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Globalization Raises Intergenerational Inequality Transmission in Chinese Villages

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Abstract

Using China's accession to World Trade Organization (WTO) in 2001, an epoch in the globalization process in recent decades, as a quasi-experiment, this paper studies the impact of globalization on intergenerational transmission of inequality in Chinese villages. Based on nationally representative rural household survey data, this study documents that the trade shocks brought about by China's WTO accession has amplified economic inequality across generations in Chinese villages. The WTO accession enhanced international trade between China and the rest of the world by reducing trade barriers. The booming of the export-oriented manufacturing located in coastal and urban areas led to unprecedented rural-to-urban migration in human history. We find that migration leads to large income benefit. We also find that sons from wealthy and better-educated families in rural areas are more likely to grab the job opportunities brought about by the WTO accession and are more likely to migrate, compared with sons from less-wealthy and less-educated families. Policies are called for to address the concern that inequality would be persisting across generations along with globalization.

Keywords: Globalization; Migration; Intergenerational mobility; Economic inequality

JEL Codes: J62; F66

1. Introduction

The global economy is facing a turning point. Globalization, once hailed by mainstream economists and policymakers worldwide, is ebbing. The mass media now portrays globalization as one of the major causes of the drastic increases in income inequality and social stratification that have sparked political turmoil and global unrest. As early as in 2002, Joseph Stiglitz, the Nobel Prize laureate in economics, cautioned in his book *Globalization and its Discontents* that globalization might raise income inequality in developing countries. Subsequent empirical analyses confirmed this conjecture (Han, et al., 2012, Topalova, 2010, Verhoogen, 2008, Zhu and Trefler, 2005). However, with deepening globalization, income inequality in developed countries, especially in the United States, has also been rising (Antràs, et al., 2017, Azzimonti, et al., 2014, Haskel, et al., 2012). Import competition from China, especially after 2001 when it acceded to the World Trade Organization (WTO), led to the polarization of job opportunities and earnings in the US labour market (Autor, et al., 2013, Autor, et al., 2016). The trade war between China and the United States that endangers the future survival of globalization finally ignited in 2018.

However, while the relationship between globalization and income inequality has been well studied, less is known about whether and how globalization affects the transmission of inequality across generations. Specifically, are children from wealthy families more likely to grasp the economic opportunities brought about by globalization and more capable of competing in the international labour market than those from less-wealthy families? If children from wealthy families are favoured, globalization would not only increase the Gini coefficient (i.e. a snapshot of income inequality across families in the same generation), but also amplify the intergenerational inequality transmission measured by the degree of income persistence across generations of the same families. This question deeply concerns both the public and policymakers because the increase in intergenerational persistence (i.e. decline in intergenerational mobility) undermines the opportunity to escape poverty and begets socioeconomic disparities that persist across generations (Heckman, 2000, Heckman, 2007); nonetheless, the effect of globalization on intergenerational mobility has not yet been empirically examined.

To bridge this gap in the body of knowledge, we investigate the effect of China's accession to the WTO, an epoch in the globalization process in recent decades, on intergenerational income mobility in Chinese villages. We focus on Chinese villages because the rural population accounted for more than 60% before China's WTO accession in 2001. Rural development and rural-to-urban migration have been two of the major policy issues in China. WTO accession reduced international trade barriers such as output tariffs, input tariffs, and trade uncertainty (Autor, et al., 2016, Pierce and Schott, 2016). Since then, China has experienced rapid increases in both exports and imports. For example, total exports increased sevenfold from 2001 to 2016 (Fig. 1). Export-oriented manufacturing, especially in coastal and urban areas, has been booming. The newly created job opportunities have attracted rural and inland workers in the agricultural sector to migrate to urban and coastal areas to work in the manufacturing sector. The resulting rural-to-urban migration has been unprecedented in human history. For example, the 2010 Chinese population census recorded more than 220 million rural-to-urban migrants, who remain temporary migrants under the Chinese household registration (*hukou*) system. However, since China's accession, its distribution of income has sharply skewed (Han, et al., 2012), with the country's Gini coefficient rising from 0.40 in 1998 to 0.49 in 2009 (Fig. 1). This situation has raised concern about whether inequality will persist across generations as globalization advances (Deng, et al., 2013, Gustafsson and Li, 2002, Gustafsson, et al., 2008, Heckman, 2006, Heckman, 2007, Li, et al., 2013, Li and Sicular, 2014, Wan, 2004, Wan, et al., 2007, Zhang, 2021).

