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Automation Exposure, Occupational Mobility, and Income Inequality in China

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Abstract

This paper examines how automation exposure is associated with income, occupational mobility, and inequality in China. Using nationally representative longitudinal data from the China Family Panel Studies for 2014--2022, we link individual occupations to a Routine Task Intensity (RTI) index and complement this task-based measure with a Bartik-style index of exposure to imported industrial robots. The results show that routine-task exposure is associated with lower individual income, with larger losses among older and more educated workers. Distributional estimates indicate that these losses are strongest among middle- and higher-income routine workers, providing evidence of income compression among exposed workers. Occupational-mobility results show that routine-intensive workers are more likely to move upward in occupational-status terms, although this does not necessarily imply economic upgrading because these workers often begin from relatively low positions in the occupational hierarchy. Intergenerational estimates suggest that RTI operates as a downward level shock to both occupational attainment and income, while family background continues to shape exposure through occupational sorting. By contrast, robot exposure is positively associated with income and occupational status in the baseline reduced-form specification, consistent with productivity and task-reinstatement effects in provinces more exposed to imported industrial robots and robot-intensive industrial upgrading. The findings underscores show how automation interacts with institutional segmentation in emerging economies.

Keywords: Automation; Robots; Occupational Mobility; Inequality; China

JEL classification: O33, J24, J31, J62, D31, O53.

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1 Introduction

The rapid development of automation and artificial intelligence (AI) is reshaping global labour markets. To date, most empirical evidence on the consequences of automation for occupation dynamics and inequality comes from advanced industrialised economies such as the United States and Europe (Acemoglu and Restrepo, 2020; Brynjolfsson et al., 2017). Much less is known about how these dynamics unfold in developing countries, where institutional factors and labour market conditions differ markedly. By focusing on China, this paper provides large-scale worker-level evidence from a middle-income economy undergoing rapid structural transformation, industrial upgrading, and exceptionally rapid robot adoption.

The analysis is grounded in the task-based framework of technological change developed by Autor et al. (2003) and extended by Autor and Dorn (2013), which conceptualises jobs as bundles of tasks with differing susceptibility to automation. This framework predicts that routine tasks are most vulnerable to technological substitution, while non-routine cognitive and interactive tasks are more likely to be complemented. Building on this, Acemoglu and Restrepo (2018, 2020) formalise how automation reshapes labour markets by shifting the balance between task substitution and task creation.

In China, the effects of automation are mediated by institutional factors. For example, the hukou system restricts rural migrants' access to mobility and social protection.[1] (Knight and Song, 1999; Giles et al., 2019). Employment opportunities are further stratified by ownership type. The state-owned enterprises (SOEs) reforms in the 1990s caused massive urban layoffs and eliminated the lifetime employment system (Zhou, 2012). Nevertheless, the probability of obtaining stable employment in SOEs remains significantly higher than in the private sector (Zhu, 2023). SOEs often continue to shield employees from displacement. However, due to the exclusionary effects of the *hukou system*, low-skilled rural migrant workers are more likely to be systematically excluded from the state sector (Wu, 2024), which intensifies their vulnerability. Migrant workers, disproportionately employed in routine-intensive sectors, are therefore especially exposed to risks associated with automation adoption (Ge and Yang, 2014; Wang and Dong, 2020; Felten et al., 2021).

To measure potential automation exposure, we link Chinese occupational codes in the CFPS to internationally established task-based indices, including routine-task intensity (RTI) (Autor and Dorn, 2013), probabilities of computerization (Frey and Osborne, 2017), and AI-task exposure (Felten et al., 2021). The RTI index is constructed following the adjustment methodology proposed by Lewandowski et al. (2022), which accounts for cross-country heterogeneity in task content based on development levels. Additional benchmarks are drawn from cross-country studies such as Nedelkoska and Quintini (2018) and the World Bank (2016).

Our study contributes to the literature by providing the first large-scale, longer-term

[1] The hukou system is China's household registration system that records citizens' official place of residence and classifies them as rural or urban. Because access to schooling, healthcare, housing, and pensions is tied to hukou status, the system has long created an institutional divide. Urban hukou holders enjoy full entitlements, while rural hukou holders face restrictions when they migrate to cities. Although reforms since the 2010s have eased barriers in smaller cities, hukou remains a central determinant of labour mobility and inequality.

analysis of the associations between automation exposure, occupational mobility and income inequality in China, focusing on how institutional factors interact with technological change. Existing evidence has largely focused on advanced economies, particularly the United States and Europe, where automation has been studied mainly through its effects on employment, wages, and job polarisation (Autor et al., 2003; Autor and Dorn, 2013; Goos and Manning, 2007; Acemoglu and Restrepo, 2020). Much less is known about how automation affects workers in developing and middle-income economies, where technological adoption coincides with structural transformation, labour-market segmentation, and weaker systems of social protection. China provides a particularly important setting because it combines rapid robot adoption with a large manufacturing workforce, continuing rural–urban migration, and strong institutional stratification through the hukou system (Cheng et al., 2019; Fan et al., 2021a; Chan and Buckingham, 2008; Wu, 2024).

By using nationally representative longitudinal household survey data, this paper provides worker-level evidence on how potential automation exposure shapes income, occupational transitions, and intergenerational mobility.

We distinguish between potential exposure to automation and robot exposure. This distinction is important because task susceptibility and technology diffusion need not have the same labour-market effects. Routine-intensive occupations may face wage losses because their task content is more easily codified and substituted, while greater predicted exposure to robot-intensive industrial upgrading may be associated with higher income and occupational status if productivity and reinstatement effects dominate displacement (Graetz and Michaels, 2018; Acemoglu and Restrepo, 2020). The empirical results support this distinction: RTI is associated with lower income and greater labour-market vulnerability, whereas robot exposure is positively associated with both total income and occupational status. This pattern is consistent with productivity-based channels in provinces more exposed to robot-intensive industrial upgrading.

Contrary to trends in some Western economies, we find that higher RTI is associated with lower income inequality in China, because income shocks seem to be concentrated among high-income and middle-income routine workers. Much of the literature on advanced economies links routine-biased technological change to wage polarisation, as routine jobs are often concentrated in the middle of the wage distribution (Goos and Manning, 2007; Autor and Dorn, 2013; Goos et al., 2014; Acemoglu and Restrepo, 2022). In China, however, routine-intensive work is not confined to low-paid manual employment. It also appears in formal-sector, clerical, technical, and production jobs that occupy the middle and upper parts of the income distribution. As a result, automation exposure is associated with broad income losses but does not mechanically increase inequality. Instead, the larger income losses among higher-income routine workers compress the income distribution. This finding adds a China-specific perspective to the literature on automation and inequality and shows that the distributional consequences of automation depend on where routine tasks are located within the national occupational and income structure.

Finally, results from the intergenerational analysis suggest that automation compounds social disadvantage by sorting offspring from low-status families into vulnerable, routine-intensive occupations. While most studies of automation focus on contemporaneous labour-market outcomes, a smaller literature has begun to examine whether technological change affects intergenerational mobility (Guo, 2022; Heyman and Olsson, 2023). This paper extends that literature to China by showing that RTI operates mainly as a downward level shock to both occupational attainment and income. The results indicate that high routine intensity weakens the parent–child transmission, not because automation equalises opportunity, but because it lowers outcomes across parental-background groups. At the same time, family origin continues to shape exposure: children from disadvantaged backgrounds are more likely to enter routine-intensive occupations and therefore remain more vulnerable to automation-related income and status losses. In this sense, automation compresses outcomes within exposed occupational tiers while reinforcing inequality through occupational sorting.

The remainder of the paper is organised as follows. Section 2 reviews the literature on automation, focusing on task-based technological change, alternative measures of automation exposure and adoption, labour-market effects, and the evidence on China. Section 3 presents the empirical framework and identification strategy, including the wage, occupational mobility, distributional, intergenerational, and reduced-form robot-exposure specifications. Section 4 describes the data, the construction of the RTI index, the robot-exposure index, and the main variables used in the analysis. Section 5 reports the empirical results on income, occupational mobility, inequality, and intergenerational transmission. Section 6 presents robustness checks using alternative automation measures, sample restrictions, task-group classifications, and local digitalisation controls. Section 7 concludes.

2 Review of the Literature

The literature on automation and labour markets has moved from the question of whether machines replace workers to a more nuanced analysis of how technological change reallocates tasks, reshapes occupations, and alters the distribution of income and opportunity (Autor et al., 2003; Autor and Dorn, 2013; Goos and Manning, 2007; Acemoglu and Restrepo, 2020). Three insights are particularly relevant for this paper. First, automation affects workers through the task content of occupations rather than through occupations as indivisible units (Autor et al., 2003; Acemoglu and Autor, 2011; Autor and Dorn, 2013). Second, the labour-market effects of automation depend on the balance between displacement effects, productivity effects, and reinstatement effects (Acemoglu and Restrepo, 2018, 2020; Graetz and Michaels, 2018). Third, these effects are mediated by labour-market institutions, education systems, migration regimes, and family background (Knight and Song, 1999; Giles et al., 2019; Li et al., 2017; Wu, 2024; Guo, 2022; Fan et al., 2021b). These mechanisms are especially important in the Chinese context, where rapid robot adoption, structural transformation, hukou segmentation, and intergenerational inequality interact in distinctive ways (Cheng et al., 2019; Fan et al., 2021a; Cai and Du, 2011; Kanbur and Zhang, 2005; Chan and Buckingham, 2008; Fan et al., 2021b).

2.1 Task-based technological change and automation exposure

The starting point for most empirical work is the task-based framework developed by Autor et al. (2003). In this approach, jobs are understood as bundles of tasks rather than as homogeneous units of labour. Technological change substitutes for tasks that are codifiable, repetitive, and rule-based, while complementing tasks that require analytical reasoning, interpersonal interaction, adaptability, or problem solving. This distinction is central because automation does not necessarily eliminate entire occupations. Rather, it changes the relative demand for different task components within and across occupations.

Building on this framework, Autor and Dorn (2013) show that routine-biased technological change can explain the polarisation of employment in advanced economies. Routine-intensive middle-skill occupations are particularly exposed to technological substitution, while employment grows in high-skill abstract jobs and low-skill non-routine service jobs. This task-based account has become the dominant framework for studying automation because it links technological change to observable occupational characteristics. It also provides the empirical rationale for using Routine Task Intensity (RTI) as a measure of potential automation exposure.

Subsequent theoretical work formalises the mechanisms through which automation affects labour demand. Acemoglu and Restrepo (2018) model the interaction between labour and machines as a race between technological substitution and the creation of new tasks. In their framework, automation reduces labour demand when machines take over tasks previously performed by workers, but technological change may also reinstate labour by creating new tasks in which workers have a comparative advantage. The displacement effect reduces labour demand in automated tasks, while the productivity effect can raise output, lower prices, and increase labour demand elsewhere. This distinction is important for the present study because RTI captures potential exposure to task substitution, whereas robot-based measures capture realised technological adoption that may also embody productivity and reinstatement effects.

2.2 Measuring automation: exposure, adoption, and task susceptibility

Because automation adoption is not directly observed in most labour-force surveys, the empirical literature has relied on a range of indirect methods to measure or approximate workers' exposure to technological substitution (Autor et al., 2003; Acemoglu and Autor, 2011; Acemoglu and Restrepo, 2020; Lewandowski et al., 2022). These methods differ in what exactly they capture. Some measure the upstream creation of automation technologies, often through patent texts or technology classifications (Mann and Püttmann, 2023; Webb, 2019; Kogan et al., 2023). Others record the diffusion of automation capital across firms, industries, or regions, particularly through industrial robot data or firm-level technology adoption surveys (Graetz and Michaels, 2018; Acemoglu and Restrepo, 2020; Fan et al., 2021a; Acemoglu et al., 2022). A third group approximates exposure through the task content of jobs, especially the extent to which occupations involve routine, codifiable, and repetitive tasks (Autor et al., 2003; Autor and Dorn, 2013; Lewandowski et al., 2020, 2022). The choice of indicator is consequential because each measure corresponds to a different conceptual stage in the automation process: invention, adoption, diffusion, or susceptibility (Frey and Osborne, 2017; Nedelkoska and Quintini, 2018; Felten et al., 2021; World Bank, 2016).

Patent-based measures capture the direction of technological innovation. They identify the development of potentially labour-saving technologies, including robotics, machine control systems, machine vision, software, and artificial intelligence (Mann and Püttmann, 2023; Webb, 2019; Felten et al., 2021). These indicators are useful for assessing whether economies are moving toward greater automation potential before technologies are embodied in capital stocks or observed in firms. However, patents do not measure realised adoption. Many patented technologies are never commercialised, and even successful inventions may diffuse slowly across firms and regions (Mann and Püttmann, 2023; Acemoglu et al., 2022). Patent indicators are therefore best interpreted as measures of technological opportunity rather than direct measures of worker-level exposure.

Robot-based measures provide a more concrete indicator of realised automation diffusion. The International Federation of Robotics (IFR) provides annual data on robot installations and operational stocks by country and industry, making it possible to construct measures of robot density or robot-exposure. Graetz and Michaels (2018) use cross-country IFR data to show that robot adoption raised productivity growth across advanced economies, while Acemoglu and Restrepo (2020) combine IFR data with baseline local employment shares to estimate regional exposure to robots. Robot-based measures are especially useful in manufacturing, where industrial robots are a visible and measurable form of automation capital. Yet they also have limitations. They are usually observed at the industry rather than worker level, capture manufacturing more effectively than services, and miss broader forms of technological change associated with software, logistics, digital platforms, and AI-enabled task restructuring.

Firm-level surveys and administrative records provide another way to observe realised adoption. These data can identify whether firms introduce automated machinery, digital production systems, industrial robots, software, or AI-based technologies (Koch et al., 2021; Acemoglu et al., 2022). In China, related evidence suggests that rising labour costs and industrial upgrading pressures have been important drivers of robot adoption (Fan et al., 2021a; Cheng et al., 2019). Firm-level data can capture forms of automation not visible in robot statistics, but they often rely on self-reporting, are difficult to compare across surveys, and are not always linkable to household-level longitudinal data. They reveal whether firms automate, but not necessarily which workers or occupations are most exposed.

Task-based measures offer a conceptually different approach. Rather than measuring technologies themselves, they measure the task content of jobs. RTI captures the extent to which occupations are dominated by routine tasks relative to non-routine tasks. Although alternative formulations exist, the general structure of the RTI index follows the same logic:

$$RTI_o = Routine_o - NonRoutine_o, \tag{1}$$

or, in relative terms,

$$RTI_o = \ln(Routine_o) - \ln\left(\frac{NonRoutine_o^{analytical} + NonRoutine_o^{interpersonal}}{2}\right), \tag{2}$$

where the index for occupation o increases with the importance of repetitive and codifiable tasks and declines with the importance of analytical and interpersonal content.

The appeal of RTI is both theoretical and empirical. Theoretically, it aligns closely with the task-based model of automation, in which technological substitution operates by replacing routine tasks and complementing non-routine ones (Autor et al., 2003; Acemoglu and Autor, 2011; Autor and Dorn, 2013). Empirically, RTI can be assigned at the occupation level and merged directly into household or labour-force surveys using occupational codes (Lewandowski et al., 2020, 2022; Das and Hilgenstock, 2022). This makes it particularly well suited to studying wage effects, occupational mobility, employment transitions, and distributional outcomes (Autor and Dorn, 2013; Du and Wei, 2020; Das and Hilgenstock, 2022; Martins-Neto et al., 2024). Unlike robot density, RTI is not confined to manufacturing. Unlike firm-level adoption measures, it can be linked consistently to individuals in household survey data. And unlike patent-based measures, it captures exposure on the demand side of work rather than innovation on the supply side of technology.

The RTI approach is especially important in developing and middle-income economies, where direct task surveys are often unavailable and occupational task content may differ from that observed in advanced economies. Researchers have therefore mapped task measures from sources such as O*NET onto international occupational classifications and calibrated the resulting indices to country-specific contexts (Lewandowski et al., 2022; Das and Hilgenstock, 2022; Martins-Neto et al., 2024). Lewandowski et al. (2020) show that the task content of occupations varies systematically with levels of development, implying that the same occupational code may involve different degrees of routine work across countries. For this reason, applying unadjusted U.S. task scores to China may introduce measurement error. The adjustment methodology proposed by Lewandowski et al. (2022), and further applied in related work such as Gradín et al. (2023), is therefore important because it allows the task structure of occupations to vary with development levels and country-specific labour-market conditions.

Occupation-level risk indices provide a further way to measure potential exposure. Frey and Osborne (2017) estimate the probability that occupations can be computerised, while Felten et al. (2021) construct measures of occupational exposure to artificial intelligence. Nedelkoska and Quintini (2018) and the World Bank (2016) further show that automation risk varies across countries because the same occupation may involve different tasks in economies at different stages of development. These measures are useful benchmarks, but they are less directly aligned with the longitudinal worker-level analysis in this paper than RTI. For this reason, this paper adopts RTI as the main occupation-level measure of potential automation exposure and complements it with a Bartik-style measure of exposure to imported industrial robots.

2.3 Automation, employment, wages, and inequality

A large empirical literature examines whether automation reduces employment and wages. The evidence does not support a single universal conclusion. Instead, the estimated effects depend on the type of technology, the level of aggregation, and the structure of the local labour market. Studies of routine-biased technological change generally show that workers in routine-intensive occupations face declining relative demand. Autor and Dorn (2013) show that computerisation contributed to the growth of low-skill service work and the decline of routine employment in the United States. Goos and Manning (2007) provide related evidence for Britain, showing the rise of ‘lovely” high-wage jobs and ‘lousy” low-wage jobs alongside the decline of middle-wage routine occupations.

Robot-based evidence is more mixed. Graetz and Michaels (2018) find that robots increase labour productivity and economic growth across advanced economies. Their results suggest that automation can raise aggregate output and may not necessarily reduce total employment. By contrast, Acemoglu and Restrepo (2018) find negative effects of robots on employment and wages in U.S. commuting zones more exposed to robot adoption. These findings are not necessarily contradictory. Aggregate productivity gains can coexist with concentrated local losses if displaced workers face mobility frictions, skill mismatch, or limited access to expanding sectors.

The wage effects of automation are also heterogeneous. The task-based literature predicts that workers performing routine tasks should face wage losses, while workers performing non-routine analytical, interpersonal, or technical tasks may benefit from complementarity with technology (Autor et al., 2003; Acemoglu and Autor, 2011). This prediction is consistent with evidence on wage polarisation, changing returns to ICT-related skills, and the rising value of non-routine cognitive and social tasks (Goos and Manning, 2007; Autor and Dorn, 2013; Goos et al., 2014; Michaels et al., 2014; Deming, 2017; Acemoglu and Restrepo, 2022). At the same time, the distributional effects of automation depend on where routine tasks are located in the income distribution. In advanced economies, routine work has often been concentrated in middle-wage occupations, producing employment and wage polarisation (Goos and Manning, 2007; Autor and Dorn, 2013; Goos et al., 2014; Acemoglu and Restrepo, 2022). In developing and middle-income economies, however, routine tasks may be distributed differently across occupational and income hierarchies because structural transformation, informality, education systems, and uneven technology adoption shape the task composition of work (Lewandowski et al., 2020, 2022; Das and Hilgenstock, 2022; Martins-Neto et al., 2024). This opens the possibility that automation can compress rather than widen measured income inequality if income losses are concentrated among middle- or upper-middle-income routine workers.

This distinction is central to the present paper. Rather than assuming that automation has uniform distributional effects, the analysis examines whether potential automation exposure is associated with different income losses across the distribution, and whether these losses resemble the polarisation patterns documented in advanced economies. It also examines whether robot exposure has the same association with labour-market outcomes as RTI. This distinction matters because routine-intensive occupations may face wage losses due to task substitutability, while greater exposure to robot-intensive industrial upgrading may be associated with higher income or occupational status if productivity and reinstatement effects dominate displacement.

