead to some bias in this paper, and we hope to further improve them in subsequent research. In addition, we only uncover the static impact. The dynamic effect of the digital economy on migrant workers' labour process needs to be further studied based on more comprehensive panel data.

References

Acemoglu D (2002) Technical change, inequality, and the labour market. *Journal of Economic Literature* 40(1), 7–72. https://doi.org/10.1257/0022051026976

Acemoglu D and Autor D (2011) Skills, tasks, and technologies: implications for employment and earnings. In Ashenfelter O and Card D (eds), *Handbook of Labour Economics*. Amsterdam: Elsevier. https://doi.org/10.1016/S0169-7218(11)02410-5

Acemoglu D and Restrepo P (2019) Automation and new tasks: how technology displaces and reinstates labor. *Journal of Economic Perspectives* 33(2), 3–30. https://doi.org/10.1257/jep.33.2.3

Akhtar M, Salman A, Ghafoor KA and Kamran M (2024) Artificial intelligence, financial services knowledge, government support, and user innovativeness: exploring the moderated-mediated path to fintech adoption. *Heliyon* 10, e39521. https://doi.org/10.1016/j.heliyon.2024.e39521

Autor DH, Levy F and Murnane RJ (2003) The skill content of recent technological change: an empirical exploration. *Quarterly Journal of Economics* 118(4), 1279–1333. https://doi.org/10.1162/003355303322552801

Balsmeier B and Woerter M (2019) Is this time different? How digitalization influences job creation and destruction. *Research Policy* 48(8), 103765. https://doi.org/10.1016/j.respol.2019.03.010

Bauder H (2006) *Labour movement: How migration regulates labour markets*. Oxford: Oxford University Press. https://doi.org/10.1093/oso/9780195180879.001.0001

Burawoy M (1979) Manufacturing consent: changes in the labour process under monopoly capitalism. Chicago: University of Chicago Press. https://doi.org/10.1177/001979398203600123

Cai HB, Chen YY and Zhou LA (2010) Income and consumption inequality in urban China: 1992–2003. *Economic Development and Cultural Change* 58(3), 385–413. https://doi.org/10.1086/650423

Chan J, Pun N and Selden M (2013) The politics of global production: apple, foxconn and China's new working class. *New Technology, Work and Employment* 28(2),100–116. https://doi.org/10.1111/ntwe.12008

Chen N, Sun D and Chen J (2022) Digital transformation, labour share, and industrial heterogeneity. *Journal of Innovation and Knowledge* 7(2), 1–14. https://doi.org/10.1016/j.jik.2022.100173.

Chen Y, Xu SR, Lyulyov O and Pimonenko T (2023) China's digital economy development: incentives and challenges. *Technological and Economic Development of Economy* 29(2), 518–538. https://doi.org/10.3846/tede.2022.18018

Chinese Social Sciences Today (2019) Addressing inequality from a global perspective. Available at http://sscp.cssn.cn/xkpd/xszx/gj/201912/t20191202_5051595.html (accessed 7 July 2024) In Chinese

Chusseau N and Dumont M (2013) Growing income inequalities in advanced countries. In Hellier, Chusseau (Eds.), *Growing Income Inequalities: Economic Analyses*. UK:Palgrave Macmillan. https://doi.org/10.2139/ssrn.2276420

Czarnitzki D, Fernández G P, Rammer C (2023) Artificial intelligence and firm-level productivity. *Journal of Economic Behavior & Organization* 211, 188–205. https://doi.org/10.1016/j.jebo.2023.05.008

Dauth W, Findeisen S, Suedekum J and Wößner N (2017) German robots- the impact of industrial robots on workers. *European Economics: Labor & Social Conditions eJournal*, Corpus ID: 55393263

https://doi.org/10.1017/elr.2025.10045 Published online by Cambridge University Press

Davids K and Martin R (1992) Shopfloor attitudes towards advanced manufacturing technology: the changing focus of industrial conflict? *Interacting with Computers* 4(2), 200–208. https://doi.org/10.1016/0953-5438(92)90004-Y

Dohse D and Ott I (2015) Heterogenous skills, growth and convergence. *Structural Change and Economic Dynamics* 30, 52–67. https://doi.org/10.1016/j.strueco.2014.01.003

Du Y and Wei X (2020) Task content routinisation, technological change and labour turnover: Evidence from China. *The Economic and Labour Relations Review* 31(3), 324–346. https://doi.org/10.1177/1035304620921569