Although globalization involves multiple facets such as trade, finance, culture, and technology, this study focuses on trade globalization. Specifically, we exploit the cross-region and cross-cohort variations in the trade shocks brought about by China's WTO accession as a quasi-experiment to study the effect of globalization on intergenerational mobility (Han, et al., 2012, Li, 2018, Tian, et al., 2020). These trade shocks vary regionally because different regions had specialized in different industries before China's accession and the tariff reductions associated with WTO accession differ significantly across industries. The trade shocks also vary across birth cohorts because China acceded to the WTO in 2001.

To measure intergenerational income mobility in Chinese villages, we use two nationally representative rural household surveys: the 2003–2013 Research Center for the Rural Economy (RCRE) survey and 1995, 2002, 2007, and 2013 Chinese Household Income Project (CHIP) surveys. The combined dataset is considered to be the best available for studying intergenerational income mobility in Chinese villages. We generate a nationally representative sample with 26,264 parent–son pairs in rural China. We divide the sample into 98 groups by the son's birth cohort and region. For each group, we separately estimate three measures of intergenerational income mobility. The first is the rank-rank slope, which is estimated by regressing the son's percentile rank on the parent's percentile rank (Chetty and Hendren, 2018, Chetty, et al., 2014). A positive (negative) rank-rank slope estimate indicates low (high) intergenerational mobility. We further estimate two measures of absolute mobility: the mean percentile ranks of sons whose parents are at the 25th and 75th percentile ranks of the national parent income distribution (Chetty and Hendren, 2018, Chetty, et al., 2014). These two estimates measure the mobility of sons from low-income (i.e. bottom quartile) and high-income (i.e. top quartile) families. When estimating these three measures of intergenerational mobility, we address conventional attenuation bias and lifecycle bias (Fan, et al., 2021).

To measure the exposure to trade shocks brought about by WTO accession, we use the 2002–2013 World Bank Trade Analysis and Information System (TRAINS) dataset, 2000 Chinese Industrial Enterprises database, and 1% sample of the 2000 Chinese population census. For each group, we separately construct two measures of exposure to trade shocks. The first is exposure to trade shocks from other prefectures, which affects intergenerational mobility in the villages through the labour market (Tian, et al., 2020). The output tariff reduction due to WTO accession created new job opportunities, which attracted rural and inland workers in the agricultural sector to work in the manufacturing sector in urban and coastal areas. The second measure is exposure to trade shocks to the prefecture in which the resident lives. Exposure to trade shocks from one's own prefecture affects intergenerational mobility through the income effect in addition to the labour demand effect. The abovementioned growth in the manufacturing sector increased the income of urban residents, leading to higher demand for agricultural products. As the agricultural product market is relatively local, higher demand for agricultural goods increased the income of local agricultural workers in general. We focus on exposure to trade shocks from other prefectures in our empirical analysis because cross-prefecture and cross-province migration has changed the Chinese economy markedly in recent decades.

We compare intergenerational mobility and exposure to trade shocks from other prefectures between earlier (1966–1981) and later (1982–1994) birth cohorts. Fig. 2 shows that an increase in the rank-rank slope (i.e. a decline in intergenerational mobility) is associated with an increase in exposure to trade shocks from other prefectures across birth cohorts. We then regress intergenerational mobility on exposure to trade shocks at the group level, controlling for a comprehensive set of socioeconomic factors, regional fixed effects (FE), and cohort FE. Our FE estimation results show that trade shocks from other prefectures lower intergenerational income mobility in Chinese villages. Trade shocks from one's own prefecture also lower intergenerational mobility, but the estimates are small and not statistically significant. We further find that the mean percentile rank of sons born to parents at the 25th percentile rank significantly decreases with trade shocks from other prefectures, whereas that of sons born to parents at the 75th percentile rank does not change significantly.