2.4 Automation in China: structural transformation and institutional mediation

Most influential empirical studies of automation have focused on advanced economies (Acemoglu and Restrepo, 2018; Martins-Neto et al., 2024). However, the effects of automation may differ in developing and middle-income economies for several reasons. First, the relative price of labour and capital differs across economies, affecting the incentives for firms to substitute machines for workers. Second, occupational task content varies with development levels, so the same occupation may involve different degrees of routine or non-routine work across countries (Lewandowski et al., 2022; Das and Hilgenstock, 2022). Third, labour-market institutions, informality, migration regimes, and social protection systems affect the ability of workers to adjust to technological change (Chan and Buckingham, 2008; Wu, 2024; Zhu, 2023). Fourth, automation in structurally transforming economies may occur simultaneously with labour reallocation from agriculture to manufacturing and services, making its effects difficult to separate from broader changes in the composition of employment (Cai and Du, 2011; Ge and Yang, 2014; Martins-Neto et al., 2024).

China is a particularly important case because it combines rapid automation adoption with a large manufacturing workforce and continuing rural–urban labour reallocation (Cheng et al., 2019; Fan et al., 2021a; Cai and Du, 2011). The rise of robots in China reflects rising wages, demographic change, industrial upgrading, and state-led strategies to promote advanced manufacturing (Cheng et al., 2019; Fan et al., 2021a; Ge and Yang, 2014). At the same time, China's experience differs from that of advanced economies because automation interacts with migration, hukou status, regional inequality, and the changing role of state and private sectors (Chan and Buckingham, 2008; Kanbur and Zhang, 2005; Wu, 2024; Zhu, 2023; Gai et al., 2025).

The hukou system is central to understanding labour-market adjustment in China. Rural migrants have historically supplied labour to manufacturing, construction, and urban services, but they often face restricted access to urban welfare, schooling, housing, and social insurance. Earlier studies of rural–urban labour-market segmentation, including Knight and Song (1999) and Giles et al. (2019), show that migration opportunities have been shaped by institutional barriers as well as market forces. More recent work, such as Wu (2024), emphasises that hukou status continues to structure access to stable employment and social protection.

This institutional segmentation matters for automation in at least three ways. First, rural hukou workers may be more likely to be concentrated in routine-intensive occupations, increasing their potential exposure to automation-related displacement. Second, migrant workers may be geographically mobile but institutionally immobile: they can move across cities or jobs without gaining equal access to urban welfare and public services. Third, hukou status affects the capacity to absorb shocks. Workers with urban hukou may have better access to social insurance and public-sector employment, while rural migrants may face greater risks of informalisation, return migration, or labour-force detachment.

Ownership structure also shapes exposure and adjustment. The restructuring of state-owned enterprises in the 1990s ended the lifetime employment system and generated large-scale layoffs (Zhou, 2012). However, state-sector employment continues to provide greater job stability than many private-sector jobs (Zhu, 2023). Because rural migrants and low-skilled workers are less likely to enter protected state-sector employment, automation may reinforce existing institutional inequalities. The relevance of hukou and ownership structure distinguishes China from much of the Western automation literature, where labour-market segmentation exists but is organised through different institutions.

The Chinese evidence therefore raises a key conceptual distinction between potential automation exposure and reduced-form exposure to robot-intensive industrial upgrading. RTI captures whether a worker's occupation contains tasks that are susceptible to substitution, following the task-based approach to technological change (Autor et al., 2003;

Acemoglu and Autor, 2011; Autor and Dorn, 2013; Lewandowski et al., 2022). Robot exposure, by contrast, captures whether automation capital has diffused across provinces or industries (Graetz and Michaels, 2018; Acemoglu and Restrepo, 2020; Cheng et al., 2019; Fan et al., 2021a). These two measures need not have the same effects. High RTI may be associated with wage losses because routine task content lowers workers' bargaining position and future income prospects (Autor and Dorn, 2013; Acemoglu and Restrepo, 2022; Das and Hilgenstock, 2022). Greater exposure to robot-intensive industrial upgrading may increase income and occupational status if productivity effects and task-reinstatement effects dominate displacement (Graetz and Michaels, 2018; Cheng et al., 2019; Fan et al., 2021a). This paper uses this distinction to examine whether potential automation exposure and robot exposure are associated with different labour-market outcomes in China.

2.5 Automation, occupational mobility, and intergenerational mobility

A related literature studies how workers move across occupations in response to technological change. In theory, automation can generate both upward and downward mobility. Workers displaced from routine tasks may move into higher-status non-routine occupations if they possess transferable skills, education, and networks. Alternatively, they may move downward into lower-paid service work, informal employment, or non-employment if their task-specific human capital loses value.

The task-based literature predicts that mobility depends strongly on the transferability of skills. Workers with occupation-specific human capital may suffer larger losses when routine tasks are displaced because their accumulated experience is less valuable outside the original occupation. This mechanism is especially important for older workers. Autor and Dorn (2009) show that occupational specificity raises adjustment costs and makes displaced workers more likely to move downward rather than upward. Related evidence from Lordan and Neumark (2018) indicates that older workers in automatable occupations face particularly sharp employment losses.

In the Chinese case, occupational mobility must be interpreted carefully. This paper measures occupational status using the International Socio-Economic Index of Occupational Status (ISEI), while automation exposure is measured using RTI. Since routine-intensive workers may begin near the bottom of the occupational-status ladder, some transitions from routine jobs may appear as upward mobility in ISEI terms even when they do not generate income gains. Occupational upgrading in status does not necessarily imply economic upgrading in wages. A worker moving from a routine factory job to a low-skill service job may receive a higher occupational-status score while experiencing lower earnings. This distinction is important for interpreting the mobility results.

The literature on structural transformation in China provides a useful background for this interpretation. Rising wages and tightening labour supply have changed the structure of low-skilled work (Cai and Du, 2011). At the same time, regional labour-market development and local industrial upgrading affect whether workers can move into better occupations (Liao and Wei, 2018; Fan et al., 2021a). Education plays a central role in this adjustment process. Workers with more schooling are better able to move into non-routine and higher-status occupations, while workers with fewer years of schooling remain more exposed to downward mobility or labour-force exit (Wang, 2025). These mechanisms motivate the paper's focus on heterogeneity by education, age, gender, hukou status, and province.

A smaller but growing literature examines whether automation affects intergenerational mobility. Most automation studies focus on workers' current employment, wages, and occupational adjustment (Graetz and Michaels, 2018; Guo, 2022; Gai et al., 2025), while intergenerational mobility studies focus on the transmission of income, education, and occupational status across parents and children (Nybom and Stuhler, 2016; Lo Bello and Morchio, 2022; Fan et al., 2021b; Deng et al., 2013). The connection between these literatures is still underdeveloped, particularly in developing and middle-income economies, where technological change often coincides with structural transformation, migration, and institutional segmentation (Martins-Neto et al., 2024; Chan and Buckingham, 2008; Wu, 2024).

Automation can influence intergenerational mobility through several channels. First, parental exposure to automation may reduce household income and limit investment in children's education. This mechanism is consistent with broader evidence that parental labour-market shocks can affect children's schooling and later economic outcomes (Oreopoulos et al., 2008; Rege et al., 2011; Hilger, 2016). Second, children from disadvantaged families may be more likely to enter routine-intensive occupations because they have less access to higher education, urban networks, or protected employment (Li et al., 2017; Giles et al., 2019; Chan and Buckingham, 2008; Wu, 2024). Third, automation may alter the returns to parental resources. If family background helps children avoid routine work, automation may strengthen intergenerational persistence. If routine-task exposure imposes broad losses regardless of background, it may attenuate the observed parent–child gradient while lowering absolute outcomes for many children (Guo, 2022; Heyman and Olsson, 2023; Lo Bello and Morchio, 2022).

The empirical evidence remains mixed. Some studies find that automation shocks are concentrated among children from disadvantaged backgrounds, thereby reinforcing intergenerational inequality. Evidence from Sweden, for example, suggests that automation exposure can have intergenerational consequences that are stronger among low-income families (Heyman and Olsson, 2023). Other work suggests that automation can operate as a general downward shock to occupational attainment, reducing outcomes across family-origin groups rather than only among the disadvantaged (Guo, 2022). These differences may reflect national variation in welfare systems, education access, labour-market institutions, and the distribution of routine jobs (Martins-Neto et al., 2024; Lewandowski et al., 2022).

For China, the intergenerational consequences of automation are likely to be shaped by hukou status, educational inequality, regional development, and family background. Children from rural or low-status families may be more likely to enter routine-intensive occupations because of constrained schooling and weaker urban networks (Knight and Song, 1999; Chan and Buckingham, 2008; Giles et al., 2019; Li et al., 2017). Existing evidence shows substantial intergenerational income persistence in China, particularly in urban settings, and suggests that rapid growth has not eliminated the transmission of advantage across generations (Deng et al., 2013; Fan et al., 2021b). This paper therefore examines whether the association between parental background and child outcomes varies across occupations with different levels of routine-task intensity, while recognising that child RTI is itself partly the outcome of occupational sorting.

3 Methodology

This section sets out the methodological framework used to examine the relationship between automation exposure, labour-market outcomes, occupational mobility, and intergenerational inequality in China. The empirical strategy is grounded in the task-based approach to technological change (Autor et al., 2003; Acemoglu and Restrepo, 2022). The central premise is that automation does not affect workers directly as undifferentiated units of labour, but operates through the task content of occupations. Occupations with a larger share of routine tasks are more exposed to substitution by automation capital, while occupations intensive in non-routine analytical, interpersonal, or adaptive manual tasks may be less directly substitutable and, in some cases, complementary to automation.

3.1 Task-based framework and automation exposure

To begin the discussion, consider an economy in which output in sector j at time t is produced using a continuum of tasks indexed by $m \in [0, 1]$. Tasks differ in the extent to which they are routine. Let $r(m) \in [0, 1]$ denote the degree of routineness of task m, with higher values indicating that the task is easier to codify and automate. Sectoral output is produced according to the constant-elasticity-of-substitution task aggregator

$$Y_{jt} = A_{jt} \left[\int_0^1 x_{jt}(m)^{\frac{\sigma-1}{\sigma}} \, dm \right]^{\frac{\sigma}{\sigma-1}}, \qquad \sigma > 1, \tag{3}$$

where A_{jt} is sector-specific productivity, $x_{jt}(m)$ is the quantity of task m performed in sector j, and σ is the elasticity of substitution across tasks.

Each task can be performed either by labour or by automation capital. Let $l_{jt}(m)$ denote labour input and $k_{jt}(m)$ automation capital. Let $\omega_{jt}(m)$ denote the unit cost of performing task m with labour and $c_{jt}(m)$ the unit cost of performing the same task with automation capital. For routine tasks, automation is a closer substitute for labour. Firms therefore choose the lower-cost input:

$$x_{jt}(m) = \begin{cases} l_{jt}(m), & \text{if } \omega_{jt}(m) \leq c_{jt}(m), \\ k_{jt}(m), & \text{if } c_{jt}(m) < \omega_{jt}(m). \end{cases} \tag{4}$$

A decline in the cost of automation for routine tasks expands the set of tasks for which firms prefer capital to labour,

$$\mathcal{A}_{jt} = \{ m \in [0, 1] : c_{jt}(m) < \omega_{jt}(m) \}. \tag{5}$$

This generates a displacement effect for workers performing routine tasks. At the same time, automation may raise the productivity of workers engaged in non-routine tasks that complement automated production, generating a reinstatement or complementarity effect.

Occupations bundle together tasks with different degrees of routineness. Let occupation o be characterised by a task-weighting function $b_o(m)$, where $\int_0^1 b_o(m)\,dm = 1$. The routine content of occupation o can be written as

$$R_o = \int_0^1 b_o(m) r(m)\,dm, \tag{6}$$

while the non-routine content is denoted by N_o. The occupation-level routine task intensity index is then defined as

$$RTI_o = R_o - N_o. \tag{7}$$

A higher value of RTI_o indicates that the occupation is more exposed to automation-induced task substitution. In the empirical analysis presented below, RTI_o is assigned to individuals according to their occupation and, where relevant, standardised to ease interpretation.

3.2 Wage returns and heterogeneous effects

Workers differ in observed productivity-related characteristics, including education, age, gender, hukou status, and family background. Let worker i, employed in occupation $o(i,t)$ at time t, have effective productivity

$$h_{it} = \exp\left(\alpha_0 + \alpha_1 Edu_i + \alpha_2 Age_{it} + \alpha_3 Age_{it}^2 + \alpha_4 Urban_i + \alpha_5 Male_i + \alpha_6 B_i\right), \tag{8}$$

where Edu_i denotes schooling, $Urban_i$ indicates urban hukou status, $Male_i$ is a gender indicator, and B_i captures family background, proxied by parental income or parental occupational status. Since $\ln h_{it}$ is linear in observed worker characteristics, the empirical wage specification includes these characteristics directly through a vector of controls.

The baseline wage equation is

$$\ln W_{it} = \beta_0 + \beta_1 RTI_{o(i,t)} + X_{it}'\Gamma + \mu_p + \lambda_s + \tau_t + \upsilon_c + \varepsilon_{it}, \tag{9}$$

where $\ln W_{it}$ denotes log annual income, X_{it} is a vector of individual-level controls, μ_p denotes province fixed effects, λ_s sector or industry fixed effects, τ_t survey-wave fixed effects, and υ_c birth-cohort fixed effects. Here, $RTI_{o(i,t)}$ denotes the routine-task intensity of the occupation held by individual i at time t. The underlying occupation-level RTI score is fixed after task adjustment, but individual exposure may vary over time when workers change occupations. The expected sign of β_1 is negative: occupations with higher RTI are more exposed to automation-induced task substitution, which is expected to reduce the value of labour performing those tasks.

To examine whether the association between routine-task exposure and income differs across worker characteristics, the baseline specification is extended by interacting RTI with selected individual characteristics:

$$\ln W_{it} = \beta_0 + \beta_1 RTI_{o(i,t)} + X_{it}'\Gamma + \left(RTI_{o(i,t)} \times H_{it}\right)'\Pi + \mu_p + \lambda_s + \tau_t + \upsilon_c + \varepsilon_{it}, \tag{10}$$

where H_{it} includes characteristics such as education and age. The interaction coefficients in Π indicate whether the wage penalty or premium associated with routine task exposure differs across worker groups. For example, a negative interaction between RTI and education would suggest that changes in earnings associated with education are weaker in routine-intensive occupations, consistent with the idea that such jobs make less use of advanced analytical or problem-solving skills. Similarly, a negative interaction between RTI and age would imply that older workers face steeper wage losses in routine-intensive occupations, possibly because of higher adjustment costs when tasks are displaced.

3.3 Identification strategy

The identification strategy relies on high-dimensional fixed effects to mitigate omitted-variable bias arising from unobserved regional, industrial, cohort, and temporal heterogeneity (Correia, 2011). By absorbing survey waves, birth cohorts, provinces, and industries, the specification nets out aggregate technological trends, regional economic disparities, cohort-specific labour-market conditions, and sector-specific production technologies. Because workers are not randomly assigned to occupations, the RTI estimates may still reflect unobserved sorting into routine-intensive jobs. The resulting estimates should therefore be interpreted as conditional associations between occupational task content and labour-market outcomes, rather than as unrestricted causal effects. Standard errors are clustered at the individual level in longitudinal specifications to account for serial correlation and heteroscedasticity within individuals over time.

3.4 Occupational mobility

The second part of the analysis examines occupational mobility. Workers may remain in their current occupational position, move upward, move downward, or exit employment. Occupational status is proxied by the International Socio-Economic Index of Occupational Status (ISEI). Let

$$\Delta ISEI_{i,t+1} = ISEI_{i,t+1} - ISEI_{it}. \tag{11}$$

Mobility outcomes are classified into six mutually exclusive categories:

$$Move_{i,t+1} \in \{Exit,\ SharpDown,\ SlightDown,\ Stay,\ SlightUp,\ SharpUp\}. \tag{12}$$

The categories are defined as follows: *Stay* corresponds to $-2 \leq \Delta ISEI_{i,t+1} \leq 2$; *SlightDown* corresponds to $-10 < \Delta ISEI_{i,t+1} < -2$; *SharpDown* corresponds to $\Delta ISEI_{i,t+1} \leq -10$; *SlightUp* corresponds to $2 < \Delta ISEI_{i,t+1} < 10$; and *SharpUp* corresponds to $\Delta ISEI_{i,t+1} \geq 10$. The *Exit* category captures transitions out of employment and is included to reduce selection bias arising from labour-market displacement.

The mobility model is motivated by a latent-value framework. Let the systematic value of choosing mobility state k at time $t+1$ be

$$\widetilde{V}_{ikt+1} = \alpha_k + \delta_k RTI_{o(i,t)} + X'_{it}\gamma_k + \mu_{pk} + \lambda_{sk} + \tau_{tk}, \tag{13}$$

where k indexes the mobility outcome. The vector X_{it} includes individual characteristics that affect both expected returns and mobility costs, such as education, age, gender, hukou status, marital status, and family background. These variables capture reallocation frictions such as limited access to information, weaker networks, rural hukou constraints, and age-related adjustment costs. Formally, these costs can be represented as

$$C_{ik} = \kappa_{0k} - \kappa_{1k} Edu_i - \kappa_{2k} Networks_i + \kappa_{3k} Rural_i + \kappa_{4k} Age_{it}. \tag{14}$$

Higher education and stronger networks are expected to reduce mobility costs, while rural hukou status and age are expected to increase them.

Assuming that the idiosyncratic shocks to latent values are independently distributed type-I extreme value, the transition probability takes the multinomial-logit form

$$Pr(Move_{i,t+1} = k \mid RTI_{o(i,t)}, X_{it}) = \frac{\exp\left(\widetilde{V}_{ikt+1}\right)}{\sum_{h \in \mathcal{K}} \exp\left(\widetilde{V}_{iht+1}\right)}, \tag{15}$$

where $\mathcal{K}$ denotes the set of six mobility outcomes. In estimation, *Stay* is used as the reference category. The coefficients are therefore interpreted as relative changes in the likelihood of entering each mobility state compared with remaining in a similar occupational position.

3.5 Distributional effects

The third part of the analysis examines whether routine task exposure contributes to aggregate inequality. To assess distributional effects, the paper estimates unconditional quantile regressions using the recentered influence function (RIF). For a given unconditional quantile q_τ of log income, the RIF is defined as

$$RIF(\ln W_{it}; q_\tau) = q_\tau + \frac{\tau - \mathbf{1}\{\ln W_{it} \leq q_\tau\}}{f_{\ln W}(q_\tau)}, \tag{16}$$

where $f_{\ln W}(q_\tau)$ is the density of log income evaluated at the τth quantile. The RIF regression is then

$$RIF(\ln W_{it}; q_\tau) = \alpha_\tau + \beta_\tau RTI_{o(i,t)} + X_{it}'\Gamma_\tau + \mu_p + \lambda_s + \tau_t + \upsilon_c + \varepsilon_{it\tau}. \tag{17}$$

Estimating Equation (17) at different quantiles allows the analysis to assess whether routine-task exposure has stronger associations with income at the bottom, middle, or top of the income distribution. The same RIF logic is also applied to the Gini coefficient, using the recentered influence function for the Gini as the dependent variable in an analogous fixed-effects regression.

3.6 Intergenerational transmission

To examine intergenerational transmission, let B_i^p denote parental background, measured by parental ISEI or parental income. The child's labour-market outcome is modelled as

$$Y_i^c = \rho_0 + \rho_1 B_i^p + \rho_2 RTI_i^c + \rho_3 \left(B_i^p \times RTI_i^c\right) + X_i'\Gamma + \mu_p + \lambda_s + \tau_t + u_i, \tag{18}$$

where Y_i^c is either the child's occupational status, measured by ISEI, or the child's log annual income, and RTI_i^c denotes the routine-task intensity of the child's occupation. The fixed-effect structure varies across specifications and includes province, industry, and survey-wave effects, represented by μ_p, λ_s, and τ_t. The coefficient ρ_1 captures intergenerational persistence in the absence of routine-task exposure, while ρ_2 captures the direct association between task exposure and the child's labour-market outcome. The key coefficient is ρ_3. If routine-task exposure mainly operates as a common downward shock, then RTI_i^c should reduce occupational attainment or income regardless of parental background, while ρ_3 should be small. If routine task exposure amplifies background inequality, then ρ_3 should be positive when the outcome is advantageous status or income, indicating that children from more advantaged families are better able to avoid or offset the consequences of routine-task exposure.