Edwards R (1979) *Contested Terrain: The Transformation of the Workplace in the Twentieth Century*. New York: Basic Books. https://doi.org/10.1177/030981688101400116

Ernst E, Merola R and Samaan D (2019) Economics of artificial intelligence: implications for the future of work. *IZA Journal of Labour Policy* 9(1), 1–35. https://doi.org/10.2478/izajolp-2019-0004

Farrer J (2016) China wants you: the social construction of skilled labour in three employment sectors. *Asian and Pacific Migration Journal* 23(4), 397–420. https://doi.org/10.1177/011719681402300405

Fu X M, Bao Q, Xie H, Fu X (2021) Diffusion of industrial robotics and inclusive growth: Labour market evidence from cross country data. *Journal of Business Research* 122, 670–684. https://doi.org/10.1016/j.jbusres.2020.05.051

Gao Z, Wang Z and Zhou M (2023) The impact of digital technology on the employment income and welfare of migrant workers: using the perspective of industrial structure transformation, *Chinese Journal of Population Science* 2, 100–114. In Chinese

Ghosh S (2017) Broadband penetration and economic growth: do policies matter? *Telematics Information* 34(5), 676–693. https://doi.org/10.1016/j.tele.2016.12.007

Gradín C, Wu B (2020) Income and consumption inequality in China: a comparative approach with India. *China Economic Review* 62, 101463. https://doi.org/10.1016/j.chieco.2020.101463

Graetz G and Michaels G (2018). Robots at work. *Review of economics and statistics* 100(5), 753–768.

Guo F, Wang J, Wang F, Kong T, Zhang X and Cheng Z (2020) Measuring China's digital financial inclusion: index compilation and spatial characteristics. *China Economic Quarterly* 19(4): 1401–1418. In Chinese

Guo Z, Peng Y and Chen Y (2022) How digital finance affects the continuous technological innovation of Chinese energy companies? *Frontiers in Energy Research* 10, 833436. https://doi.org/10.3389/fenrg.2022.833436

Hall R (2010) Renewing and revising the engagement between labour process theory and technology. In P. Thompson and C. Smith (eds), *Working Life: Renewing Labour Process Analysis*. Basingstoke: Palgrave Macmillan.

Hjort J and Poulsen J (2019) The arrival of fast internet and employment in Africa. *America Economic Review* 109(3), 1032–1079. https://doi.org/10.1257/AER.20161385

Hou J and Huo X (2019) Does computer usage change farmers production and consumption? Evidence from China. *China Agricultural Economic Review* 11(2),387–410. https://doi.org/10.1108/CAER-09-2016-0149

Hu Y, Yu H and Chen, Q (2023). Digitalization driving high-quality converged development of rural primary, secondary, and tertiary industries: mechanisms, effects, and paths. *Sustainability* 15(15), 11708. https://doi.org/10.3390/su151511708

Huo ML and Jiang Z (2023) Work-role overload, work-life conflict, and perceived career plateau: the moderating role of emotional stability. *Human Resource Management* 62(6), 867–882. https://doi.org/10.1002/hrm.22167

Jiang J and Zhang G (2016) Can on-the-job training stabilize employment among rural migrant workers? *China Agricultural Economic Review* 8(3), 498–515. https://doi.org/10.1108/CAER-09-2015-0113

Kalleberg AL (2017) *Good jobs, bad jobs: The rise of polarized and precarious employment systems in the United States, 1970s–2000s*. New York: Russell Sage Foundation. https://doi.org/10.1111/j.1467-954X.2012.02137.x

Kellogg KC, Valentine MA and Christin A (2020) Algorithms at work: the new contested terrain of control. *Academy of Management Annals* 14(1), 366–410. https://doi.org/10.5465/annals.2018.0174

Kim S (2012) Two faces of comprehensive information technology, knowledge acquisition, and polarized wage structure. *Journal of Economic Research* 17(2):139–158. https://doi.org/10.17256/jer.2012.17.2.002.

Klenert D, Fernandez-Macias E and Antón J I (2023) Do robots really destroy jobs? Evidence from Europe. *Economic and Industrial Democracy* 44(1), 280–316. https://doi.org/10.1177/0143831X211068891

Kranzberg M (1985) The information age: evolution or revolution. *Information Technologies and Social Transformation* 7(3), 40–42.

Leng C, Ma W, Tang J and Zhu Z (2020) ICT adoption and income diversification among rural households in China. *Applied Economics* 52(33), 3614–3628. https://doi.org/10.1080/00036846.2020.1715338

Leng X, Hou J, Huo X and Yin R (2018) Digital revolution and rural family income: evidence from China. *Journal of Rural Studies* 94, 336–343. https://doi.org/10.1016/j.jrurstud.2022.07.004.