How does globalization, measured by the trade shocks brought about by WTO accession, lower intergenerational mobility in Chinese villages? WTO accession reduced trade barriers and thus enhanced trade between China and the rest of the world, subsequently leading to widescale rural-to-urban migration. Hence, migrant selectivity might explain our estimated negative effect of globalization on intergenerational mobility. Using the RCRE survey data, we find that migration is associated with a 45% increase in income. We further find that sons from wealthy and better-educated families in rural areas are more likely to grasp the job opportunities brought about by WTO accession and be migrant workers than sons from less-wealthy and less-educated families. To address the concern that inequality is persisting across generations as globalization advances, policies must more equally allocate newly created job opportunities to children from both poor and wealthy families, and subsidise human capital investment for children from poor families from their early stages.

Our study contributes to the burgeoning literature on intergenerational mobility through a subnational rural perspective. Building on Becker and Tomes' (1979) seminal model of intergenerational human capital transmission, many empirical studies have documented persistent downward trends in intergenerational mobility in most developed and developing economies, including the United States and China (Chetty, et al., 2017, Corak, 2013, Fan, et al., 2021). However, existing literature remains mainly focused on national-level aggregates and urban contexts, particularly in the Chinese case (Deng, et al., 2013, Fan, 2016, Huang, et al., 2021, Qin, et al., 2016, Yang, et al., 2024). Our study highlights the significant role of rural areas in the Chinese economy and analyses the change in intergenerational income mobility in Chinese villages.

Our study also contributes to the literature on the economic impacts of globalization, and advances understanding of the mechanism by which globalization impacts intergenerational mobility. While globalization's impacts on income inequality (Antràs, et al., 2017, Haskel, et al., 2012), labour market (Autor, et al., 2013, Autor, et al., 2016), and productivity and export growth (Brandt, et al., 2012, Handley and Limão, 2017) have been well-studied, its intergenerational consequences remain poorly understood. By leveraging China's WTO accession as a quasi-experiment, our paper examines the effect of globalization on intergenerational mobility and explores the underlying mechanisms.

The rest of the paper is organized as follows. Section 2 presents data and variables. Section 3 specifies the econometric model. Section 4 shows the main results. Section 5 discusses the mechanisms. The last section concludes.

2. Data and Variables

2.1. Intergenerational Income Mobility

To measure intergenerational income mobility in Chinese villages, we combine datasets from two nationally representative rural household surveys: the 2003–2013 RCRE survey and 1995, 2002, 2007, and 2013 CHIP surveys.

The RCRE survey is a nationally representative and annually longitudinal survey of Chinese rural individuals, households, and villages. The survey was started in 1986 by the RCRE under the Ministry of Agriculture in China. The latest wave was conducted in 2019. The survey includes about 23,000 rural households in 360 administrative villages, located in 31 provinces, municipalities, or autonomous regions. The CHIP is a nationally representative and cross-sectional survey of Chinese individuals and households. The survey was started in 1988 by researchers from the Chinese Academy of Social Sciences (CASS) together with associated Chinese and international scholars, with the assistance of the National Bureau of Statistics (NBS). Four follow-up surveys were conducted in 1995, 2002, 2007, and 2013. The survey covers both rural and urban households from 19 out of 34 province-level administrative units in China. We focus on rural households for this study, and combine them with those from the RCRE survey.

The combined dataset is the best available for studying intergenerational mobility in Chinese villages for three reasons. First, the samples of both the RCRE and the CHIP are nationally representative. The RCRE and CHIP surveys cover rural areas in 31 and 19 provinces, municipalities, and autonomous regions, respectively. Moreover, the distributions of important demographic and socioeconomic variables such as age, sex, and schooling years in the two surveys are consistent with those from the population census. Second, the panel structure of the RCRE survey facilitates calculating lifetime income. The rural individuals included in the RCRE survey are tracked across multiple waves. In each wave, the RCRE survey collects information on individual and household income in the previous year. The solid technical support employed by the RCRE survey and assistance of provincial observation point management departments ensure the reliability of the income information. We thus calculate lifetime income by averaging total individual income across the waves to estimate intergenerational income mobility. Third, and most importantly, the two surveys collect a comprehensive set of demographic and socioeconomic information for all household members.