3.7 Reduced-form robot exposure

Finally, the analysis complements the occupation-level RTI measure with a reduced-form Bartik-style index of exposure to imported industrial robots. RTI captures potential exposure to automation at the occupational level, whereas the Bartik-style index captures predicted provincial exposure to imported industrial robots, weighted by pre-existing exposure to robot-intensive industries. For simplicity, we refer to this index as robot exposure in the remainder of the paper. Because direct robot adoption is not observed at the worker or firm level in the CFPS, this measure is used as a reduced-form proxy for exposure to automation diffusion. Importantly, the index captures exposure to imported industrial robots, not total robot adoption, because domestically produced robots and firm-level use of automation capital are not directly observed.

The robot-exposure index allocates national growth in imported industrial robots to provinces according to predetermined industrial employment shares:

$$Bartik_{pt} = \sum_{j=1}^{13} Share_{pj,2015} \times W_j \times \text{ImportGrowth}_t. \tag{19}$$

Here, $Share_{pj,2015}$ is the share of province p's employment in industry j in the base year:

$$Share_{pj,2015} = \frac{Employment_{pj,2015}}{Employment_{p,2015}}. \tag{20}$$

Using base-year employment shares reduces the risk that the exposure index reflects endogenous labour reallocation during the sample period.

The term W_j captures industry-level susceptibility to robot adoption:

$$W_j = \frac{\Delta Robot_j}{\sum_{h=1}^{13} \Delta Robot_h}, \tag{21}$$

where $\Delta Robot_j$ denotes the increase in robot penetration in industry j over a pre-sample or baseline period. This component captures the fact that some industries, such as motor-vehicle manufacturing, are technically more susceptible to robot adoption than others.

The national growth in imported industrial robots is denoted by $ImportGrowth_t$ and defined as

$$\text{ImportGrowth}_t = \frac{TotalRobotImports_t}{TotalRobotImports_{2015}}. \tag{22}$$

The baseline reduced-form specification includes survey-wave fixed effects and industry fixed effects, while standard errors are clustered at the province level. This specification uses cross-provincial differences in predetermined exposure to robot-intensive industries, interacted with national growth in imported industrial robots. We also report a more demanding province fixed-effect specification as a robustness check in the Appendix. Because the robot-exposure index is constructed from fixed baseline provincial industry shares and a common national import-growth factor, the province fixed-effect specification absorbs much of the cross-provincial exposure variation and is therefore interpreted as a stricter within-province sensitivity test.

The baseline reduced-form outcome specification is

$$Y_{ijpt} = \alpha_0 + \alpha_1 Bartik_{pt} + X'_{it}\Gamma + \theta_j + \mu_t + \varepsilon_{ijpt}. \tag{23}$$

Here, Y_{ijpt} denotes either log annual income or occupational status, measured by ISEI. The term θ_j denotes industry fixed effects and μ_t denotes survey-wave fixed effects. The coefficient α_1 captures the reduced-form association between predicted provincial exposure to imported industrial robots and the outcome of interest. The Bartik index shows whether workers in provinces with greater baseline exposure to robot-intensive industries experience different labour-market outcomes when imports of industrial robots increase. Since the Bartik index varies at the province-year level, standard errors in these specifications are clustered at the province level.

3.8 Task-group heterogeneity in robot exposure

The robot-exposure analysis is then combined with the task-based classification of occupations. Let $TaskGroup_i$ classify the worker's occupation into one of five dominant task-content families: non-routine cognitive analytical (NRCA), non-routine cognitive personal (NRCP), non-routine manual (NRM), routine cognitive (RC), and routine manual (RM). Heterogeneity by task group is estimated as

$$\begin{aligned} \ln W_{ijpt} = \alpha_0 + \beta_0 Bartik_{pt} + \sum_{g \neq g_0} \beta_g \left(Bartik_{pt} \times \mathbf{1}\{TaskGroup_i = g\}\right) \\ + \sum_{g \neq g_0} \phi_g \mathbf{1}\{TaskGroup_i = g\} + X'_{ijpt}\Gamma + \theta_j + \mu_t + \varepsilon_{ijpt}. \end{aligned} \tag{24}$$

where g_0 is the omitted task-group category, θ_j denotes industry fixed effects, and μ_t denotes year or survey-wave fixed effects. The baseline heterogeneity specification includes industry and survey-wave fixed effects, but not province fixed effects, so that it does not absorb the cross-provincial exposure variation in the Bartik index. A province fixed-effect version is reported separately as a stricter robustness check that identifies within-province differential responses across task groups rather than the average robot-exposure association.

Together, these specifications allow us to examine automation through two complementary channels. RTI captures the potential exposure of occupations to task substitution, while robot exposure captures predicted provincial exposure to robot-intensive industrial upgrading. The wage, mobility, distributional, and intergenerational specifications jointly assess whether automation affects only contemporaneous earnings, or whether it also reshapes occupational trajectories and the persistence of socioeconomic advantage across generations. In the next section we discuss the data sources used in the empirical analysis.

4 Data

To conduct the empirical analysis, we use the China Family Panel Studies (CFPS) survey, which is a nationally representative, longitudinal household survey covering the period 2010-2022. The CFPS provides detailed information on employment, occupation, industry, income, and household characteristics (Hu et al., 2014). Due to the inconsistency in questionnaire design for the first two waves, our analysis focuses from the third wave in 2014 through the latest available wave in 2022.[2]

We construct the Routine Task Intensity (RTI) index following the task-based framework of Acemoglu and Autor (2011). Specifically, occupational task measures derived from U.S. O*NET data are mapped to the ISCO-08 classification. Based on Lewandowski et al. (2020)'s definition, we categorise the sample into five occupational task groups: non-routine cognitive analytical (NRCA), non-routine cognitive personal (NRCP), routine cognitive (RC), non-routine manual (NRM), and routine manual (RM). To account for cross-country heterogeneity in task content, these scores are further calibrated to the Chinese context based on its specific development levels, following the adjustment methodology proposed by Lewandowski et al. (2022) and Gradín et al. (2023).

To construct the robot-exposure index, we integrate several datasets. First, the imported-industrial-robot series is derived from the General Administration of Customs of China. Following the approach of Fan et al. (2021a), we use the HS6 code 847950 to identify industrial robot imports from 2015 to 2022.

The macro-level industrial employment data are sourced from the China Industry Statistical Yearbook. The industry weights are derived from the sector robot penetration rates calculated by Wang and Dong (2020) based on data from the International Federation of Robotics (IFR). We further process these data to construct the industry-susceptibility component of the robot exposure index.

The sample selection and data cleaning process were conducted as follows: The first and second generations were linked via unique family identifiers. Observations with an age difference between the two generations of less than 14 years were excluded. Second, the raw data were reshaped into long format to capture repeated observations on the

[2]In Appendix Sections F–G, we present the analysis using the full available dataset from 2010 to 2022. The results remain consistent.

same individuals and construct a pseudo-panel dataset. Third, the analytical sample was restricted to the employed population aged 16 to 75 years at the time of the survey, which includes those who were currently employed or reported positive labour income, which ensures the availability of data on occupational tasks and income. This criterion naturally excludes students, retirees, and those outside of the labour force. Fourth, annual labour income was deflated to 2010 constant RMB using the Consumer Price Index (CPI) provided by the National Bureau of Statistics of China. Fifth, individuals were categorised into cohorts based on year of birth, gender and household registration (hukou) status (rural or urban), with a unique cohort identifier assigned in the format of $YYYYGS$, representing Year, Gender, and Status. Finally, to ensure the statistical power of cohort-level averages and mitigate measurement error, cohorts with a sample size of fewer than 50 individuals were excluded from the final analysis.

4.1 Variable Definitions

The primary explanatory variable is the Routine Task Intensity (RTI) score. To facilitate the interpretation of regression coefficients, this score is standardised using Z-scores, yielding a sample mean of zero and a standard deviation of one. For the income analysis, we utilise the natural logarithm of annual labour income to capture the economic returns to task composition.

To measure the occupational status and mobility, we employ the International Socio-Economic Index (ISEI). We divide the occupation hierarchy into six mutually exclusive categories: Exit, SharpDown, SlightDown, Stay, SlightUp, and SharpUp. Stay corresponds to $-2 \leq \Delta ISEI_{i,t+1} \leq 2$; SlightDown to $-10 < \Delta ISEI_{i,t+1} < -2$; SharpDown to $\Delta ISEI_{i,t+1} \leq -10$; SlightUp to $2 < \Delta ISEI_{i,t+1} < 10$; and SharpUp to $\Delta ISEI_{i,t+1} \geq 10$. The Exits group captures transitions out of employment to reduce selection bias arising from labour-market displacement. Meanwhile, the intergenerational analysis utilises the continuous ISEI scores of both parents and children to measure the strength of status transmission.

The vector of control variables includes demographic and human capital indicators. Gender and household registration are controlled for using dummy variables, with a value of 1 indicating male and an urban hukou, respectively. Human capital is measured by the total years of formal schooling. Age and the square of age are included to control for potential life-cycle bias in the calculation of intergenerational mobility. Finally, the dataset included several categorical identifiers. These comprise indicators for survey waves and provinces of residence.

5 Analysis

5.1 Descriptive Statistics

We begin the analysis by presenting an overview of descriptive statistics. Table 1 presents summary statistics for the core analytical sample. The average log annual income is

9.984, corresponding to a geometric mean of approximately 21,676 RMB per year, with substantial dispersion across individuals. The mean standardised RTI is generally zero by construction, with values ranging from -3.091 to 1.177. The average occupational status score (as measured by the International Socio-Economic Index of Occupational Status, ISEI) is 33.3, indicating a predominantly low-to-middle status composition of China's labour force during this period. The sample is roughly evenly split between male and urban hukou holders, at 51 and 49 per cent respectively, with a mean age of 45.2 years old and 7.97 years of schooling.

Table 1: Summary Statistics

Variable	Mean	SD	Min	Max	N
Income (log)	9.984	0.974	6.795	15.973	59,394
RTI (standardised)	-0.001	0.997	−3.091	1.177	105,672
Occupational status (ISEI)	33.332	14.493	12	90	110,804
Years of education	7.97	4.922	0	23	128,552
Age	45.2	15.064	16	75	136,210
Male	0.510	0.500	0	1	136,210
Urban hukou	0.492	0.500	0	1	129,566

Notes: Sample restricted to individuals aged 16–75 active in the labour market across CFPS waves 2014–2022.

Before examining the empirical associations between automation and labour market outcomes, it is essential to clarify the trajectory of occupational task content in China over the survey period. Figure 1 documents the evolution of mean standardised RTI by CFPS survey wave. The standardised RTI declines markedly from around 0.15 in 2014 to nearly zero by 2018, remaining low thereafter. The decline is generally monotonic. The pattern holds broadly across the majority provinces, as shown in Figure 2, though the pace and timing of decline vary by region. Taken together, these trends suggest that the average occupation task content of China's labour force shifted markedly toward non-routine tasks over the sample period, consistent with evidence reported from middle-income economies Das and Hilgenstock (2022).

Differences across birth cohorts further show the structural shift (see Table 18 in the Appendix). Labour forces born between 1935 and 1950 have mean RTI values ranging from 0.487 to 0.595, indicating a labour market dominated by highly routine manual or cognitive tasks. In contrast, cohorts born after 1975 have a negative mean RTI, reflecting their concentration in occupations that require high levels of non-routine analytical and interpersonal tasks. The youngest cohort (born around 2005) is an exception, with a high RTI of 0.179. Since these individuals were at most 17 years old at the time of the updated survey, this exception likely reflects early labour-market entry among those with limited formal education. These workers are typically concentrated in highly routine manual roles.

These aggregate trends hide important differences between hukou groups. Rural hukou holders have a mean of 0.275, while urban holders have a mean of -0.300, resulting in a gap of 0.575 standard deviations (see Table 19 in the Appendix). This differential exposure implies that rural workers face a systematically higher risk of automation, a pattern examined in detail in Section 5.3.

This descriptive pattern is consistent with evidence from developing and middle-income

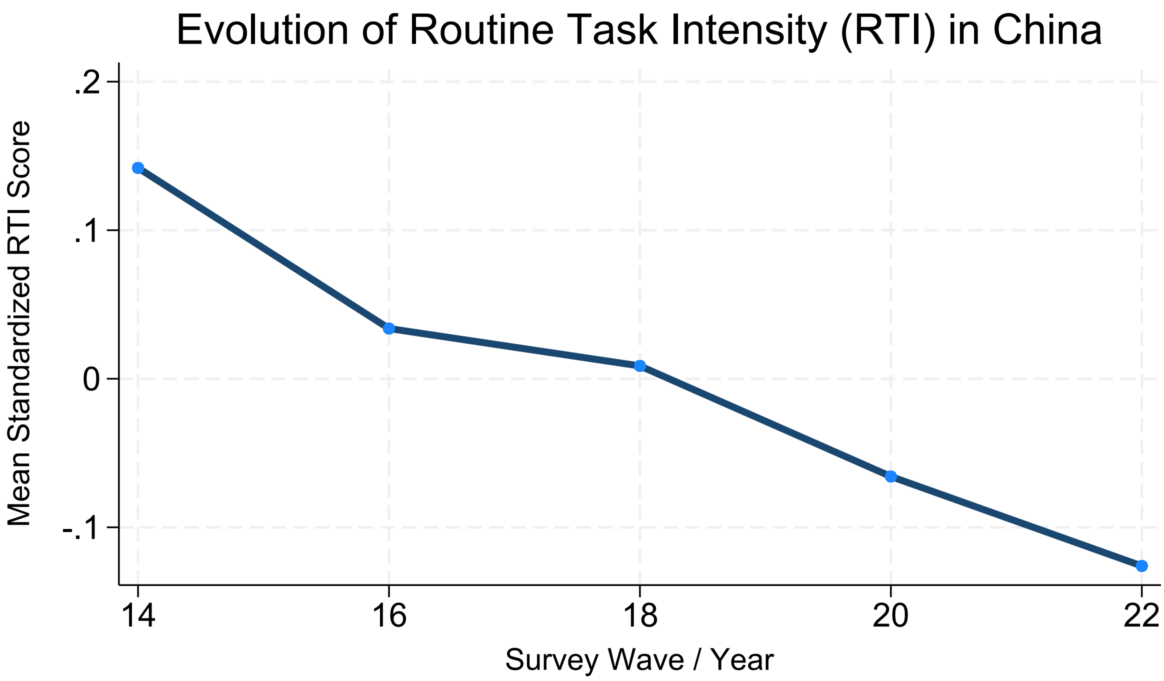


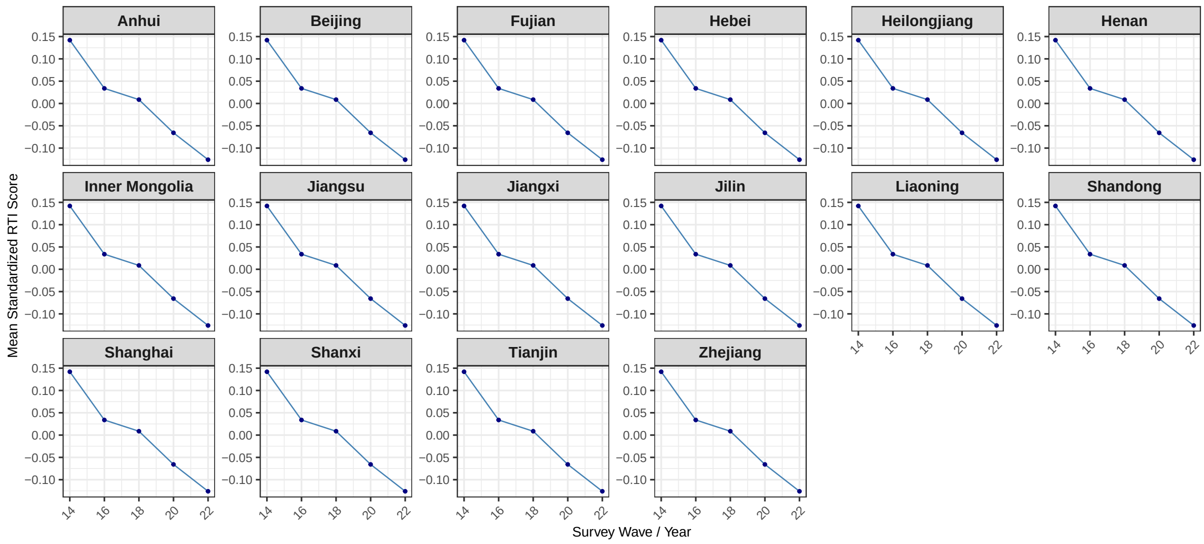
Figure 1: Evolution of Routine Task Intensity in China, 2014–2022

economies showing that the task content of work changes systematically with structural transformation. Cross-country evidence indicates that occupations with the same title may involve different task bundles depending on the level of development, the organisation of production, and the structure of labour markets (Lewandowski et al., 2020, 2022; Das and Hilgenstock, 2022; Martins-Neto et al., 2024). The decline in mean RTI across CFPS waves suggests that China's labour market has undergone a broad compositional movement away from routine-intensive work and towards more non-routine task content. At the same time, the higher RTI among rural hukou holders indicates that this transition is unevenly distributed. This is consistent with China-specific evidence that labour-market adjustment is shaped by hukou status, rural–urban migration, regional development, and access to formal employment (Knight and Song, 1999; Chan and Buckingham, 2008; Ge and Yang, 2014; Wu, 2024; Gai et al., 2025).

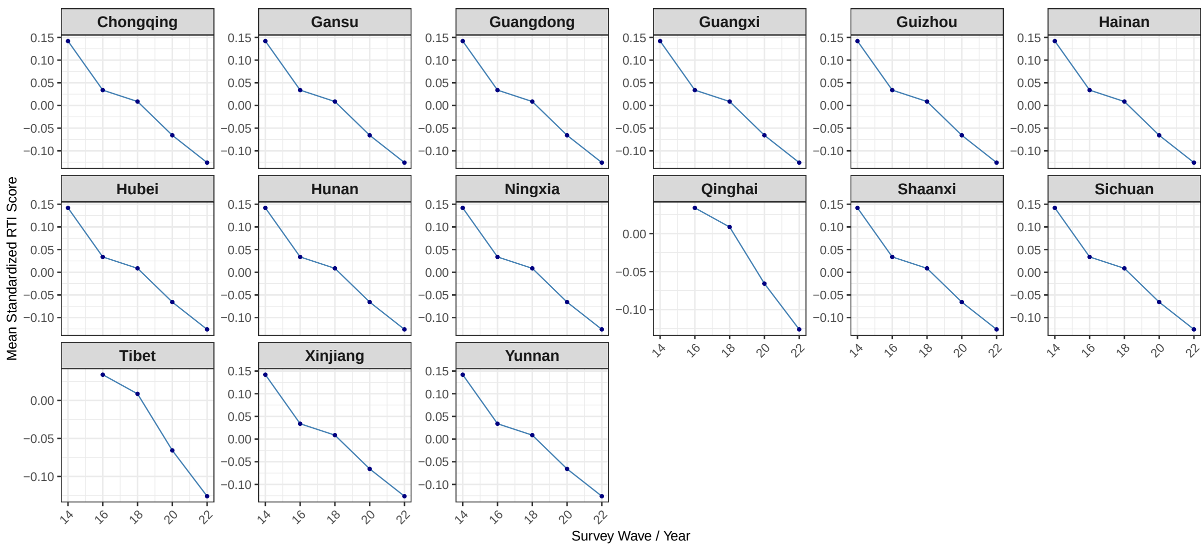
5.2 Automation and Income

Table 2 reports the estimated association between routine task intensity (RTI) and annual income. Column (1) presents the baseline specification with only wave fixed effects. The results show that a one-standard-deviation increase in RTI is associated with a 21.8% reduction in annual income ($e^{-0.246} - 1$). This negative relation is highly significant at the 1% level, indicating a substantial loss in earnings for workers in routine-intensive occupations.