Liu K, Hu K, Wang Y and Sun Y (2023) Robot imports and employment location choice: Evidence from the survey of labour dynamics in China. *Journal of Global Information Management* 31(6), 1–27. https://doi.org/10.4018/JGIM.321181

Lopes A S, Sargento A and Farto J (2023) Training in digital skills—the perspective of workers in public sector. *Sustainability* 15(13), 10577. https://doi.org/10.3390/su151310577

https://doi.org/10.1017/elr.2025.10045 Published online by Cambridge University Press

Manning A (2004) We can work it out: the impact of technological change on the demand for low-skill workers. *Scottish Journal of Political Economy* 51(5), 581–608. https://doi.org/10.1111/j.0036-9292.2004.00322.x

Marcolin L, Miroudot S and Squicciarini M (2019) To be (routine) or not to be (routine), that is the question: a cross-country task-based answer. *Industrial and Corporate Change* 28(3), 477–501. https://doi.org/10.1093/icc/dty020

Matsuura-Kannari M, Islam AMS and Tauseef S (2024) Mobile phones, income diversification, and poverty reduction in rural Bangladesh. Review of Development Economics 1–19. https://doi.org/10.1111/rode.13110

Moll B, Rachel L and Restrepo P (2022). Uneven growth: automation's impact on income and wealth inequality. *Econometrica*, 90(6), 2645–2683. https://doi.org/10.3982/ECTA19417

Ning G, Cui H and Fu W (2023) How does information technology development affect labour mobility across industries? An empirical study based on job tasks and skill types. *Journal of Management World* 8, 1–21. In Chinese

People.cn. (2024) Digital China construction has been further enhanced. Available at http://fj.people.com.cn/n2/2024/0602/c181466-40865685.html (accessed 18 July 2024). In Chinese

Ra S, Shrestha U, Khatiwada S, Yoon SW and Kwon K (2019) The rise of technology and impact on skills. *International Journal of Training Research* 17(sup1), 26–40. https://doi.org/10.1080/14480220.2019.1629727

Reijnders LT and Ye MP (2021) Labour demand in global value chains: is there a bias against unskilled work? *World Economy* 44(9), 2547–2571. https://doi.org/10.1111/twec.13092.

Schor JB, William A, Mehmet C, Isak L and Robert W (2020) Dependence and precarity in the platform economy. *Theory and Society* 49(5), 1–29. https://doi.org/10.1007/s11186-020-09408-y

Schwabe H and Castellacci F (2020) Automation, workers' skills and job satisfaction. *PLoS ONE* 15(11), e0242929. https://doi.org/10.1371/journal.pone.0242929.

Seemab A, Khan D and Haq I (2022) Assessing the role of information and communication technology in reducing the gap between rich and poor: the case of South Asia. *International Journal of Social Economics* 49(11), 1663–1679. https://doi.org/10.1108/IJSE-10-2021-0638

Shah CS and Krishnan S (2024) ICT, gender inequality, and income inequality: a panel data analysis across countries. *Information Systems Frontiers* 26(2), 709–727. https://doi.org/10.1007/s10796-023-10396-4

Staiger D and Stock JH (1997) Instrumental variables regression with weak instruments. *Econometrica* 65(3), 557. https://doi.org/10.2307/2171753

Tai CC (2010) Young rural workers' living ecologies and self-identification: From the perspective of "information-led". *Sociological Studies* 25(2),106–123. In Chinese

Tao R and Xu Z (2007) Urbanization, rural land system and social security for migrants in China. *The Journal of Development Studies* 43(7), 1301–1320. https://doi.org/10.1080/00220380701526659

The State Council of The People's Republic of China (2021) The 14th Five-Year Plan of the digital economy (2021–2025). Available at https://www.gov.cn/gongbao/content/2022/content_5671108.htm (accessed 17 July 2024) In Chinese

Van Dijk J (2020) *The Digital Divide*. Cambridge: Polity Press.

Wang X, Li X and Zhou H (2025) Digital finance use and household consumption inequality: Evidence from rural China. *Review of Development Economics* 29(3), 1. https://doi.org/10.1111/rode.13194.

Wisskirchen G, Biacabe BT, Bormann U, Muntz A, Niehaus G, Soler G and von Brauchitsch B (2017) Artificial intelligence and robotics and their impact on the workplace. *IBA Global Employment Institute* 11(5), 49–67.