We refine the combined sample in four ways: (1) dropping the parent–son pairs with sons born before 1966 whose education is affected by historic events (Meng and Gregory, 2002, Meng and Zhao, 2021) and the pairs with sons aged 18 and below in 2013, whose income is a poor measure of lifetime income, (2) dropping the parent–son pairs with either a father or a mother aged 65 and above in 2003 because people of that age usually no longer work in China, (3) dropping the pairs for which the age difference between parents and sons is either smaller than 16 or larger than 46 and keeping the pairs for which the age difference between fathers and mothers is smaller than 13 and larger than -6, and (4) dropping samples from Beijing, Tianjin, Inner Mongolia, Shanghai, Hainan, Tibet, Qinghai, and Ningxia because of their small size and merging Chongqing municipality, an area historically included in Sichuan province since its formal establishment in 1997, with Chengdu prefecture for simplicity.

Finally, we generate a nationally representative sample with 27,078 parent–son pairs[①] in rural areas, in which 11,213 pairs are from the RCRE and 15,865 pairs are from the CHIP. Information on individual demographics and socioeconomic variables includes age, sex, schooling years, occupation, ethnicity, income, and residence. By using the information, we compute lifetime income for sons, fathers, and mothers, respectively, as detailed in Appendix A.

We divide the full sample into 98 groups by the son's birth cohort and region. Specifically, we first divide the full sample into two cohorts by the son's birth year: 1966–1981 (i.e. the earlier cohort) and 1982–1994 (i.e. the later cohort). Second, we divide the prefectures in each province into three regions: (1) provincial capitals, (2) all prefectures neighbouring provincial capitals, and (3) other prefectures. We should have 126 groups by birth cohort and region because the data cover two birth cohorts and 21 provinces, with three regions per province. By dropping groups with

[①] We focus on parent–son pairs for two reasons. First, sons either co-reside or reside in the same village with parents when sons grow up and are married in rural China; by contrast, daughters usually reside in other villages when they get married. Thus, the income information for sons is more accurate than that for daughters. Second, the income information is more likely to be available for sons because men have higher labour force participation rate and employment rate than women. So the sample of parent–son pairs is less likely to be truncated when we study intergenerational income mobility.

fewer than 50 parent–son pairs, our analysis sample includes 98 groups with 26,264 parent–son pairs in total. Appendix Table B1 summarizes individual demographics and socioeconomic variables for sons, fathers, and mothers, separately. Appendix Table B2 tabulates the sample size for each group.

We separately estimate three measures of intergenerational income mobility for each group. The first measure is the rank-rank slope. We compare each son's/parent's income with that of their peers and calculate the respective percentile rank at the national level by the son's birth cohort, ranging from 0 to 100. The rank-rank slope is then estimated by regressing the son's percentile rank on the parent's percentile rank for each group:

$$rank_{scr} = \alpha_{0cr} + \alpha_{1cr} rank_{pcr} + \varepsilon_{scr}, \tag{1}$$

where $rank_{scr}$ is the income percentile rank of son s in birth cohort c and region r and $rank_{pcr}$ is his parent's income percentile rank. We control for both the son's demographic variables including age and age squared and the parent's demographic variables including the mean of the father's and mother's age and its squared value. The coefficient α_{1cr} is the estimate of the income rank-rank slope for birth cohort c and region r. It measures the units of change in the son's percentile rank with respect to a one percentile rank increase in the parent's income (Chetty and Hendren, 2018, Chetty, et al., 2014). A positive rank-rank slope estimate indicates high income persistence across generations and therefore low intergenerational income mobility.

Although the rank-rank slope provides an intuitive linear estimate, one drawback is that the high degree of intergenerational mobility measured by this estimate can be driven by either the upward mobility of sons from families in the bottom income percentiles or the downward mobility of sons born to parents in the top percentiles. To address this concern, we estimate two measures of absolute mobility: the mean percentile ranks (in the national child income distribution) of sons whose parents are at the 25th and 75th percentile ranks of the national parent income distribution (Chetty and Hendren, 2018, Chetty, et al., 2014). These two estimates measure the mobility of sons from low-income (i.e. bottom quartile) and high-income (i.e. top quartile) families, respectively. Specifically, the mean income percentile rank of sons born to parents at the 25th income percentile rank is calculated as follows:

$$\widehat{income}_{cr}^{25} = \widehat{\alpha_{0cr}} + \widehat{\alpha_{1cr}} \times 25, \tag{2}$$

where $\widehat{\alpha_{0cr}}$ and $\widehat{\alpha_{1cr}}$ are estimates from equation (1) and $\widehat{income}_{cr}^{25}$ is the mean income percentile rank of sons born to parents at the 25th income percentile rank for birth cohort c in region r.