Column (2) introduces individual-level controls. With the inclusion of gender, hukou status, education, and age, the income loss associated with RTI decreases to 15.4% but remains highly significant. This suggests that while part of the routine task penalty is



(a) Evolution of RTI by province (i), 2014–2022



(b) Evolution of RTI by province (ii), 2014–2022

Figure 2: Trends in Routine Task Intensity

Table 2: Income Effects of Routine Task Intensity

	(1) lnwage	(2) lnwage	(3) lnwage	(4) lnwage	(5) lnwage	(6) lnwage
RTI (standardlised)	-0.246***	-0.167***	-0.137***	-0.154***	-0.124***	-0.122***
	(0.0102)	(0.00731)	(0.00678)	(0.00741)	(0.00586)	(0.00595)
Gender		0.470***	0.398***	0.483***	0.407***	0.408***
		(0.0280)	(0.0261)	(0.0260)	(0.0252)	(0.0256)
Urban		0.159***	0.108***	0.0998***	0.0591***	0.0660***
		(0.0299)	(0.0250)	(0.0201)	(0.0162)	(0.0168)
Year of Schooling		0.0336***	0.0336***	0.0333***	0.0333***	0.0315***
		(0.00290)	(0.00298)	(0.00209)	(0.00211)	(0.00216)
Marriage		0.104***	0.0459**	0.105***	0.0555***	0.0300*
		(0.0216)	(0.0184)	(0.0184)	(0.0169)	(0.0151)
Age		-0.0161***	-0.0126***	-0.0168***	-0.0137***	-0.00764
		(0.00122)	(0.00128)	(0.000980)	(0.000959)	(0.00652)
Age squared		-0.00114***	-0.00116***	-0.00117***	-0.00117***	-0.00115***
		(0.0000631)	(0.0000628)	(0.0000432)	(0.0000445)	(0.0000935)
Observations	42415	38207	31665	38207	31665	31665
R-squared	0.123	0.262	0.240	0.301	0.280	0.287
Survey-wave FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry/Sector FE	No	No	Yes	No	Yes	Yes
Province FE	No	No	No	Yes	Yes	Yes
Birth-cohort FE	No	No	No	No	No	Yes

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

driven by the demographic composition of the labour force, a significant effect remains even among similar individuals. Among the controls, the male income premium is remarkably large, with men earning 60% more than women, even controlling for education and task content. Each additional year of schooling yields a 3.4% increase in income. Age exhibits the expected inverted-U-shaped profile, with earnings peaking at approximately 38.1 years of age.

Columns (3) through (5) progressively add industry and province fixed effects to account for regional and industry differences. The RTI penalty remains stable across these specifications, ranging between 11.7% and 14.3%. This stability indicates that the income disadvantage of routine tasks is a pervasive feature of the labour market and is not simply driven by workers being concentrated in specific low-paying industries or less-developed provinces.

Notably, the inclusion of province fixed effects in Column (4) significantly reduces the urban hukou premium. The income advantage for urban hukou holders drops from 17.2% in Column (2) to 6.1%. This reduction indicates that almost two-fifths of the observed urban-rural income gap is explained by regional economic disparities captured by province fixed effects, rather than by the institutional advantage of hukou status itself. Even in the most rigorous specification (Column 5), the RTI-related earnings gap persists, confirming that job task content is a clear determinant of earnings in China.

The negative association between RTI and income is consistent with developing-country evidence showing that routine task content remains an important source of labour-market vulnerability even outside advanced industrialised economies. While the task-based framework was developed largely with reference to the United States and Europe, recent work shows that automation exposure in developing and middle-income countries depends strongly on how routine tasks are embedded in domestic production systems, informality, and structural transformation (Lewandowski et al., 2020; Das and Hilgenstock, 2022; Martins-Neto et al., 2024). The Chinese evidence adds to this literature by showing that routine-task exposure is associated with lower earnings in a context characterised by rapid industrial upgrading, continuing rural–urban migration, and strong institutional segmentation. The result is therefore not simply a replication of advanced-economy wage-polarisation findings, but evidence that occupational task content matters for earnings in a middle-income economy with a distinctive labour-market structure.

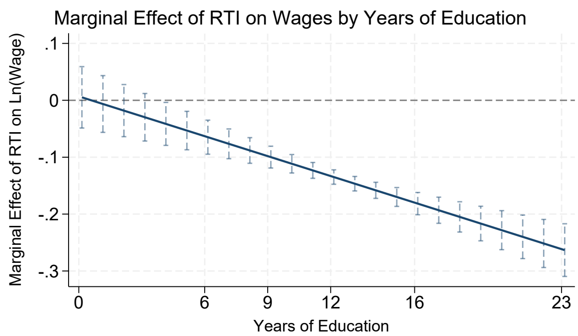
Table **??** examines whether the income loss varies with educational attainment by introducing an interaction term between RTI and years of schooling. The RTI main effect ranges from -0.149 to -0.245, and the interaction term between RTI and education is negative and significant at the 1% level across all specifications. Evaluated at the sample mean age of 45.2 years, the marginal effect of RTI on log income is negative across the entire education distribution, ranging from -0.156 at zero years of schooling to -0.412 at 16 years of schooling. The interaction term between the RTI and age is likewise negative and significant across all specifications, indicating that older workers bear a disproportionately larger income penalty from routine task exposure. The income loss increases monotonically with education, consistent with the view that higher-skilled workers sort into more cognitively complex occupations where automation-associated displacement may carry larger income consequences.

Table 3: Heterogeneous Income Effects by Education and Age

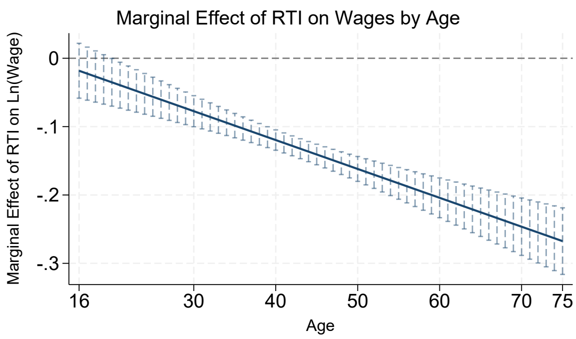
	(1) Wave FE	(2) +Ind. FE	(3) +Prov. FE	(4) +Both FE	(5) +Cohort FE
RTI (standardised)	-0.245***	-0.156***	-0.232***	-0.149***	-0.149***
	(0.0109)	(0.0103)	(0.0109)	(0.0106)	(0.0112)
RTI × Education (centred)	-0.0111***	-0.0221***	-0.0105***	-0.0205***	-0.0186***
	(0.00167)	(0.00208)	(0.00146)	(0.00169)	(0.00163)
RTI × Age (centred)	-0.00633***	-0.00574***	-0.00648***	-0.00579***	-0.00716***
	(0.000717)	(0.000714)	(0.000715)	(0.000693)	(0.000788)
Observations	39347	32631	39347	32631	32631
Survey-wave FE	Yes	Yes	Yes	Yes	Yes
Industry/Sector FE	No	Yes	No	Yes	Yes
Province FE	No	No	Yes	Yes	Yes
Birth-cohort FE	No	No	No	No	Yes

Controls included in all specifications. Standard errors clustered at the individual and province level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 3a illustrates this pattern through marginal effects. For a worker with six years of schooling (completion of primary school), a one-standard-deviation increase in RTI is associated with a 6.5% decline in income. However, for those with 16 years of education (the equivalent of a bachelor's degree), the same increase in RTI results in a much larger reduction of approximately 16.4%.



(a) Marginal Effect of RTI on Income by Education



(b) Marginal Effect of RTI on Income by Age

Figure 3: Marginal Effect of RTI on Income by Education and Age

The result remains robust to the inclusion of province and industry fixed effects (Columns 2-4). The stability of the interaction term suggests that routine task exposure lowers the returns to education, consistent with Acemoglu and Restrepo (2022)'s task displacement framework. Although highly educated individuals can still earn more than those with less schooling, the marginal gain from an additional year of schooling is smaller in routine-intensified environments. Consequently, because these roles do not allow for the full utilisation of advanced skills, highly educated workers experience a steeper percentage drop in their potential earnings (Jones et al., 2025).

The stronger RTI penalty among older workers can be interpreted through the lens of task-specific human capital and limited transferability of experience. In China, older workers are likely to have accumulated skills in occupations shaped by earlier phases of industrialisation, manufacturing expansion, and state-sector restructuring. When those jobs become more routine-intensive or more exposed to technological substitution, accumulated experience may be less easily transferred to expanding non-routine occupations. This interpretation is consistent with evidence that China's labour-market transition has generated uneven adjustment costs across cohorts, education groups, and hukou status (Cai and Du, 2011; Ge and Yang, 2014; Gai et al., 2025). The stronger income loss among more educated workers is also important. It suggests that education is protective only when it is matched with occupations that use non-routine analytical, technical, or interpersonal skills. In developing and middle-income economies, where educational upgrading may outpace the creation of high-quality non-routine jobs, some educated workers may remain concentrated in routine-intensive clerical, technical, or production roles, limiting the returns to schooling (Lewandowski et al., 2020, 2022; Das and Hilgenstock, 2022; Wang, 2025).

The interaction between RTI and age is also negative and significant across all specifications. As illustrated in Figure 3b, the negative association between RTI and income becomes more pronounced as workers get older. The marginal effect of a one-standard-deviation increase in RTI results in a 3.2% income reduction at age 20, which increases to a much larger 21.6% loss by age 70.

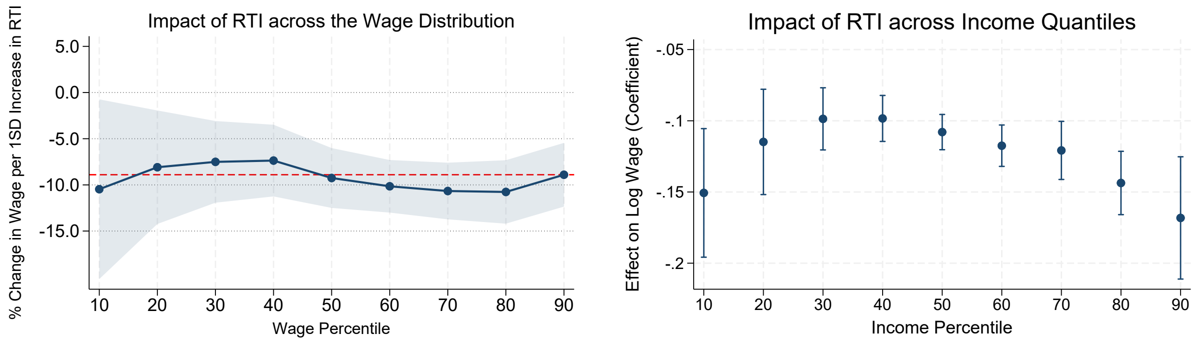
Taken together, these patterns are consistent with China-specific evidence that labour-market transition has generated uneven adjustment costs across cohorts, education groups, and hukou status (Cai and Du, 2011; Ge and Yang, 2014; Gai et al., 2025), and with the broader argument that occupation-specific human capital becomes less transferable when routine tasks lose value (Autor and Dorn, 2009; Lordan and Neumark, 2018).

After establishing that the average income reduction resulting from routine task exposure is robust and increases with education and age, we now examine whether these effects are uniform across the income distribution.

To examine whether the income effect of routine task exposure is uniform across the income distribution, Figure 4a reports unconditional quantile regression (UQR) estimates. The dashed red line represents the OLS estimate of approximately -8.9%, serving as a benchmark. The association between RTI and income remains consistently negative across all percentiles but exhibits significant heterogeneity. Workers in the 20th to 30th percentiles experience a relatively smaller income reduction of approximately 7.5% to 8.5%. In contrast, those at the upper tail of the distribution incur a larger loss, with an 11% reduction at the 80th percentile. While the confidence intervals widen at the tails of the distribution due to smaller effective sample sizes, the consistently negative impact across the distribution is robust.

Figure 4b provides RIF regression estimates of the RTI effect across income quantiles. These results are consistent with the UQR findings. The adverse association with income is negative throughout the distribution. The increasingly negative coefficients at higher quantiles suggest that exposure to routine-intensive tasks leads to larger reductions for high-income workers.

To evaluate the aggregate association with inequality, we supplement the quantile



(a) Unconditional quantile estimates (b) RIF regression estimates

Figure 4: Association between RTI and income across the income distribution

analysis with an RIF regression of the Gini coefficient (Table 20 in the Appendix). The sample mean Gini index is 0.42, reflecting a high degree of income inequality in China during this period. The estimated RTI coefficient is -0.024, significant at 10% level.

This provides suggestive evidence that an increase in RTI is associated with a lower Gini coefficient. The result should be interpreted with caution as the coefficient is significant at the 10% level. It suggests income compression rather than a clear increase in measured inequality, because higher-income and more educated routine workers face larger marginal losses when performing routine-intensive tasks. This contrasts with the pattern in some advanced economies, where routine-task displacement disproportionately affects workers in the middle of the wage distribution (Acemoglu and Restrepo, 2022). The divergence may reflect structural differences in how routine tasks are distributed across the income scale. In China's labour market, routine-intensive roles are not only concentrated in low-wage manual jobs, but also in formal-sector occupations that tend to occupy the upper-middle of the wage distribution, a pattern consistent with developing-country evidence reported by Martins-Neto et al. (2024).

The distributional results are particularly important for situating the Chinese case within the broader developing-country literature. Much of the advanced-economy literature links routine-biased technological change to wage polarisation because routine jobs are often concentrated in the middle of the wage distribution. In developing and middle-income economies, however, the location of routine work in the income distribution may differ substantially because of informality, late industrialisation, uneven educational upgrading, and sectoral heterogeneity (Lewandowski et al., 2020; Das and Hilgenstock, 2022; Martins-Neto et al., 2024). The Chinese results are consistent with this broader comparative evidence. Routine-intensive work appears not only in low-paid manual employment, but also in formal-sector production, clerical, and technical occupations located in the middle and upper parts of the income distribution. This helps explain why RTI is associated with larger income losses among middle- and higher-income routine workers and why the RIF-Gini results provide suggestive evidence of income compression rather than a clear increase in measured inequality. The finding therefore qualifies the expectation that automation necessarily widens inequality and shows that the distributional consequences of automation depend on the domestic structure of occupations and earnings.

In summary, the findings in this section indicate a general and robust income loss associated with routine-intensive work in China. This effect is amplified by age and education, distributed across the entire income spectrum, and does not appear to widen aggregate inequality. Section 5.3 examines the occupational mobility consequences of this shift in task demand.

5.3 Automation and Occupational Mobility

After documenting the income effects of routine task exposure, the analysis now turns to the implications of routine task exposure for occupational mobility. While income analysis captures within-occupation wage effects, mobility offers a complementary lens for assessing the structural consequences of automation. It allows us to examine whether workers move up the occupational ladder, remain in place, or are pushed downward as routine tasks are displaced. Upward and downward mobility are defined relative to each worker's initial occupational status (ISEI) score, with remaining in the same status category as the reference outcome.

The upward-mobility finding reported below and the income losses documented in Section 5.2 may appear contradictory, but they are not. Upward mobility here is defined in terms of ISEI, a measure of occupational status based on task structure, not income. Since RTI and ISEI are strongly negatively correlated, high-RTI workers may appear more likely to move upward in ISEI terms because they start from lower-status occupations. However, this does not imply economic upgrading, since RTI remains associated with lower income and higher labour-force exit. A factory worker who shifts to a low-skill service job may gain ISEI points while experiencing lower income. The two sets of results therefore capture different dimensions of labour-market adjustment.

Table 4 presents multinomial logistic regression estimates of the association between RTI and occupational mobility. In the baseline specification, a one-standard-deviation increase in RTI corresponds to significantly higher log-odds of both slight and sharp upward mobility, and significantly lower log-odds of both slight and sharp downward mobility. Although this finding may seem counterintuitive, it likely reflects the initial position of routine-intensive workers. As noted above, the strong negative RTI-ISEI correlation indicates that workers in routine-intensive jobs disproportionately start from the lower status of the occupational ladder. For these workers, any occupational transition is more likely to be recorded as an upward movement. One potential interpretation is that China had entered a phase of structural transformation at that time in which tightening labour supply and rising wages for low-skilled workers (Cai and Du, 2011) created conditions conducive to observable occupational upgrading on average.

The mobility results should also be interpreted in relation to structural transformation in developing economies. In contexts where workers move out of low-status routine occupations, occupational-status measures may record upward mobility even when transitions do not generate higher earnings or more secure employment. This is particularly relevant in China, where rising wages, demographic change, industrial upgrading, and rural–urban labour reallocation have transformed the structure of low-skilled and routine work (Cai and Du, 2011; Ge and Yang, 2014; Fan et al., 2021a; Liao and Wei, 2018). The positive association between RTI and upward mobility in ISEI terms should therefore not be read as evidence that routine-task exposure improves economic mobility. Rather, it reflects the fact that many high-RTI workers begin from relatively low-status occupations, so movements away from those jobs may appear as upward occupational mobility even when RTI remains associated with lower income.

Table 4: Multinomial Logit: Occupational Mobility

	Baseline				+RTI×Education			
	Downward		Upward		Downward		Upward	
	Sharply	Slightly	Slightly	Sharply	Sharply	Slightly	Slightly	Sharply
RTI (standardised)	-1.151^{***}	-0.424^{***}	0.225^{***}	0.459^{***}	-1.461^{***}	-0.732^{***}	0.097	0.106
	(0.040)	(0.038)	(0.042)	(0.040)	(0.057)	(0.056)	(0.072)	(0.091)
RTI × Education (centred)					0.120^{***}	0.098^{***}	0.032^{***}	0.076^{***}
					(0.008)	(0.013)	(0.011)	(0.012)
Years of schooling (centred)	-0.093^{***}	-0.047^{***}	0.031^{***}	0.129^{***}	-0.017^{**}	-0.040^{***}	0.025^{*}	0.118^{***}
	(0.007)	(0.007)	(0.011)	(0.008)	(0.009)	(0.006)	(0.013)	(0.008)
Age (centred)	-0.029^{***}	-0.027^{***}	-0.039^{***}	-0.041^{***}	-0.025^{***}	-0.023^{***}	-0.037^{***}	-0.038^{***}
	(0.003)	(0.004)	(0.004)	(0.003)	(0.003)	(0.004)	(0.004)	(0.003)
Age^2 (centred)	0.000	-0.000^{*}	0.000^{***}	0.000	0.000	-0.000	-0.000^{**}	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-2.551^{***}	-2.349^{***}	-2.407^{***}	-2.180^{***}	-3.258^{***}	-2.820^{***}	-2.854^{***}	-2.495^{***}
	(0.065)	(0.047)	(0.050)	(0.075)	(0.116)	(0.081)	(0.090)	(0.067)
Observations	51,125				51,125			

Notes: Base outcome: Stay. Robust standard errors clustered at the province level in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

While the baseline results establish the general direction of the relationship, they mask significant heterogeneity across workers. The models labelled *RTI* x *Education* introduce an interaction between RTI and years of schooling. The interaction is positive and significant for both directions. The relative risk ratios in Table 5 are more easily interpreted. In the baseline model, a one-standard-deviation increase in RTI raises the relative risk of sharp upward mobility (relative to staying) by a factor of 1.583. When accounting for the interaction, once it is introduced, the direct RTI effect on upward mobility is substantially attenuated, remaining only marginally significant at the 10% level, suggesting that the positive association between RTI and upward mobility is entirely mediated by education level. For downward mobility, higher education reduces but does not eliminate risk at low RTI values.

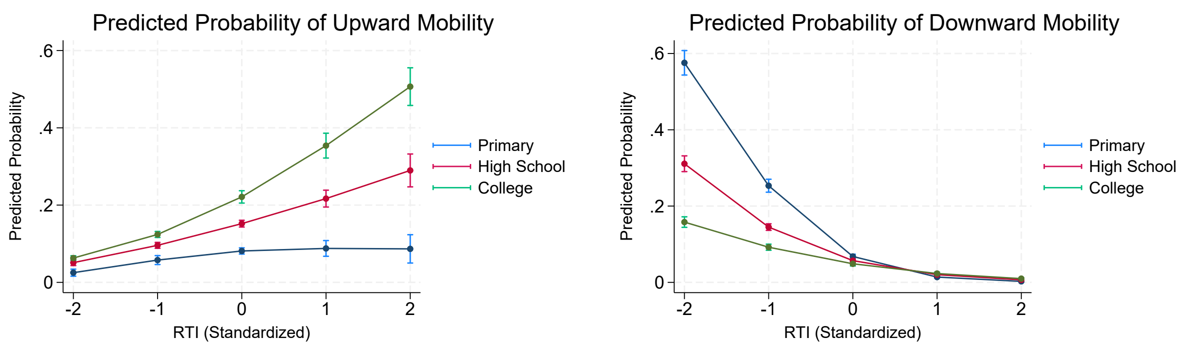
Figure 5a and 5b illustrate these patterns through predicted probabilities. If RTI equals 2, workers with 16 years of schooling (a bachelor's degree) face an upward mobility probability of 0.507, compared to 0.087 for those with 6 years of schooling (primary school) across the RTI spectrum. If RTI is -2, low-education workers face a downward probability of 0.576, compared to 0.158 for university graduates. As RTI increases, the risk of downward mobility declines substantially for all groups. These findings align with the view that education shields the labour force from vulnerability (Wang, 2025).