Wolcott EL (2021) Employment inequality: Why do the low-skilled work less now? *Journal of Monetary Economics* 118, 161–177. https://doi.org/10.1016/j.jmoneco.2020.09.004.

Wood A J, Graham M, Lehdonvirta V and Hjorth I (2019) Good gig, bad gig: Autonomy and algorithmic control in the global gig economy. *Work, Employment and Society* 33(1), 56–75. https://doi.org/10.1177/0950017018785616

World Health Organization (WHO) (2021) Long working hours increasing deaths from heart disease and stroke. Available at https://www.who.int/news/item/17-05-2021-long-working-hours-increasing-deaths-from-heart-disease-and-stroke-who-ilo?utm_source=chatgpt.com (accessed 20 July 2025).

Wu M, Ma Y, Gao Y and Ji ZH (2024) The impact of digital economy on income inequality from the perspective of technological progress-biased transformation: evidence from China. *Empirical economic* 124, 106819. https://doi.org/10.1007/s00181-024-02563-6

Xin B and Ye X (2024) Robotics applications, inclusive employment and income disparity. *Technology in Society* 78, 102621. https://doi.org/10.1016/j.techsoc.2024.102621.

Xiong B and Sui Q (2025) The effect of digital economy on rural workforce occupation transformation ability: evidence from China. *Humanities And Social Sciences Communications* 12, 13. https://doi.org/10.1057/s41599-024-04326-1

Yamin MAY and Abdalatif OAA (2024) Examining consumer behavior towards adoption of quick response code mobile payment systems: transforming mobile payment in the fintech industry. *Humanities and Social Sciences Communications* 11(1), 1–11. https://doi.org/10.1057/s41599-024-03189-w

https://doi.org/10.1017/elr.2025.10045 Published online by Cambridge University Press

Ye R and Zhang Y (2025) The dynamic impact of industrial robot penetration on chain resilience: city evidence from China. *Systems* 13(5), 362. https://doi.org/10.3390/systems13050362

Zhang M (2025) The health cost of industrial automation: evidence from Chinese migrant workers. *Applied Economics* 1–16. https://doi.org/10.1080/00036846.2025.2522378

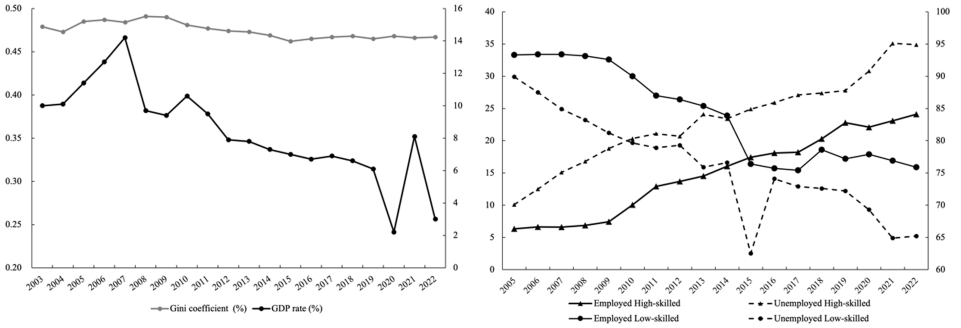
Zhang Y, Li Y, Zhuang X, Liu H, Xu Y, Zhang S, Yan Y and Li Y (2024) Can digital financial inclusion help reduce migrant workers' overwork? Evidence from China. *Frontiers in Public Health* 12. https://doi.org/10.3389/fpubh.2024.1357481

Zhao T, Zhang Z and Liang S (2020) Digital economy, entrepreneurship, and high-quality economic development: empirical evidence from urban China. *Journal of Management World* 10, 65–75. In Chinese

Zou J and Deng X (2022) To inhibit or to promote: how does the digital economy affect urban migrant integration in China? *Technological Forecasting and Social Change* 179, 1216–47. https://doi.org/10.1016/j.techfore.2022.121647.

Appendix A. Gini coefficient -GDP growth rate from 2003 to 2022 in China

Appendix B: The skill attainment composition of employed and unemployed workers in China



(Data souse: China Yearbook of household survey, 2023; China Social Statistical Yearbook, 2006-2023)

Cite this article: Che L, Liu Q, and Lu J (2026). How China's digital economy amplifies migrant workers' inequality through demand-supply mismatch. *The Economic and Labour Relations Review* **37**, 143–165. https://doi.org/10.1017/elr.2025.10045

https://doi.org/10.1017/elr.2025.10045 Published online by Cambridge University Press