Similarly, the mean income percentile rank of sons born to parents at the 75th income percentile rank is calculated as follows:

$$\widehat{income}_{cr}^{75} = \widehat{\alpha_{0cr}} + \widehat{\alpha_{1cr}} \times 75, \tag{3}$$

where $\widehat{income}_{cr}^{75}$ is the mean income percentile rank of sons born to parents at the 75th income percentile rank for birth cohort c in region r. When estimating the three measures of intergenerational mobility, we address conventional attenuation bias and lifecycle bias (Fan, et al., 2021), as detailed in Appendix A.

To further examine the consistency of the three measures, we conduct correlation analyses, with results presented in Appendix Table B3. First, the significantly negative correlation between rank-rank slope and the mean income percentile rank of sons born to parents at the 25th income percentile rank aligns with expectations: groups with lower relative mobility (i.e. higher degree of the rank-rank slope) tend to have lower upward mobility of sons from families in the bottom income percentiles. Second, the correlation between rank-rank slope and the mean income percentile rank of sons born to parents at the 75th income percentile rank is positive and statistically insignificant. Third, the positive correlation between the mean income percentile rank of sons born to parents at the 25th income percentile rank and the mean income percentile rank of sons born to parents at the 75th income percentile rank implies that groups with higher upward mobility of sons from low-income families also show less downward mobility of sons from high-income families. This implies that opportunity and stratification coexist in rural China.

2.2. Exposure to Trade Shocks

To construct measures of exposure to trade shocks brought about by China's WTO accession, we use data from the 2002–2013 TRAINS dataset, the 2000 Chinese Industrial Enterprises database, and the 1% sample of the 2000 Chinese population census.

The TRAINS is a comprehensive computerized information system at the HS-based tariff line level (HS 6-digit). The database provides data on trade control measures including tariffs, para-tariffs, non-tariff measures, and imports by suppliers at HS 6-digit level. More than 150 countries report these data. Depending on the country the data are available from 1988 onwards. The Chinese Industrial Enterprises database is the most comprehensive enterprise database in China, which records both operational and financial information for all state-owned industrial enterprises and non-state-owned industrial enterprises above designated size. The database was administrated by the NBS in 1998 and was updated annually until 2013, with more than two million observations.

The surveyed industrial enterprises can be categorized into three industries: extractive industry, manufacturing industry, and electricity gas and water production and supply industry. The Chinese population census is a national survey of Chinese individuals, aimed to understand the changes in population development and gender ratio in regions. It was started in 1953 by the State Council of the People's Republic of China, and six follow-up surveys were conducted in 1964, 1982, 1990, 2000, 2010, and 2020.

We construct two measures of the exposure to trade shocks brought about by WTO accession for each group using the TRAINS dataset, 2000 Chinese Industrial Enterprises database, and 1% sample of the 2000 Chinese population census. The first measure is exposure to trade shocks from other prefectures. The construction of this measure is detailed as follows.

Firstly, we calculate output tariff in prefecture i and year t, τ_{it} (Kovak, 2013):

$$\tau_{it} = \sum_k \beta_{ik} \times \tau_{kt}, \tag{4}$$

where k denotes industry. The first term on the right-hand side is

$$\beta_{ik} = \frac{\lambda_{ik}\frac{1}{\theta_{ik}}}{\sum_{k'} \lambda_{ik'}\frac{1}{\theta_{ik'}}}, \tag{5}$$

where $\lambda_{ik} = \frac{labor_{ik}}{\sum_{k'} labor_{ik'}}$ is the proportion of labour allocated to industry k in prefecture i and θ_{ik} is the cost share of non-labour (Kovak, 2013, Tian, et al., 2020). We calculate λ_{ik} and θ_{ik} using the Industrial Enterprises Survey in 2000 (i.e. before WTO accession). Only manufacturing industries are included. The second term on the right-hand side is