Beyond education, gender represents another dimension along which the mobility consequences of shifting task demand may differ. Figure 6a shows that male workers exhibit a consistently higher predicted probability of downward mobility than female workers across all RTI values. If RTI is -2, the predicted downward probability is 0.37 for males compared to 0.35 for females. This pattern contrasts with the income findings, in which male workers have a premium of 60%. This suggests that higher incomes do not necessarily translate into greater occupational stability in the face of routine task

Table 5: Multinomial Logit: Relative Risk Ratios

	Baseline				+RTI × Education			
	Downward		Upward		Downward		Upward	
	Sharply	Slightly	Slightly	Sharply	Sharply	Slightly	Slightly	Sharply
RTI (standardised)	0.316***	0.654***	1.252***	1.583***	0.233***	0.486***	1.127*	1.163*
	(0.013)	(0.025)	(0.053)	(0.063)	(0.013)	(0.027)	(0.078)	(0.097)
RTI × Education (centred)					1.127***	1.102***	1.031***	1.076***
					(0.008)	(0.014)	(0.011)	(0.013)
Years of schooling (centred)	0.911***	0.954***	1.032***	1.138***	0.981**	0.958***	1.025**	1.124***
	(0.006)	(0.006)	(0.012)	(0.009)	(0.009)	(0.006)	(0.013)	(0.008)
Age (centred)	0.971***	0.973***	0.962***	0.960***	0.975***	0.976***	0.963***	0.962***
	(0.003)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Age^2 (centred)	1.000	1.000*	1.000***	1.000	1.000	1.000	1.000**	1.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant (Baseline RRR)	0.035***	0.052***	0.046***	0.083***	0.047***	0.071***	0.052***	0.104***
	(0.006)	(0.006)	(0.004)	(0.006)	(0.007)	(0.007)	(0.005)	(0.006)
Observations	52,493				52,493			

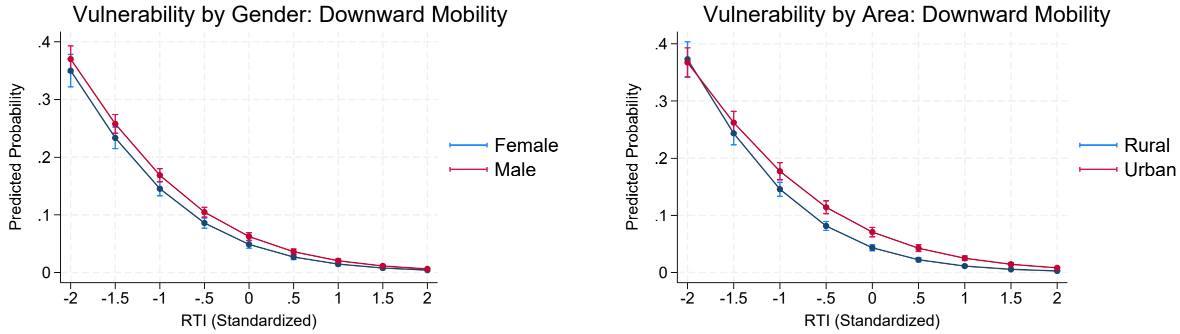
Notes: Base outcome: Stay. Robust standard errors clustered at the individual and province level in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.



(a) Predicted probability of upward mobility (b) Predicted probability of downward mobility

Figure 5: Predicted probability of mobility by education

displacement.

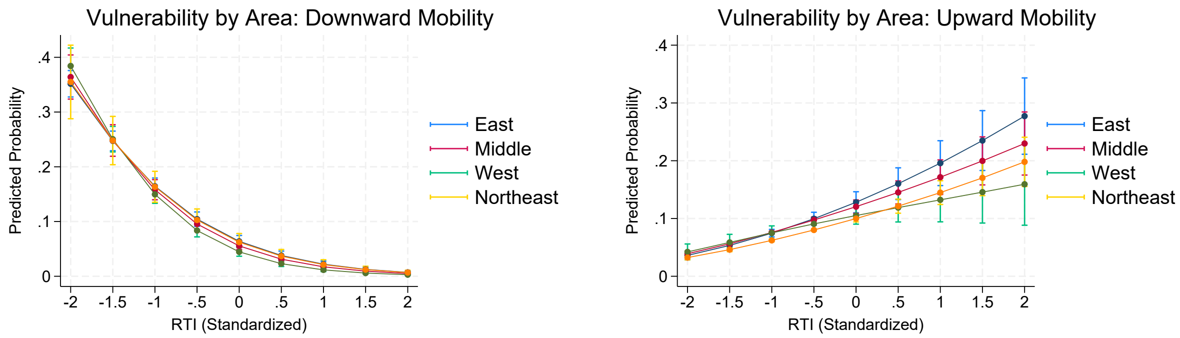


(a) By Gender

(b) By Area

Figure 6: Vulnerability by Gender and Area

A further dimension of heterogeneity emerges along the rural–urban divide (Figure 6b). At very low levels of RTI, individuals with rural hukou face a higher predicted probability of downward mobility (approximately 0.373) compared to their urban counterparts (approximately 0.367). However, as RTI increases, these patterns cross over. For most of the RTI distribution, urban workers exhibit a slightly higher risk of downward mobility than rural workers. This suggests that rural workers may be more vulnerable in low-RTI, non-routine occupations, while urban workers in routine-intensive jobs may be more susceptible to downward displacement in competitive urban labour markets. One possible interpretation is that these patterns reflect lower human-capital accumulation among rural workers and the institutional barriers created by the hukou system, as suggested by Gai et al. (2025).



(a) Downward mobility by region

(b) Upward mobility by region

Figure 7: Predicted occupational mobility by region

The analysis also reveals substantial regional heterogeneity with a consistent pattern emerging across both panels. Regional differences in mobility outcomes are concentrated primarily at the lower end of the RTI distribution, where occupations are more non-routine cognitive, while differences across regions converge as RTI increases towards the routine-intensive end. Notably, the eastern region exhibits both a marginally higher risk of downward mobility and a substantially higher probability of upward mobility among low-RTI workers relative to other regions. For workers in routine-intensive occupations, by contrast, the predicted probabilities of both downward and upward mobility are broadly uniform across regions, suggesting that mobility risks associated with routine-task exposure

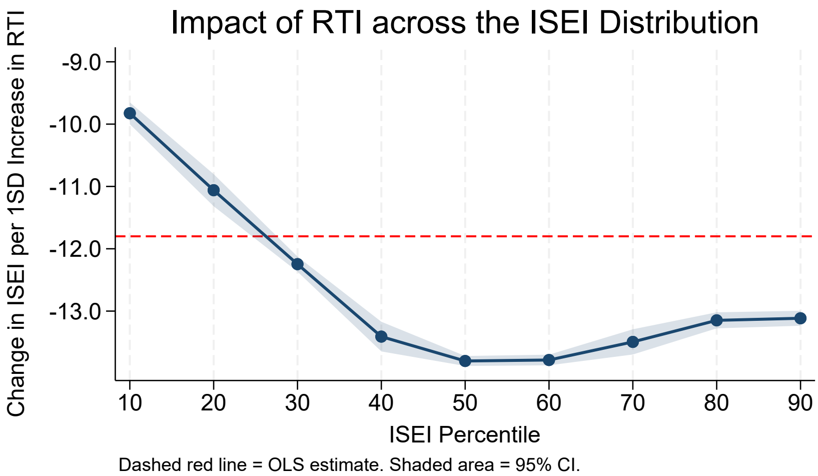


Figure 8: Association between RTI and occupational status across the ISEI distribution

are not strongly geographically differentiated at the high-RTI end of the distribution (Fan et al., 2021a; Liao and Wei, 2018). This indicates that regional labour-market development shapes occupational mobility prospects primarily through its effect on non-routine cognitive occupations.

The heterogeneity in mobility outcomes reinforces the importance of institutions in shaping adjustment to technological change. Education appears to improve the likelihood of upward status mobility, consistent with evidence that schooling facilitates movement into non-routine and higher-status occupations in China (Wang, 2025). However, hukou status and regional location also shape mobility prospects. Rural hukou workers may be geographically mobile but remain institutionally constrained by weaker access to urban welfare, formal employment, and social protection (Knight and Song, 1999; Chan and Buckingham, 2008; Wu, 2024). Regional differences are also consistent with evidence that industrial upgrading and robot adoption in China are geographically uneven and concentrated in more developed manufacturing regions (Fan et al., 2021a; Cheng et al., 2019; Liao and Wei, 2018). These findings suggest that automation-related mobility is not determined by task content alone, but by the interaction between task exposure, education, hukou status, and local labour-market opportunities.

Finally, Figure 8 presents UQR estimates of the RTI effect across the ISEI distribution, providing a distributional perspective on occupational status. The association between RTI and occupation is significantly negative throughout the distribution, with its magnitude forming a U-shaped pattern. The magnitude of the RTI effect increases sharply from the 10th to the 50th percentile, before levelling off towards the upper end of the distribution. The concentration of status reduction in the middle of the distribution is broadly consistent with the polarisation hypothesis (Autor et al., 2003; Goos and Manning, 2007).

5.4 Automation and Intergenerational Mobility

The analysis in sections 5.2 and 5.3 establishes two findings: routine-intensive occupations are associated with sizeable income losses, while mobility in ISEI terms is more complex because high-RTI workers often start from lower-status occupations and may therefore appear more likely to move upward without necessarily experiencing economic upgrading. A natural extension is to ask whether these losses compound across generations. Whether growing up in a family whose occupational position is shaped by automation alters the transmission of economic advantage from parents to children remains an open question. This section addresses this question by examining both the income and occupational status dimensions of intergenerational persistence and determining whether RTI moderates the strength of that persistence or instead operates through a separate, additive channel.

The first empirical question is whether the association between parental occupational status and child occupational status differs across children's routine-task exposure. The interaction model regressing child ISEI on father's ISEI, child RTI, and their product yields an interaction coefficient of -0.029. The father ISEI main effect is 0.022, and the RTI main effect is large and negative (approximately -11.7 ISEI points per standard deviation) (6). On the surface, the statistically significant interaction term might appear to suggest that routine-task exposure attenuates the intergenerational transmission of occupational status. It is worth noting, however, that the direct effect of fathers' ISEI becomes statistically insignificant once richer industry and province fixed-effect structures are introduced (Columns 3–4), suggesting that the intergenerational transmission of occupational status operates partly through time-invariant individual characteristics rather than through direct status inheritance.

Figure 9 plots the marginal effect of parental ISEI on child ISEI across the RTI distribution. The intergenerational elasticity declines from roughly 0.081 at RTI = -2 to below zero at RTI = 2. To be sure, the confidence intervals widen at both extremes of the RTI distribution. At the lower end, this reflects the relative rarity of highly specialised, non-routine roles. At the higher end, the increased variance likely stems from the precarious and informal nature of highly routine work, in which occupational assignment is often less stable. In both cases, the reduced effective sample size at the tails of the distribution limits statistical power. However, the consistent downward trajectory of the point estimates suggests that routine-task exposure is associated with a weaker link between family background and occupational attainment.

Table 6: Automation and Intergenerational Occupational Status Transmission

	(1) Wave	(2) Prov+Wave	(3) Ind+Wave	(4) Ind+Prov+Wave
Father ISEI (centralised)	0.0223***	0.0226***	0.00414	0.00566
	(0.00727)	(0.00738)	(0.00797)	(0.00748)
RTI (std)	-11.73***	-11.73***	-11.55***	-11.55***
	(0.137)	(0.142)	(0.133)	(0.133)
Father ISEI × RTI	-0.0290***	-0.0291***	-0.0334***	-0.0332***
	(0.00881)	(0.00877)	(0.00856)	(0.00853)
Age (centralised)	-0.0814**	-0.0778*	0.00306	0.00781
	(0.0379)	(0.0384)	(0.0665)	(0.0681)
Age^2 (centralised)	-0.00420***	-0.00414***	-0.00146	-0.00138
	(0.00121)	(0.00120)	(0.00192)	(0.00192)
Gender	-0.735**	-0.749***	-0.457	-0.462
	(0.275)	(0.272)	(0.291)	(0.295)
Years of schooling (centralised)	0.290***	0.291***	0.259***	0.265***
	(0.0341)	(0.0361)	(0.0300)	(0.0322)
Urban	0.609**	0.596**	0.187	0.251
	(0.249)	(0.237)	(0.233)	(0.237)
Marriage	-0.699**	-0.732**	-0.610	-0.626*
	(0.312)	(0.316)	(0.363)	(0.361)
Constant	33.661***	33.732***	34.785***	34.783***
	(0.571)	(0.574)	(0.802)	(0.808)
Observations	11393	11393	9360	9360
R-squared	0.797	0.798	0.775	0.776
Survey-wave FE	Yes	Yes	Yes	Yes
Industry/Sector FE	No	No	Yes	Yes
Province FE	No	Yes	No	Yes
Birth-cohort FE	No	No	No	No

Standard errors in parentheses
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Figure 10 reinforces the scale of the level association. Holding parental status at the sample mean and varying RTI from -2 to +2, predicted child ISEI falls from around 56 to 11, which is a decrease of 45 points across a scale from 10 to 90. Crucially, this drop is nearly uniform across the parental ISEI distribution. The level shift is the dominant feature, suggesting that the negative association between RTI and occupational attainment is not concentrated among children of low-status parents but is consistent with a broad downward level association, in line with Guo (2022). Meanwhile, the flattening of the slopes as RTI increases indicates that routine-task exposure is also associated with a weaker relative advantage of having high-status parents. This is relevant for understanding inequality: RTI does not primarily reshape who inherits parental advantage, but lowers the absolute level of attainment for an exposed occupational tier.

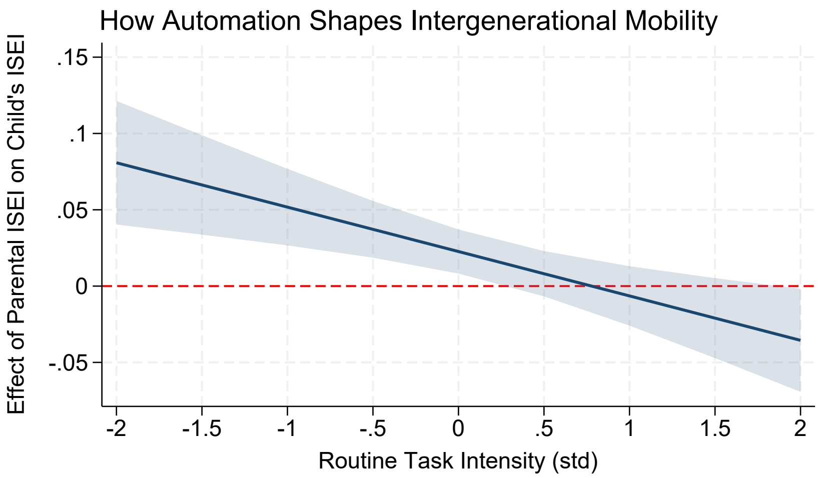


Figure 9: Marginal effect of parental ISEI and child ISEI by child RTI

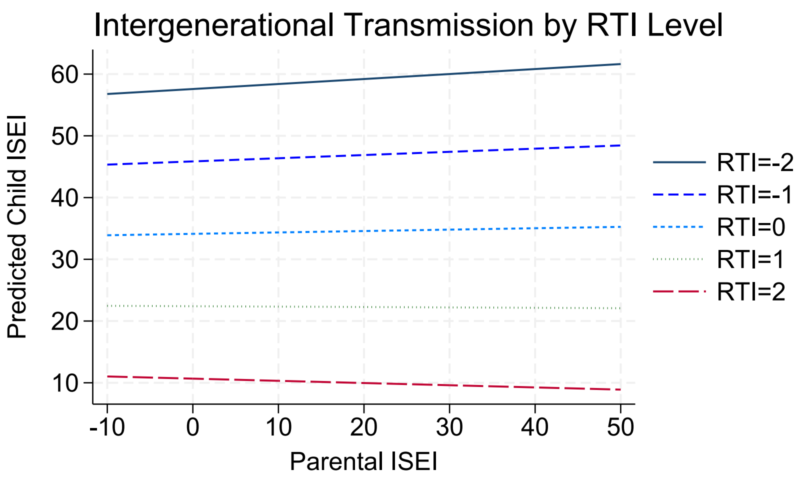


Figure 10: Predicted child ISEI by parental ISEI and child RTI

Estimating the same interaction model on log income yields a parental wage elasticity of 0.031 and a significant negative interaction coefficient of -0.034 (7). As with the ISEI results, the direct effect of parental income becomes statistically insignificant once fixed effects are introduced (Columns 2–4). The interaction remains significant, and the direction is consistent with the ISEI results. Unlike Heyman and Olsson (2023), who find that automation's intergenerational effects are concentrated among low-income families in Sweden, our results suggest that in China, rather than strengthening the parent-child wage transmission, higher RTI is associated with a weaker parental wage effect, pointing to a more diffuse attenuation of intergenerational transmission. Note that the smaller sample size in this analysis (N = 3,906) reflects the requirement for matched parent-child income observations, which necessarily restricts the estimation sample relative to the main income regressions. Figure 11 illustrates that the marginal effect of parental wages on child income is strongest (approximately 0.060 at RTI=-1.5) and significant at low RTI values, but becomes statistically insignificant at RTI values above 0.5.

Table 7: Automation and Intergenerational Income Transmission

	(1) Wave	(2) Prov+Wave	(3) Ind+Wave	(4) Ind+Prov+Wave
Parental log income	0.0309*	0.0138	0.0213	0.00337
	(0.0181)	(0.0206)	(0.0243)	(0.0258)
RTI (std)	0.254*	0.189	0.373**	0.300*
	(0.138)	(0.145)	(0.162)	(0.158)
Parental log income × RTI	-0.0339**	-0.0263*	-0.0459***	-0.0378**
	(0.0135)	(0.0139)	(0.0165)	(0.0157)
Age	-0.0872***	-0.0900***	-0.0867***	-0.0892***
	(0.0131)	(0.0137)	(0.0140)	(0.0142)
Age^2	-0.00411***	-0.00411***	-0.00417***	-0.00412***
	(0.000446)	(0.000482)	(0.000469)	(0.000474)
Gender	0.322***	0.304***	0.269***	0.268***
	(0.0461)	(0.0468)	(0.0590)	(0.0571)
Education (yrs)	0.0173***	0.0122**	0.0194***	0.0141**
	(0.00515)	(0.00486)	(0.00534)	(0.00547)
Urban	0.0173	-0.0232	0.00238	-0.0349
	(0.0351)	(0.0328)	(0.0327)	(0.0320)
Observations	3906	3906	3701	3701
R-squared	0.238	0.296	0.251	0.306
Survey-wave FE	Yes	Yes	Yes	Yes
Industry/Sector FE	No	No	Yes	Yes
Province FE	No	Yes	No	Yes
Birth-cohort FE	No	No	No	No

Standard errors in parentheses
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

The intergenerational results extend a literature that has so far focused mainly on contemporaneous labour-market effects of automation. In China, intergenerational mobility is already shaped by parental income, education, hukou status, and regional inequality (Deng et al., 2013; Fan et al., 2021b; Li et al., 2017). The results reported here suggest that routine-task exposure adds another channel through which social origin affects labour-market outcomes. The negative interaction between parental background and child RTI should not be interpreted as evidence that automation improves equality of opportunity. Rather, it suggests that routine-intensive occupations reduce the absolute returns to parental advantage once children enter such jobs. This is closer to the mechanism highlighted by Guo (2022), in which automation operates as a broad downward level shock, than to evidence from high-income welfare-state contexts where automation effects may be more concentrated among children from low-income families (Heyman and Olsson, 2023). The Chinese case therefore points to a dual mechanism: RTI compresses outcomes within exposed occupational tiers, while family background continues to shape who enters those tiers in the first place.

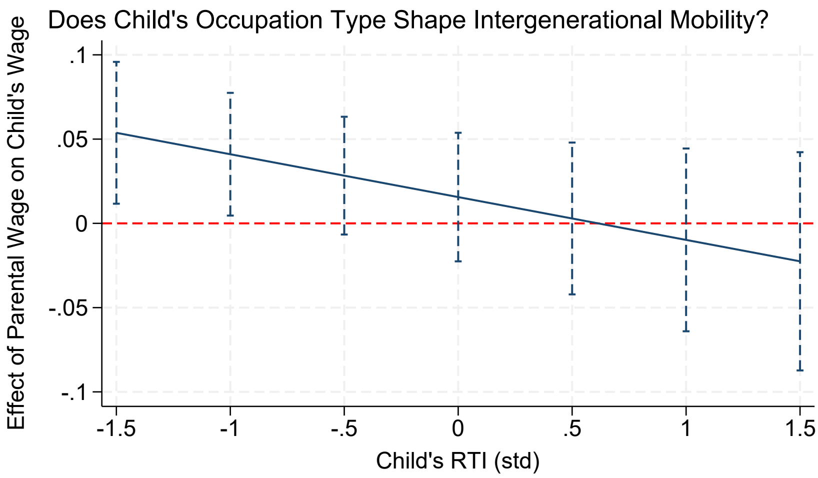


Figure 11: Marginal effect of parental income and child income by child RTI

The wage loss associated with child RTI is economically large and precisely estimated. Predicted log wages decline from 10.4 at RTI=-2 to 9.95 at RTI=2 (Figure 12), a difference of approximately 0.45 log points. This corresponds to an income reduction of about 36%, using $1 - \exp(-0.45)$, for children who move from the least to the most routine-intensive occupation. This loss is larger than the absolute value of the parental wage elasticity of 0.031. Thus, the occupational position a child enters is strongly associated with observed earnings, even after accounting for parental background.

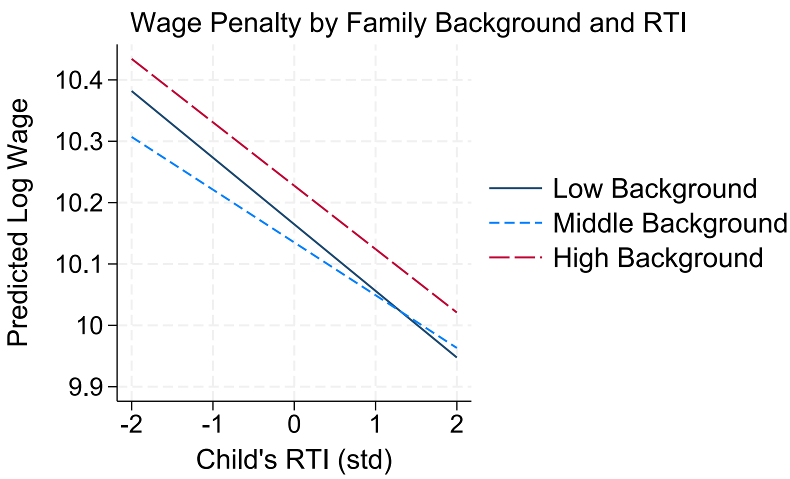


Figure 12: Predicted child income by parental background and child RTI

The preceding results suggest that the association between RTI and child outcomes operates primarily through level losses rather than by reshaping transmission slopes. A further question is whether these losses are distributed equally across children from different family backgrounds, or whether socio-economic origin amplifies them. Separating the sample into terciles of parental wages and estimating RTI-related wage losses within each group, we find that children from disadvantaged backgrounds face an earnings loss of 33.46%, compared with 28.42% for middle-background children and 34.26% for advantaged-background children. The parallel analysis using parental ISEI terciles yields larger magnitudes: low (46.33%), middle (33.56%), and high (34.04%). Notably, under the parental wage classification, the loss is largest for low-background children but remains substantial for high-background children, exceeding that of the middle group. This non-monotonic pattern suggests that vulnerability to routine-task exposure is not strictly stratified by family background, and that children from high-income families are not fully insulated from routine-task losses.

Table 8: Wage Penalty of Automation by Family Background

	By Parental Wage		By Parental ISEI	
Background Group	% Penalty	95% CI	% Penalty	95% CI
Low	-33.46*** (5.97)	[-45.17, -21.75]	-46.33*** (4.21)	[-54.58, -38.09]
Middle	-28.42*** (9.74)	[-47.51, -9.32]	-33.56*** (7.11)	[-47.49, -19.63]
High	-34.26*** (5.06)	[-44.18, -24.33]	-34.04*** (4.82)	[-43.48, -24.61]

Notes: Province and wave fixed effects absorbed. Robust standard errors clustered at the family and province level. $^{***}p < 0.01$.

A formal test of equality of RTI coefficients across background groups (Table 21) fails to reject the null of homogeneous losses when background is measured by parental wage terciles, but marginally rejects it when measured by parental ISEI terciles, indicating that the magnitude of the RTI-related loss differs significantly by parental occupational status. Nevertheless, the core finding is clear that no socio-economic background group is insulated from wage losses associated with routine-task exposure, with all groups incurring losses exceeding 28%.

This finding adds an intergenerational dimension to a literature that has largely focused on contemporaneous wage adjustment and cross-sectional wage polarisation (Acemoglu and Restrepo, 2022; Autor and Dorn, 2013). The results suggest a dual mechanism: social origin shapes the probability of entering routine-intensive occupations, and routine-task exposure is associated with sizeable income losses once children enter those occupations. In this sense, RTI may compress outcomes within exposed occupational tiers while reinforcing disadvantage through occupational sorting.

5.5 Reduced-form robot exposure

The analysis in this section shifts from potential automation exposure, measured by RTI, to a reduced-form measure of exposure to imported industrial robots. The Bartik-style index combines baseline province-industry employment shares, industry robot-susceptibility weights, and national growth in imported industrial robots. Given that the earliest customs data for robot imports date back to 2015, the analysis in this section starts from the 2016 CFPS wave.

In the baseline specification without province fixed effects, robot exposure is positively associated with both total income and occupational status (ISEI). This pattern is consistent with the possibility that productivity and task-reinstatement effects are stronger in provinces more exposed to imported industrial robots and robot-intensive industrial upgrading. However, the association is attenuated in the more demanding province fixed-effect specification, indicating that the baseline result is driven primarily by cross-provincial differences in predetermined exposure to robot-intensive industrial structure rather than by strong within-province changes over time.

Table 9: Baseline Regression Results: Impact of Robot Exposure on Wages

Variables	(1) ln(Wage)	(2) ln(Wage)	(3) ISEI	(4) ISEI
Bartik	0.1720***	0.1600***	0.9930***	0.3240*
	(0.0347)	(0.0327)	(0.2660)	(0.1870)
Year of Schooling	0.0507***	0.0431***	1.2940***	0.9940***
	(0.0027)	(0.0030)	(0.0430)	(0.0420)
Gender	0.4620***	0.4070***	−0.5960**	0.6450**
	(0.0279)	(0.0247)	(0.2470)	(0.2820)
Urban	0.1540***	0.0987***	3.9860***	1.0780***
	(0.0212)	(0.0208)	(0.2460)	(0.3120)
Married	0.0819***	0.0435**	−1.1490***	0.1920
	(0.0229)	(0.0205)	(0.2590)	(0.3050)
Age	0.0896***	0.0931***	−0.0076	0.1120
	(0.0047)	(0.0047)	(0.0675)	(0.0696)
Age Squared	−0.0012***	−0.0012***	−0.0011	−0.0013
	(0.0001)	(0.0001)	(0.0007)	(0.0008)
Constant	7.3610***	7.4830***	23.9600***	26.6300***
	(0.1080)	(0.1090)	(1.5480)	(1.4820)
Observations	32,680	27,019	67,918	37,428
R-squared	0.2460	0.2360	0.3080	0.3250
Survey-wave FE	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	Yes
Province FE	No	No	No	No

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

A limitation of our specification is that the robot exposure index is constructed from customs data on imported industrial robots. It captures exposure to imported robots rather than total robot adoption, since it does not directly observe domestically produced robots or firm-level use of automation capital. To the extent that imported robot flows are positively correlated with broader robot adoption, and that imported and domestically produced robots have similar labour-market effects, the estimated coefficients can be interpreted under this assumption as lower-bound estimates of the broader association between robot exposure and labour-market outcomes. If domestic robot adoption is weakly correlated with imported robot exposure, however, the estimates should be read more narrowly as reduced-form associations with exposure to imported industrial robots.

To examine the industry composition underlying the robot exposure measure, we report an industry-contribution diagnostic, motivated by the Rotemberg-weight interpretation of Bartik designs in Goldsmith-Pinkham et al. (2020). The diagnostic in Table 10 shows that the motor vehicles and trailers industries account for a large share of the industry component of the robot exposure index, reflecting the high concentration of robot penetration growth in China's automotive industry during the baseline period.

This concentration is plausible, given the high automation intensity of the automotive sector, but it also narrows the interpretation of the Bartik estimates. The baseline estimates should therefore be read as evidence from automobile-intensive manufacturing automation rather than as fully broad-based evidence on economy-wide robot diffusion. To examine whether the positive association is entirely driven by this sector, we conduct a leave-one-out sensitivity analysis by re-estimating the baseline model using a modified robot-exposure index that excludes the automotive industry.

Table 10: Rotemberg-style industry-contribution decomposition

Industry	Rotemberg Weight
Food, beverages, and tobacco	0.00088
Textiles, apparel, and leather	0.00002
Wood products and furniture	0.00003
Paper, paper products, and printing	0.00008
Chemical, plastic, and rubber products	0.00211
Non-metallic mineral products	-0.00002
Basic metals	0.00039
Fabricated metal products	0.01384
Industrial machinery and equipment	0.00010
Motor vehicles and trailers	0.97032
Railway, ship, aerospace, and other transport eq.	0.00208
Electrical, computer, electronic, and optical prod.	0.01379
Other manufacturing	-0.00363

The leave-one-out estimates remain statistically significant and broadly consistent in magnitude with the baseline estimates for both wages and ISEI (Table 11). This suggests that the positive association is not entirely driven by the automotive sector. However, the strong concentration of the industry component in motor vehicles and trailers means that the reduced-form Bartik estimates should be interpreted as evidence from manufacturing-led, automobile-intensive automation exposure, rather than as evidence of pervasive automation effects across the whole economy.

6 Robustness checks

To assess the stability of our findings, this section conducts a series of robustness checks using alternative RTI transformations, sample restrictions, task-group classifications, mobility definitions, and local digitalisation indicators. The aim is to examine whether the

Table 11: Robot Exposure Index Excluding the Automobile Industry

Variables	(1) ln(Wage)	(2) ISEI
Bartik (Excl. Automotive)	0.252***	0.651***
	(0.0758)	(0.279)
Individual Controls	Yes	Yes
Survey-wave FE	Yes	Yes
Industry/Sector FE	Yes	Yes
Province FE	No	No
Observations	27,019	37,428
Adjusted R-squared	0.231	0.325

baseline results are sensitive to measurement choices, sample composition, or alternative proxies for the local technological context.

A series of checks is performed after using alternative measures of RTI in Table 12 to ensure that the findings about the relationship between automation exposure and total income are not sensitive to the construction of RTI. Column (1) shows that a one-percentile increase in RTI rank leads to a 0.42% drop in total income, which eliminates the influence of absolute scale and reveals the income loss led by the ranking movement. Column (2) illustrates a non-linear pattern where the 2nd quartile incurs a 13.1% income loss relative to the 1st quartile, the 3rd quartile a smaller 8.4%, and the 4th quartile the largest penalty of 27.2%, confirming a non-linear relationship between routine task intensity and income. Column (3) interprets the results using the raw Chinese RTI index, yielding a coefficient of −0.2851, confirming that the baseline findings are not driven by standardisation or ranking procedures. In all specifications, the negative relationship between RTI and the total income persists with high significance, while the coefficients of the control variables are generally consistent with previous estimates.

The persistence of the negative income association across standardised RTI, percentile ranks, quartiles, and the RTI index suggests that the main result is not an artefact of scaling or normalisation. It instead points to a systematic association between routine task content and lower income in China.

To verify the results are not driven by specific sample compositions, Table 13 presents several checks using different sample groups. We test groups by excluding the agricultural sectors (Column 1), focusing on prime-age workers (aged 25 to 54, Column 2), restricting the sample to wage earners, and currently employed individuals (Column 4). The relationship between RTI and total income is still highly significantly negative and stable in magnitude across all specifications, ranging from −0.120 to −0.132. Furthermore, the performance of the control variables is consistent with our baseline estimates.

Table 14 reports wage differentials across five task-based occupational groups, using non-routine cognitive analytical (NRCA) occupations as the reference category. After controlling for individual characteristics, including gender, hukou status, years of schooling, marital status, age, and age squared, Panel A shows a positive but statistically insignificant

Table 12: Impact of Different RTI Measures on Wages

Variables Dependent Variable: lnwage	(1) Percentile Rank (1–100)	(2) RTI Quartiles (1–4)	(3) Unstd. RTI (Raw Level)
RTI Percentile Rank	−0.0042***		
	(0.0003)		
RTI Quartiles (Base: 1st)			
2nd Quartile		−0.1403***	
		(0.0195)	
3rd Quartile		−0.0882***	
		(0.0277)	
4th Quartile		−0.3180***	
		(0.0256)	
Unstandardized RTI			−0.2851***
			(0.0135)
Gender	0.4001***	0.3896***	0.4073***
	(0.0252)	(0.0237)	(0.0252)
Urban	0.0612***	0.0600***	0.0591***
	(0.0168)	(0.0164)	(0.0162)
Years of Schooling	0.0366***	0.0373***	0.0333***
	(0.0023)	(0.0024)	(0.0021)
Married	0.0510***	0.0504***	0.0555***
	(0.0170)	(0.0175)	(0.0169)
Age	−0.0133***	−0.0135***	−0.0137***
	(0.0010)	(0.0010)	(0.0010)
Age Squared	−0.0012***	−0.0012***	−0.0012***
	(0.0000)	(0.0000)	(0.0000)
Constant	9.9552***	9.9134***	9.8858***
	(0.0235)	(0.0211)	(0.0231)
Industry/Province/Wave FE	Yes	Yes	Yes
Observations	31,665	31,665	31,665

*** p<0.01, ** p<0.05, * p<0.1.
Column (3) uses the raw, unstandardized Chinese RTI index (`rti_chn`).

Table 13: RTI Effects on Income: Excluding Specific Sub-groups

Variables Dependent Variable: lnwage	(1) Excl. Agriculture	(2) Prime-age Only	(3) Wage Earners	(4) Employed Only
RTI	-0.1249^{***}	-0.1198^{***}	-0.1307^{***}	-0.1315^{***}
	(0.0061)	(0.0089)	(0.0058)	(0.0075)
Gender	0.4041^{***}	0.4098^{***}	0.4193^{***}	0.4165^{***}
	(0.0245)	(0.0247)	(0.0253)	(0.0254)
Urban	0.0612^{***}	0.0838^{***}	0.0547^{***}	0.0461^{***}
	(0.0157)	(0.0232)	(0.0160)	(0.0146)
Years of Schooling (centralised)	0.0333^{***}	0.0381^{***}	0.0327^{***}	0.0328^{***}
	(0.0021)	(0.0025)	(0.0021)	(0.0023)
Married	0.0547^{***}	0.0389^{**}	0.0678^{***}	0.0515^{***}
	(0.0183)	(0.0146)	(0.0174)	(0.0172)
Age (centralised)	-0.0134^{***}	-0.0111^{***}	-0.0141^{***}	-0.0136^{***}
	(0.0010)	(0.0015)	(0.0010)	(0.0011)
Age Squared (centralised)	-0.0012^{***}	-0.0005^{***}	-0.0012^{***}	-0.0012^{***}
	(0.0000)	(0.0001)	(0.0000)	(0.0001)
Constant	9.7624^{***}	9.7130^{***}	9.7589^{***}	9.7877^{***}
	(0.0270)	(0.0235)	(0.0253)	(0.0272)
Industry/Province/Wave FE	Yes	Yes	Yes	Yes
Observations	31,089	23,535	31,169	27,005
R-squared	0.2774	0.2807	0.2894	0.2891

*** p<0.01, ** p<0.05, * p<0.1.

Sample criteria: (1) excludes agriculture workers; (2) includes prime-age workers only (age$\geq$ 25 and age $\leq$ 54); (3) includes wage earners only; (4) includes currently employed individuals only.

association for the NRCP group, whereas significant negative associations are observed for the routine cognitive, routine manual, and non-routine manual groups.

Panel B complements the task-group analysis by interacting task type with robot exposure. The results suggest that the positive association between robot exposure and income is concentrated among non-routine cognitive workers, whereas manual workers display weaker or negative associations. This is consistent with China-specific evidence that robot adoption is part of broader manufacturing upgrading, but that its benefits depend on workers' skills, tasks, and sectoral location (Cheng et al., 2019; Fan et al., 2021a; Wang and Dong, 2020). Taken together, the results indicate that the average positive association with robot exposure masks important heterogeneity across task groups.

Table 15 provides additional evidence on the robustness of the occupational mobility analysis. First, the lagged RTI is introduced to mitigate endogeneity issues. Second, to ensure the results are not led by the classification of mobility intensity, the move type groups aggregate into coarser Downward and Upward categories. Third, we expand the choice set by introducing Exit as a competing outcome to include individuals who quit the labour market. Despite these modifications and a reduced sample size due to lagging, the results in Table 15 show that the directional association between RTI and occupational mobility persists. Higher routine intensity is associated with a reduced likelihood of downward mobility, though this effect is not statistically significant, while significantly promoting upward moves relative to the Stay group. Notably, the association between RTI and labour force exit is positive but statistically insignificant.

As a final step, we introduce two control variables from the policy of Made in China 2025, which are the intensity of numerical control (NC) rate of key process and intensity of penetration rate of digital R&D and design tools. The variables are constructed as follows:

$$NC = \frac{Expected\ NC\ Rate_{2025} - Realised\ NC\ Rate_{2015}}{100 - Realized\ NC\ Rate_{2015}} \tag{25}$$

$$RD = \frac{Expected\ RD\ Rate_{2025} - Realised\ RD\ Rate_{2015}}{100 - Realized\ RD\ Rate_{2015}} \tag{26}$$

The expected and realised values are released and set by each provincial government. These indicators measure the province-level planned increase in digitalisation relative to the remaining feasible gap from the 2015 baseline to full adoption. They should therefore be interpreted as indicators of local digitalisation ambition or potential upgrading needs under the Made in China 2025 framework, rather than as direct measures of realised firm-level technology adoption. While RTI identifies which jobs are theoretically more susceptible to automation based on task structure, it does not directly capture the local technological environment in which workers operate.

NC and RD partly address this limitation by proxying province-level digitalisation potential and local technology-diffusion conditions. By including these measures, the analysis distinguishes task-based exposure from the broader provincial technological

Table 14: Robot Exposure and Task-group Heterogeneity

	(1) ln(Wage)	(2) Occupational Status (ISEI)
Panel A: Task-group Main Effects		
Non-routine Cognitive Personal (NRCP)	0.0486	-13.82***
	(0.0592)	(1.024)
Routine Cognitive (RC)	-0.0936*	-26.49***
	(0.0471)	(0.656)
Routine Manual (RM)	-0.254***	-33.69***
	(0.0592)	(0.721)
Non-routine Manual (NRM)	-0.290***	-34.41***
	(0.0502)	(0.684)
Panel B: Robot Exposure × Task-group Interactions		
Robot exposure (Bartik shift-share)	0.204***	-0.829**
	(0.0319)	(0.349)
× Non-routine Cognitive Personal (NRCP)	0.00931	1.508***
	(0.0284)	(0.436)
× Routine Cognitive (RC)	-0.0535**	0.992**
	(0.0237)	(0.385)
× Routine Manual (RM)	-0.0857**	0.959**
	(0.0363)	(0.432)
× Non-routine Manual (NRM)	-0.0789***	0.875**
	(0.0251)	(0.386)
Observations	30,355	41,730
R-squared	0.125	0.667
Survey-wave FE	Yes	Yes
Industry/Sector FE	Yes	Yes
Province FE	No	No
Birth-cohort FE	No	No

Notes: Standard errors clustered at the province level in parentheses. Base task group is Non-routine Cognitive Analytical (NRCA). Robot exposure measured via Bartik shift-share instrument. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 15: Multinomial Logit Estimates of Occupational Mobility

Variables Base Outcome: Stay	(1) Downward	(2) Upward	(3) Exit
Lagged RTI	−0.0986	0.3346***	0.0524
	(0.0845)	(0.0600)	(0.0360)
Gender	0.9516***	0.8314***	−0.4449***
	(0.2006)	(0.1012)	(0.0616)
Urban	0.5358***	0.4092***	0.0302
	(0.1796)	(0.1224)	(0.0857)
Years of Schooling (centralised)	0.0102	−0.0147	−0.0212***
	(0.0218)	(0.0145)	(0.0071)
Age (centralised)	−0.0474***	−0.0380***	0.0172***
	(0.0077)	(0.0059)	(0.0043)
Age Squared (centralised)	−0.0008	−0.0009***	0.0013***
	(0.0005)	(0.0002)	(0.0002)
Constant	−5.6876***	−4.1489***	−3.1465***
	(0.2333)	(0.1044)	(0.1322)
Observations	37,498	37,498	37,498

The base category for the multinomial logit is Stay (outcome 0).
*** p<0.01, ** p<0.05, * p<0.1.

environment. Table 16 reports the results after controlling for these digitalisation measures.