$$\tau_{kt} = \sum_g \tau_{kgt} \times \frac{export_{kg1999}}{\sum_{g'} export_{kg'1999}}, \tag{6}$$

where τ_{kgt} is the output tariff imposed on industry k in country g and year t and $export_{kg1999}$ is the export value between country g and China for industry k in 1999. Thus, τ_{kt} is the industry-year-specific tariff. We use each country's export value with China in 1999—the pre-WTO period—as the weight for the output tariff to pre-empt any endogenous adjustment of trade to contemporaneous trade shocks. The data on the output tariff and export value are from the TRAINS dataset. Based on Sheng (2002) and the *Import and Export Tariff of the People's Republic of China* (2020), we match the two-digit industry codes in the Industrial Enterprises Survey in 2000 with the HS codes in the TRAINS dataset.

Secondly, we calculate output trade shocks by prefecture and year (Tian, et al., 2020):

$$shock_{it} = \tau_{i2002} - \tau_{it}, t \in [2003, 2013]. \tag{7}$$

Thirdly, we calculate exposure to trade shocks from other prefectures in year t for son s born in prefecture i and year y (age $a = t - y$):

$$exp_{syit}^{other} = \left[\sum_{j \neq i} shock_{jt} \times \frac{m_{ij}}{m_i}\right] \times \frac{m_i}{p_i} \times \frac{m_{t-y}}{p}, \tag{8}$$

where m_{ij} is the number of people who migrate from prefecture i to work in prefecture j in the 2000 census; m_i is the number of cross-prefecture migrants in prefecture i such that $m_i = \sum_{j \neq i} m_{ij}$; p_i is the population in prefecture i in the 2000 census; m_{t-y} is the number of cross-prefecture migrants aged a $(= t - y)$ in the 2000 census; and p is the population in the 2000 census.

Here, $shock_{jt}$ measures the trade shock from prefecture j in year t, $\frac{m_{ij}}{m_i}$ measures the probability of migrating from prefecture i to prefecture j conditional on son s being a migrant, $\frac{m_i}{p_i}$ is the probability of being a cross-prefecture migrant in prefecture i, and $\frac{m_{t-y}}{p}$ is the probability of being a cross-prefecture migrant at age a at the national level in 2000. Hence, the measure of exp_{syit}^{other} varies by prefecture, survey year, and birth cohort.

Fourthly, we calculate total exposure to trade shocks from other prefectures for son s born in prefecture i and year y:

$$texp_{syi}^{other} = \sum_{t=2003}^{2013} exp_{syit}^{other}. \tag{9}$$

Finally, for each group, we calculate the variable of exposure to trade shocks from other prefectures, Exp_{cr}^{other}, by averaging the value $texp_{syi}^{other}$ across all the sons in each group. The variable Exp_{cr}^{other}, which varies across birth cohort and region, captures exposure to trade shocks from other prefectures, weighted by the cross-prefecture migration networks existing before WTO accession and probability of migration. Trade shocks from other prefectures affect intergenerational mobility through the labour market.

The second measure is exposure to trade shocks from one's own prefecture (i.e. where one's *hukou* is registered). The construction of this measure is similar to that of trade shocks from other prefectures. We first calculate total exposure to trade shocks from one's own prefecture for son s born in prefecture i and year y:

$$texp_{syi}^{own} = \sum_{t=2003}^{2013} shock_{it}. \tag{10}$$

Then, for each group, we calculate the variable of exposure to trade shocks from one's own prefecture, Exp_{cr}^{own}, by averaging the value $texp_{syi}^{own}$ across all the sons in each group. We do not weight the variable of Exp_{cr}^{own} by the cross-prefecture migration networks existing before WTO accession and probability of migration because the channels through which trade shocks from one's own prefecture affect intergenerational mobility differ from those through which trade shocks from other prefectures affect intergenerational mobility.