The RTI coefficient remains significantly negative, confirming that the income loss associated with routine tasks is not absorbed by province-level digitalisation indicators. The large negative direct coefficient on NC should be interpreted with caution because NC captures planned digitalisation growth relative to the remaining 2015 gap, rather than realised firm-level numerical-control adoption; it may therefore partly proxy lower initial digitalisation or larger upgrading needs. The interaction term $RTI \times NC$ is marginally significant ($p < 0.1$), providing limited evidence that local manufacturing digitalisation may attenuate the RTI-related income loss, while $RTI \times RD$ does not reach statistical significance. The results are in line with a scant literature from China, which suggests that automation and digital upgrading can raise productivity and reorganise production while distributing gains unevenly across workers, sectors, and regions (Cheng et al., 2019; Fan et al., 2021a; Wang and Dong, 2020; Gai et al., 2025).

Table 17 demonstrates regional heterogeneity in the digitalisation results. The negative wage association is more concentrated in eastern provinces, as evidenced by significantly negative RD and NC coefficients in the eastern region (−0.986 and −2.959, respectively). The pattern in the central, western, and northeast regions is less consistent, with digitalisation coefficients statistically insignificant, suggesting that the regional labour-market effects of digitalisation do not follow a simple geographic gradient.

The persistence of the negative RTI coefficient suggests that the routine-task income loss is not simply a proxy for technologically advanced provinces. At the same time, the marginally significant interaction between RTI and numerical-control intensity provides limited evidence that local manufacturing digitalisation may attenuate some routine-task income losses. This seems to support previous findings indicating that automation can raise productivity and reorganise production, while distributing gains unevenly across workers and regions (Cheng et al., 2019; Fan et al., 2021a; Wang and Dong, 2020; Gai et al., 2025).

Table 16: Heterogeneous Effects: RTI, Digitalization, and Wages

Variables Dependent Variable: lnwage	(1) Digital R&D Tools (RD)	(2) Numerical Control (NC)
RTI	−0.2019**	−0.2545***
	(0.0719)	(0.0640)
Digital Intensity	1.7069***	−9.3486***
	(0.1486)	(0.6383)
RTI × Digital Intensity	0.1062	0.2404*
	(0.1038)	(0.1273)
Gender	0.3731***	0.3992***
	(0.0272)	(0.0317)
Urban	0.0625**	0.0655***
	(0.0219)	(0.0209)
Years of Schooling (centralised)	0.0353***	0.0348***
	(0.0027)	(0.0027)
Married	0.0531**	0.0618***
	(0.0195)	(0.0187)
Age (centralised)	−0.0134***	−0.0142***
	(0.0011)	(0.0011)
Age Squared (centralised)	−0.0012***	−0.0012***
	(0.0001)	(0.0001)
Constant	8.6014***	14.2071***
	(0.1059)	(0.2953)
Industry & Wave FE	Yes	Yes
Observations	23,676	24,685

*** p<0.01, ** p<0.05, * p<0.1.

Digital Intensity in column (1) refers to the penetration rate of digital R&D and design tools (RD); in column (2), it refers to the intensity of numerical control rate of key processes (NC).

Table 17: Regional Heterogeneity in Digitalisation Effects on Wages

	East	Central	West	Northeast
Panel A: Model RD (Penetration rate of digital R&D and design tools)				
RTI (lagged)	-0.1343^{***}	-0.1128^{***}	-0.1215^{***}	-0.1479^{***}
	(0.0149)	(0.0159)	(0.0180)	(0.0222)
RD	-0.9857^{***}	-0.1895	-0.1652	1.0230
	(0.1432)	(0.1647)	(0.2582)	(0.6563)
Observations	7,430	6,857	6,094	3,295
Panel B: Model NC (Numerical control rate of key processes)				
RTI (lagged)	-0.1469^{***}	-0.1131^{***}	-0.1185^{***}	-0.1479^{***}
	(0.0131)	(0.0159)	(0.0187)	(0.0223)
NC	-2.9585^{***}	-0.0867	-0.1903	0.7719
	(0.2786)	(0.2263)	(0.1751)	(0.4952)
Observations	9,031	6,857	5,502	3,295

Notes: Standard errors clustered at the individual level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

7 Conclusion

In this paper, we have examined the relationship between automation exposure, occupational mobility, and income inequality in China between 2014 and 2022. Using nationally representative longitudinal data from the China Family Panel Studies, the analysis combines occupation-level Routine Task Intensity (RTI) measures with a Bartik-style measure of exposure to imported industrial robots. This allows us to distinguish between potential exposure to automation, measured through the task content of occupations, and robot exposure, measured through predicted provincial exposure based on baseline industrial structure and national growth in industrial robot imports.

The first main finding is that routine task exposure is robustly associated with lower individual income. A one-standard-deviation increase in RTI is linked to a sizeable reduction in annual income, and this relationship remains stable after controlling for individual characteristics, industry, province, cohort, and survey-wave fixed effects. The income loss is not evenly distributed across workers. It is larger among older workers and among workers with higher educational attainment, suggesting that routine-intensive jobs reduce the returns to accumulated skills and occupation-specific human capital.

The second main finding concerns inequality. Contrary to much of the evidence from advanced economies, where routine-biased technological change is often associated with wage polarisation and rising inequality, the distributional analysis provides evidence that routine task exposure is associated with lower measured income inequality. The analysis shows that income losses are present across the income distribution but are larger among middle- and higher-income routine workers. This suggests that routine-intensive work in China is not confined to low-paid manual employment, but also appears in formal-sector, technical, clerical, and production occupations located in the middle and upper parts of the income distribution. As a result, routine task exposure compresses the income distribution rather than mechanically widening it.

The third main finding is that the occupational-mobility effects of automation exposure are more complex than the income effects. RTI is associated with higher probabilities of upward mobility in ISEI terms, but this pattern should not be interpreted as unambiguous economic upgrading. Because RTI and occupational status are strongly negatively correlated, routine-intensive workers often begin from relatively low positions in the occupational-status hierarchy. Some transitions therefore appear as upward mobility in status terms even when they do not translate into higher income. This distinction is central to the analysis as it underscores the fact that occupational status mobility and income mobility do not necessarily move together in the context of structural transformation and automation exposure.

The fourth main contribution is that automation exposure has an intergenerational dimension. The results suggest that high RTI operates primarily as a downward level shock to both occupational attainment and income among children. Routine task exposure weakens the observed association between parental background and child outcomes, but not because it equalises opportunity. Rather, it lowers outcomes across parental-background groups. At the same time, social origin continues to matter because children from disadvantaged families are more likely to sort into routine-intensive occupations in the first place. Automation exposure therefore compresses outcomes within exposed occupational tiers while reinforcing disadvantage through occupational sorting.

The distinction between potential automation exposure and robot exposure is an important element in our analysis. While RTI is negatively associated with income and occupational status, robot exposure is positively associated with both total income and occupational status in the baseline reduced-form specification. This contrast suggests that greater predicted exposure to imported industrial robots and robot-intensive industrial upgrading may be associated with productivity and reinstatement effects that offset displacement effects at the aggregate level. However, this positive association is attenuated in more demanding province fixed-effect robustness checks, so the robot-exposure results should be interpreted as reduced-form evidence of cross-provincial exposure to robot-intensive industrial structure rather than as strong causal estimates of robot adoption. The robustness checks using alternative RTI measures, sample restrictions, task-group classifications, and local digitalisation indicators further support the central finding that routine task exposure carries an income loss, while greater exposure to robot-intensive industrial upgrading and local digitalisation may partly buffer or reverse this loss depending on local technological conditions.

Our findings have an important caveat. The robot exposure index only captures imported industrial robots, not total robot adoption, since domestically produced robots are not directly observed in the customs data. Since China has become a major producer of robots worldwide[3], our estimates should therefore be interpreted, under this assumption, as conservative lower-bound estimates of the broader association between robot adoption and labour-market outcomes.

These findings have important policy implications. In emerging economies undergoing rapid structural transformation, the consequences of automation depend not only on the technical substitutability of tasks but also on the institutional and occupational structure of the labour market. Policies aimed at mitigating automation-related vulnerability should therefore focus on workers in routine-intensive occupations, especially older workers, rural hukou holders, and individuals with limited access to protected employment or retraining opportunities. At the same time, the baseline positive association between robot exposure and income suggests that robot-intensive industrial upgrading need not be uniformly harmful if accompanied by productivity gains, task creation, and complementary skill formation. However, this interpretation should be taken with caution as the association is attenuated in province fixed-effect robustness checks and because the index is strongly shaped by exposure to automobile-intensive manufacturing automation.

Further work is needed to examine whether emerging AI technologies will extend automation risk from routine manual and cognitive jobs to non-routine cognitive occupations. Understanding these dynamics will be essential for assessing the long-term implications of automation for inequality, mobility, and social stratification in China and other developing economies.

[3]The International Federation of Robotics reports that China is the world's largest industrial robot market, accounting for 54% of global deployments in 2024. Chinese manufacturers' share of the domestic market also grew substantially, rising from 47% in 2023 to 57% in 2024 (International Federation of Robotics, 2025).

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Appendix

A. RTI by cohort

Table 18: Mean RTI by Birth Cohort

Birth Cohort	Mean	SD	Min	Max
1935	0.595	0.320	−1.411	0.670
1940	0.544	0.512	−2.599	1.177
1945	0.524	0.536	−2.601	1.177
1950	0.487	0.620	−2.601	1.177
1955	0.375	0.749	−3.091	1.177
1960	0.247	0.862	−3.091	1.177
1965	0.225	0.851	−2.601	1.177
1970	0.100	0.922	−3.091	1.177
1975	−0.063	0.986	−3.091	1.177
1980	−0.259	1.073	−3.091	1.177
1985	−0.403	1.091	−3.091	1.177
1990	−0.507	1.108	−3.091	1.177
1995	−0.500	1.094	−3.091	1.177
2000	−0.322	1.035	−3.091	1.177
2005	0.179	0.689	−2.297	1.177
Total	−0.001	0.997	−3.091	1.177

Notes: Sample restricted to individuals aged 16–75. Cohorts with fewer than 50 individuals are excluded. Birth cohort defined as five-year intervals.

B. Mean RTI by Hukou status

Table 19: Mean RTI by Hukou Status

Hukou Status	Mean	SD
Rural	0.275	0.792
Urban	−0.300	1.107
Total	0.008	0.994

Notes: Sample restricted to individuals aged 16–75.

C. Distributional Effects

Table 20: RIF Regression: Gini Coefficient

	Coefficient	Std. Error
RTI (standardised)	-0.024^{*}	(0.013)
Male	-0.042^{***}	(0.013)
Urban hukou	-0.019^{**}	(0.009)
Marriage	-0.026	(0.024)
Age (centralised)	0.002^{***}	(0.000)
Age^2 (centralised)	0.000^{***}	(0.000)
Years of Education (centralised)	-0.002	(0.002)
Observations	31,674	
Sample mean Gini	0.421	
Survey-wave FE	Yes	
Industry/Sector FE	Yes	
Province FE	Yes	
Birth-cohort FE	No	

Standard errors in parentheses
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

D. Wald test

Table 21: Tests of Equality of RTI Losses Across Family Background Groups

	F-statistic	df	p-value
By parental wage tercile	1.49	(2, 29)	0.2419
By parental ISEI tercile	3.25	(2, 30)	0.0529

Notes: Null hypothesis: RTI coefficients are equal across three groups, Standard errors clustered at the family and province level.

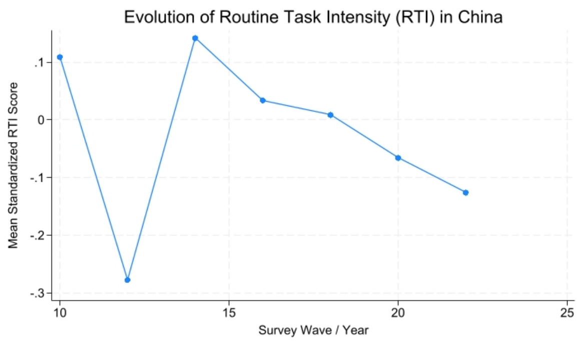
E. Automation and Income for the sample period between 2010 and 2022

This section provides supplementary evidence on the relationship between automation and income using the full span of the CFPS from 2010 to 2022. Table 22 and Figure 13 describe the summary statistics of the full sample and a decline in mean standardised RTI across China and its provinces. There is a downward trend in wave 2012, which might be caused by the inconsistent questionnaire design, leading us to exclude the first two waves in the main part. The regression results in Tables 23 and 24, supported by marginal plots in Figures 14 and **??**, demonstrate that the negative association between RTI and income is robust over the longer term. These findings reinforce the main text by showing that the income losses remain concentrated among older and more educated workers, with the most significant earnings losses occurring at the higher quantiles of the income distribution.

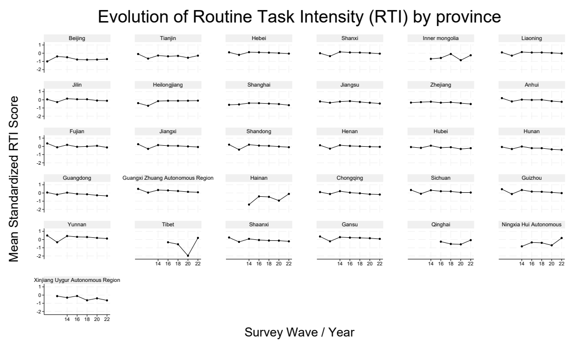
Table 22: Summary Statistics

Variable	Mean	SD	Min	Max	N
Income (log)	9.595	1.235	5.430	15.973	100,486
RTI (standardised)	-0.005	1.002	-3.091	1.180	126,365
Occupational status (ISEI)	32.962	14.272	12	90	143,236
Years of education	7.676	4.887	0	23	192,336
Age	44.565	15.124	16	75	199,991
Male	0.508	0.500	0	1	199,991
Urban hukou	0.474	0.499	0	1	193,090

Notes: Sample restricted to individuals aged 16–75
active in the labour market across CFPS waves 2010–2022.
Cohorts with fewer than 50 individuals are excluded.
Variation in N across variables reflects differences in item non-response.

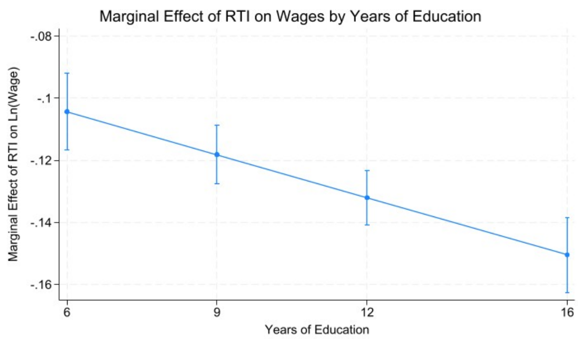


(a) Evolution of Routine Task Intensity in China, 2010–2022

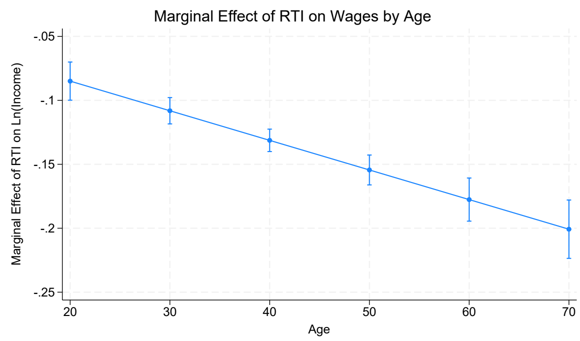


(b) Evolution of RTI by province, 2010–2022

Figure 13: Trends in Routine Task Intensity



(a) Marginal Effect of RTI on Income by Years of Schooling



(b) Marginal Effect of RTI on Income by Age

Figure 14: Marginal effects of RTI on income by education and age, 2010–2022

Table 23: Income Effects of Routine Task Intensity

	(1) Cohort & Wave FE	(2) +Controls	(3) +Ind. FE	(4) +Prov. FE	(5) +Both FE
RTI (standardised)	-0.238***	-0.180***	-0.140***	-0.166***	-0.128***
	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)
Male		0.498***	0.440***	0.512***	0.451***
		(0.009)	(0.010)	(0.009)	(0.009)
Urban hukou		0.283***	0.184***	0.181***	0.114***
		(0.009)	(0.009)	(0.009)	(0.009)
Years of schooling		0.041***	0.038***	0.038***	0.037***
		(0.001)	(0.001)	(0.001)	(0.001)
Married		0.152***	0.113***	0.149***	0.117***
		(0.012)	(0.012)	(0.012)	(0.012)
Age		0.071***	0.073***	0.074***	0.074***
		(0.002)	(0.003)	(0.002)	(0.003)
Age^2		-0.001***	-0.001***	-0.001***	-0.001***
		(0.000)	(0.000)	(0.000)	(0.000)
Observations	68,004	64,778	57,245	64,778	57,245

Robust standard errors clustered at the individual level in parentheses.

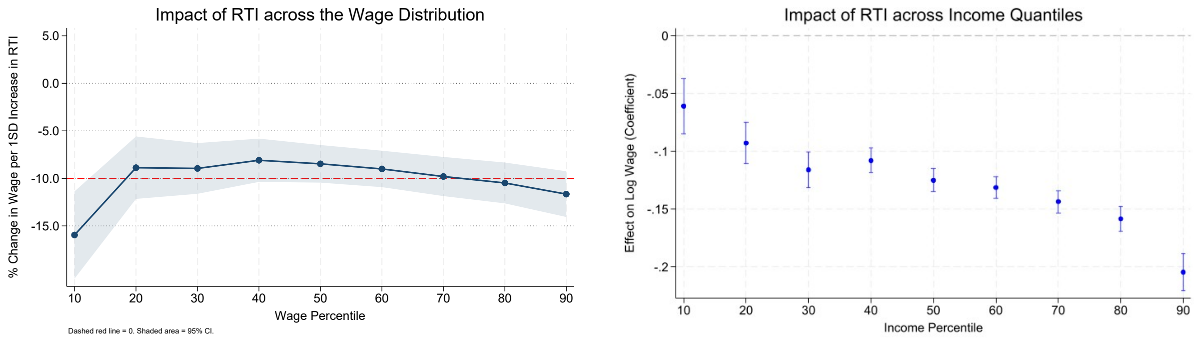
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 24: Heterogeneous Income Effects by Education and Age

	(1) Wave FE	(2) +Ind. FE	(3) +Prov. FE	(4) +Both FE
RTI (standardised)	-0.075***	-0.075***	-0.025	0.070***
	(0.011)	(0.020)	(0.019)	(0.020)
RTI × Education	0.002**	0.002**	0.001	-0.007***
	(0.001)	(0.001)	(0.001)	(0.001)
RTI × Age	-0.003***	-0.003***	-0.003***	-0.003***
	(0.000)	(0.009)	(0.000)	(0.000)
Observations	64,778	54,245	64,778	54,245

Controls included in all specifications. Standard errors clustered at individual level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$



(a) Unconditional quantile estimates

(b) RIF regression estimates

Figure 15: Association between RTI and income across the wage and income distribution, 2010–2022

F. Automation and Occupation for the sample period between 2010 and 2022

Appendix G explores the impact of automation across specific task-based occupational groups and their associated mobility pathways. Table 25 confirms the transition patterns, showing consistent results for occupational mobility across the decade. Table 26 reveals that, relative to non-routine cognitive analytical tasks (NRCA), workers in routine manual (RM) and non-routine manual (NRM) occupations suffer the largest significant wage losses. Figure 16 illustrates the protective role of human capital, where higher educational attainment significantly boosts the probability of upward mobility while shielding workers from downward shifts as RTI increases. Additionally, Figure 17 and 18 highlight the heterogeneous vulnerabilities across gender, hukou status, and status tiers, showing that while male and rural workers face higher initial risks of downward mobility, the reduction in occupational status (ISEI) is most pronounced for those in the middle of the status distribution.

Table 25: Multinomial Logit: Occupational Mobility

	Baseline				+RTI×Education			
	Downward		Upward		Downward		Upward	
	Sharply	Slightly	Slightly	Sharply	Sharply	Slightly	Slightly	Sharply
RTI (standardised)	-1.175^{***}	-0.453^{***}	0.223^{***}	0.423^{***}	-2.426^{***}	-1.541^{***}	-0.189^{**}	-0.725^{***}
	(0.017)	(0.017)	(0.023)	(0.020)	(0.048)	(0.045)	(0.078)	(0.075)
RTI × Education					0.119^{***}	0.099^{***}	0.036^{***}	0.093^{***}
					(0.004)	(0.004)	(0.006)	(0.006)
Years of schooling	-0.052^{***}	-0.028^{***}	0.045^{***}	0.171^{***}	0.024^{***}	-0.026^{***}	0.036^{***}	0.155^{***}
	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.004)	(0.005)	(0.005)
Age	-0.027^{***}	0.000	-0.003	-0.037^{***}	-0.032^{***}	-0.007	-0.006	-0.038^{***}
	(0.008)	(0.008)	(0.008)	(0.007)	(0.008)	(0.007)	(0.008)	(0.007)
Age^2	0.000	-0.000^{***}	-0.000^{***}	0.000	0.000	-0.000^{**}	-0.000^{***}	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-1.105^{***}	-1.507^{***}	-1.851^{***}	-1.937^{***}	-1.506^{***}	-1.219^{***}	-1.639^{***}	-1.629^{***}
	(0.166)	(0.168)	(0.172)	(0.150)	(0.168)	(0.165)	(0.176)	(0.153)
Observations	69,408				69,408			
Pseudo R^2	0.105				0.119			

Notes: Base outcome: Stay. Robust standard errors clustered at the individual level in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

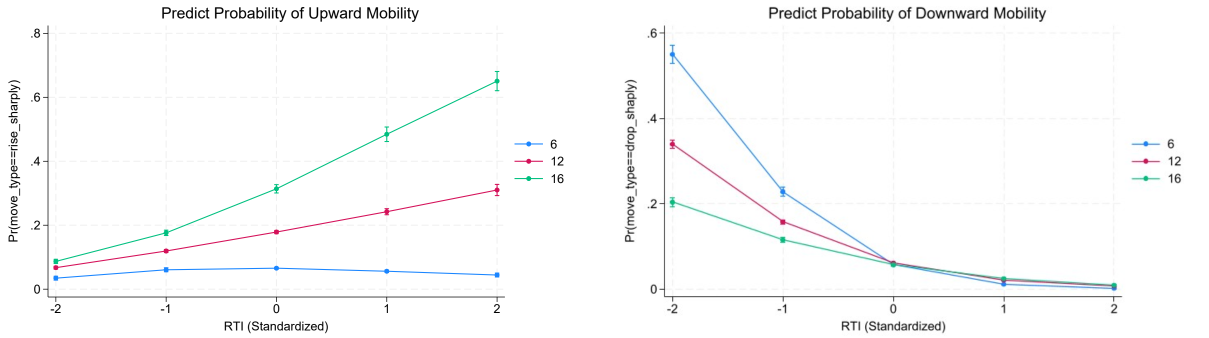
Table 26: Income Effects of Task Groups

Variables	Log Income
NRCP	0.062 *** (0.017)
RC	-0.109 *** (0.015)
RM	-0.243 *** (0.016)
NRM	-0.296 *** (0.015)
Individual Controls	Yes
Industry Fixed Effects	Yes
Province Fixed Effects	Yes
Wave Fixed Effects	Yes
Observations	65272
R-squared	0.444

Robust standard errors are clustered at the individual level
Group NRC is treated as the reference
*** p <0.01, ** p <0.05, * p <0.1

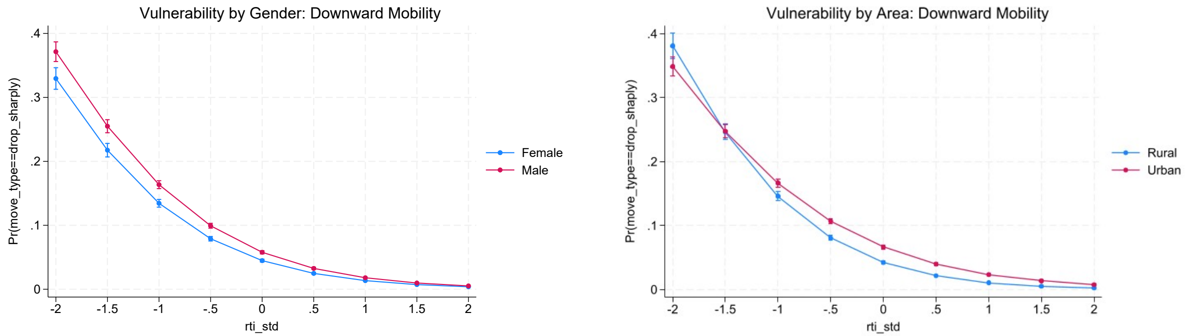
G. Automation and Intergenerational Mobility for the sample period between 2010 and 2022

This section provides evidence on the intergenerational consequences of automation using the full sample from 2010 to 2022. Tables 27 and 28 demonstrate that while parental



(a) Predict probability of upward mobility (b) Predict probability of downward mobility

Figure 16: Predict probability of mobility by education



(a) By Gender (b) By Area

Figure 17: Vulnerability by gender and area, 2010–2022

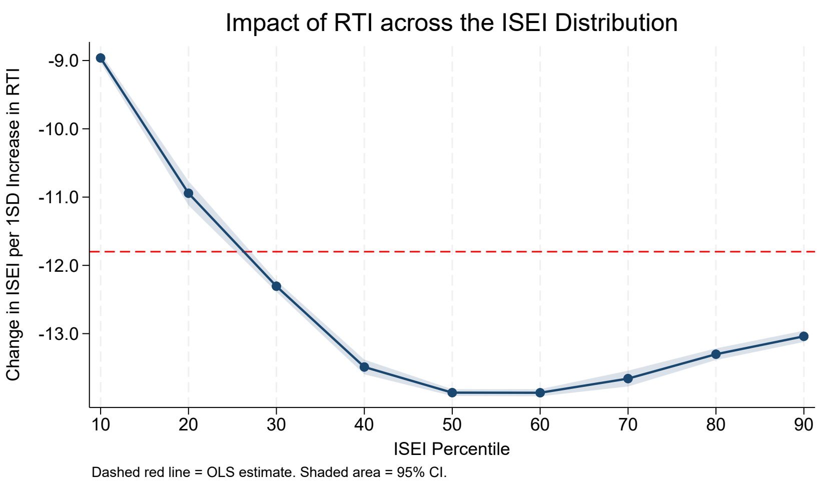


Figure 18: Association between RTI and occupational status across the ISEI distribution, 2010–2022

income and occupational status (ISEI) remain significant predictors of children's success, automation exposure (RTI) acts as a powerful downward level shock that compresses these advantages. Specifically, the negative interaction term in Table 28 and the marginal effect plots in Figures 19 and 20 suggest that high routine intensity significantly attenuates the intergenerational transmission of status, not by improving social mobility, but by lowering the absolute attainment of all children in routine roles regardless of their family origins. Table 29 further clarifies this level penalty, showing that children from all socio-economic backgrounds face substantial wage losses associated with routine-task exposure, with those from disadvantaged backgrounds often incurring the most severe losses (up to 49.84%). Finally, Figure 21 illustrates that the occupational position a child enters is strongly associated with observed earnings, even after accounting for parental background, highlighting routine-task exposure as an important correlate of contemporary social stratification.

Table 27: Automation and Intergenerational Income Transmission

	(1) Wave	(2) Prov+Wave	(3) Ind+Wave	(4) Ind+Prov+Wave
Parental log income	0.1155***	0.0824***	0.0829***	0.0584***
	(0.0138)	(0.0137)	(0.0137)	(0.0137)
RTI (std)	-0.4270***	-0.4389***	-0.0811	-0.1329
	(0.0947)	(0.0926)	(0.0953)	(0.0936)
Parental log income × RTI	0.0334***	0.0354***	-0.0011	0.0051
	(0.0096)	(0.0094)	(0.0096)	(0.0095)
Age	0.2000***	0.1998***	0.2031***	0.2010***
	(0.0119)	(0.0115)	(0.0117)	(0.0115)
Age^2	-0.0027***	-0.0028***	-0.0027***	-0.0028***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Gender	0.3267***	0.3296***	0.2881***	0.2957***
	(0.0248)	(0.0240)	(0.0262)	(0.0256)
Education (yrs)	0.0244***	0.0195***	0.0220***	0.0183***
	(0.0031)	(0.0031)	(0.0033)	(0.0032)
Urban	0.1451***	0.0595**	0.1018***	0.0317
	(0.0235)	(0.0239)	(0.0237)	(0.0242)
Constant	4.9246***	5.4037***	5.2449***	5.6481***
	(0.2089)	(0.2080)	(0.2084)	(0.2088)
Observations	7,289	7,289	7,035	7,035
Clusters (*fid*)	4,813	4,813	4,695	4,695
R^2 (within)	0.1787	0.1491	0.1530	0.1315

Notes: Dependent variable is child's log income. Robust standard errors clustered at the family level (*fid*) in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 28: Automation and Intergenerational Occupational Status Transmission

	(1) Wave	(2) Prov+Wave	(3) Ind+Wave	(4) Ind+Prov+Wave
Parental ISEI	0.0316***	0.0290***	0.0136**	0.0143**
	(0.0060)	(0.0060)	(0.0057)	(0.0058)
RTI (std)	-10.746***	-10.709***	-10.448***	-10.458***
	(0.205)	(0.206)	(0.208)	(0.208)
Parental ISEI × RTI	-0.0275***	-0.0284***	-0.0291***	-0.0291***
	(0.0060)	(0.0060)	(0.0059)	(0.0059)
Age	0.2345***	0.2438***	0.0975	0.1086
	(0.0519)	(0.0518)	(0.0682)	(0.0682)
Age^2	-0.0032***	-0.0033***	-0.0009	-0.0010
	(0.0008)	(0.0008)	(0.0011)	(0.0011)
Gender	-0.986***	-0.984***	-0.798***	-0.814***
	(0.153)	(0.153)	(0.176)	(0.176)
Education (yrs)	0.3058***	0.3114***	0.2565***	0.2636***
	(0.0180)	(0.0183)	(0.0195)	(0.0197)
Urban	0.6028***	0.5455***	0.1880	0.2693*
	(0.150)	(0.150)	(0.161)	(0.163)
Married	-0.5937***	-0.6138***	-0.3916**	-0.4118**
	(0.167)	(0.166)	(0.186)	(0.185)
Constant	26.476***	26.369***	29.922***	29.599***
	(0.827)	(0.832)	(1.024)	(1.028)
Observations	16,477	16,477	14,040	14,040
Clusters (*fid*)	8,322	8,322	7,711	7,711
R^2 (within)	0.7710	0.7634	0.6617	0.6602

Notes: Dependent variable is child's ISEI score. Robust standard errors clustered at the family level (*fid*) in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 29: Wage Penalty of Automation by Family Background

	By Parental Wage		By Parental ISEI	
Background Group	% Penalty	95% CI	% Penalty	95% CI
Low	-49.84***	[-56.14, -43.54]	-46.42***	[-51.57, -41.27]
	(3.21)		(2.63)	
Middle	-19.37***	[-29.24, -9.50]	-34.70***	[-44.03, -25.37]
	(5.04)		(4.76)	
High	-26.21***	[-34.65, -17.77]	-33.84***	[-41.57, -26.11]
	(4.30)		(3.95)	

Notes: Province and wave fixed effects absorbed. Robust standard errors clustered at the family level (*fid*). $^{***}p < 0.01$.

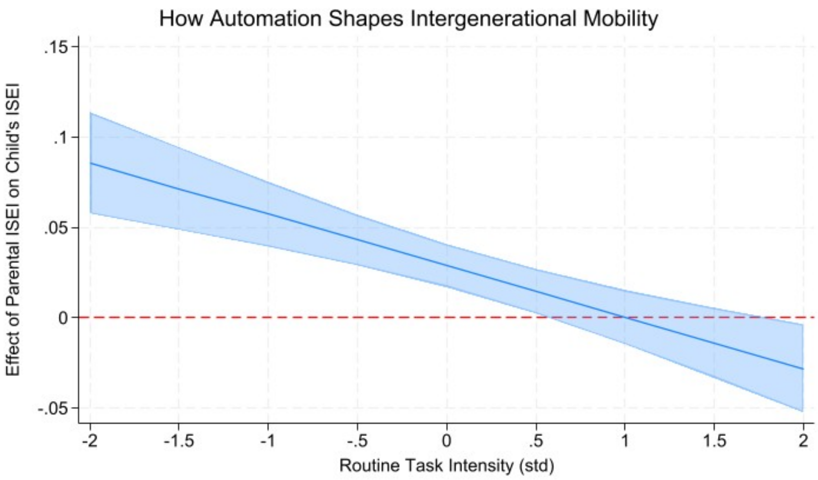


Figure 19: Marginal effect of parental ISEI on child ISEI by child RTI, 2010–2022

Table 30: Multinomial Logit: Relative Risk Ratios

	Drop sharply	Drop slightly	Rise slightly	Rise sharply
RTI (standardised)	0.088***	0.214***	0.828**	0.484***
	(0.004)	(0.010)	(0.065)	(0.036)
RTI × Education	1.126***	1.104***	1.036***	1.097***
	(0.004)	(0.004)	(0.006)	(0.006)
Years of education	1.024***	0.974***	1.036***	1.168***
	(0.006)	(0.004)	(0.005)	(0.006)
Age	0.969***	0.993	0.994	0.963***
	(0.008)	(0.007)	(0.008)	(0.007)
Age^2	1.000	0.9998**	0.9997***	1.000
	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.222***	0.295***	0.194***	0.196***
	(0.037)	(0.049)	(0.034)	(0.030)
Observations	69,408			
Pseudo R^2	0.119			

Notes: Base outcome: Stay. Relative risk ratios reported. Robust SE clustered at individual level.

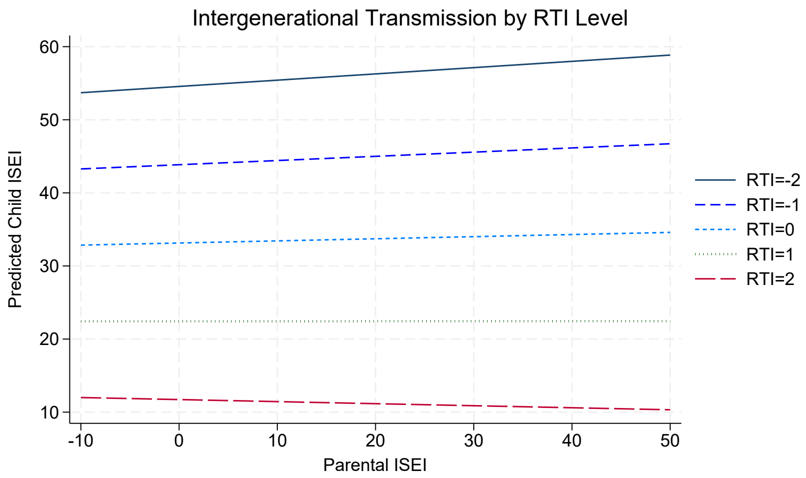


Figure 20: Predicted child ISEI by parental ISEI and child RTI, 2010–2022

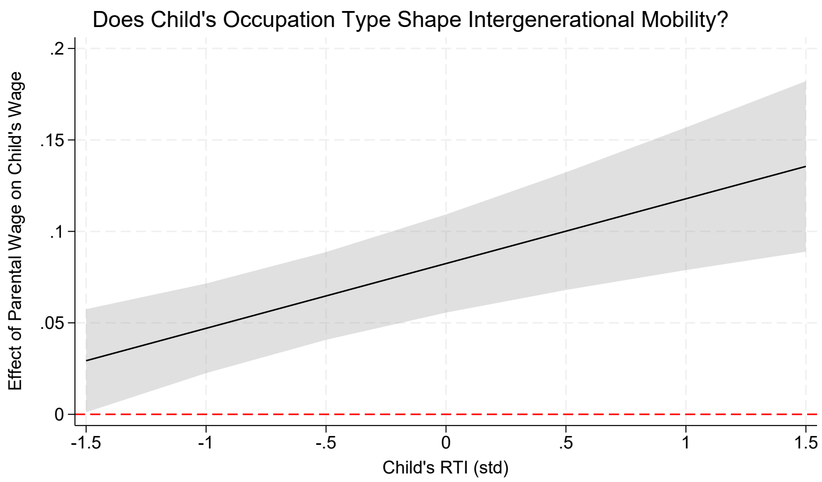


Figure 21: Marginal effect of parental income on child income by child RTI, 2010–2022

H. Bartik robot-exposure robustness checks with province fixed effects, 2014–2022

Table 31 presents the robustness check using a Bartik robot-exposure index that excludes the automobile industry, estimated with province fixed effects. The coefficients are attenuated and statistically insignificant, because province fixed effects absorb the cross-provincial variation in baseline exposure that the index is designed to capture, leaving only weak residual variation for identification.

Table 32 replicates the task-group heterogeneity specification with province fixed effects included. This version should be interpreted as a stricter differential-slope robustness check that identifies within-province differences across task groups, rather than as the main estimate of the average robot-exposure association.

Table 31: Robot Exposure Index Excluding the Automobile Industry with Province-level FE

Variables	(1) ln(Wage)	(2) ISEI
Bartik (Excl. Automotive)	-0.0027	0.509
	(0.0365)	(0.888)
Individual Controls	Yes	Yes
Survey-wave FE	Yes	Yes
Industry/Sector FE	Yes	Yes
Observations	27,019	37,428
Adjusted R-squared	0.261	0.329

Table 32: Robot Exposure and Task-group Heterogeneity with Province-level FE

	(1) ln(Wage)	(2) Occupational Status (ISEI)
Panel A: Task-group Main Effects		
Non-routine Cognitive Personal (NRCP)	0.0376	-13.88***
	(0.0580)	(1.029)
Routine Cognitive (RC)	-0.0898**	-26.51***
	(0.0432)	(0.675)
Routine Manual (RM)	-0.231***	-33.67***
	(0.0619)	(0.711)
Non-routine Manual (NRM)	-0.286***	-34.39***
	(0.0473)	(0.705)
Panel B: Robot Exposure × Task-group Interactions		
Robot exposure (Bartik shift-share)	0.0508*	-0.245
	(0.0284)	(0.457)
× Non-routine Cognitive Personal (NRCP)	0.0167	1.542***
	(0.0284)	(0.435)
× Routine Cognitive (RC)	-0.0478**	1.020**
	(0.0222)	(0.383)
× Routine Manual (RM)	-0.0862**	0.996**
	(0.0393)	(0.414)
× Non-routine Manual (NRM)	-0.0671***	0.914**
	(0.0221)	(0.383)
Observations	30355	41730
R-squared	0.147	0.669
Survey-wave FE	Yes	Yes
Industry/Sector FE	Yes	Yes
Province FE	Yes	Yes
Birth-cohort FE	No	No

Notes: Standard errors clustered at the province level in parentheses. Base task group is Non-routine Cognitive Analytical (NRCA). Robot exposure measured via Bartik shift-share instrument. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$