A particular important concern in our study is the potential endogeneity of the measure of exposure to trade shocks from other prefectures. To construct this measure, we employ a three-stage approach. First, we calculate prefecture-specific trade shocks from other prefectures stemming from differential tariff changes across industries and variations in pre-WTO industrial composition, following established methods in the literature (Kovak, 2013, Tian, et al., 2020). Second, we innovatively calculate individual-level exposure to trade shocks by weighting prefecture-level trade shocks using two exogenous components: (1) pre-existing cross-prefecture migration networks and (2) age-specific migration probabilities observed prior to WTO accession. Crucially, these migration-related weights—determined by historical patterns and demographic factors—are unlikely to be influenced by subsequent post-WTO economic changes. Third, we aggregate the individual-level measure to region-cohort level by calculating a population-weighted average of individual-level exposure using the combined sample from the RCRE and the CHIP. By doing so, the primary endogeneity risk arises not from our novel migration-based weighting but from potential correlations between prefecture-specific trade shocks (or pre-WTO industry characteristics) and unobserved confounders. To address this, we rigorously test whether post-WTO tariff changes (2002–2013) correlate with pre-treatment trends, such as pre-WTO export growth (1999–2002) and pre-WTO tariff changes (1999–2002), at the industry level. Results confirm no significant relationship, consistent with the exclusion restriction assumptions critical to shift-share instrumental variable designs (Goldsmith-Pinkham, et al., 2020). This validation alleviates concerns that pre-existing industry dynamics or policy shifts could bias our estimates, reinforcing the credibility of our identification strategy. Thus, we are able to identify the causal effect of globalization on intergenerational mobility using China's accession to the WTO as a quasi-experiment.

Another important concern is that the external validity of our results may be limited if the RCRE and CHIP surveys are not fully representative at regional or group levels. We emphasize that our measures of intergenerational mobility and measures of exposure to trade shocks are constructed at the same group level using the same datasets. This alignment largely ensures the internal validity of our empirical analyses. We further discuss this limitation in our conclusion.

Globalization may affect intergenerational mobility in Chinese villages through different channels. The first is the labour market (i.e. the new job opportunities created in the manufacturing sector brought about by WTO accession). As exposure to trade shocks from other prefectures mainly captures this labour demand effect, we weight trade shocks from other prefectures by the existing cross-prefecture migration networks and age-specific probability of migration before WTO accession (Tian, et al., 2020). If children from wealthy families are more capable of grasping the job opportunities induced by WTO accession than those from less-wealthy families, the effect of globalization on intergenerational mobility through the labour market is expected to be negative.

Second, globalization can affect intergenerational mobility in Chinese villages through an income effect. The growth in the manufacturing sector increased urban residents' income, leading to higher demand for agricultural products, and this increased the income of local agricultural workers. If the increased income is equally distributed between wealthy and less-wealthy families, the effect of globalization on intergenerational mobility through the income effect is expected to be positive. Exposure to trade shocks from one's own prefecture thus captures both the income effect and the labour demand effect (Tian, et al., 2020).

2.3. Other Variables

To measure income inequality in the son's generation, we calculate the 90^{th}–10^{th} percentile income gap, which is the difference in the logarithm of the son's lifetime income between the 90^{th} and 10^{th} percentiles (Han, et al., 2012). A larger 90^{th}–10^{th} percentile income gap indicates higher income inequality in the son's generation.

We control for a set of demographic and socioeconomic variables at the group level to measure the son's developmental environment at age 12, including the logarithm of the population, proportion of people aged under 14, land per capita, number of mobile phones per capita, and Internet penetration at the prefecture level. We measure Internet penetration by dividing the number of Internet users by the population. The data on the population and proportion of people aged under 14 are drawn from China's population censuses in 1982, 1990, 2000, 2005, and 2010 published by the National Bureau of Statistics. The data on land per capita, number of mobile phones per capita, and number of Internet users are drawn from the China City Statistical Yearbook in 2003–2013 published by the National Bureau of Statistics.

2.4. Summary Statistics

Table 1 reports the summary statistics for these variables. The mean of the income rank–rank slope, which is the main dependent variable, is 0.464, with a standard deviation of 0.305. On average, a son's income percentile rank increases by 0.464, following a one-percentile increase in the parent's rank. The mean of the exposure to trade shocks from other prefectures, which is the main independent variable, is 0.816, with a standard deviation of 0.562. The mean of the 90th–10th percentile income gap is 0.568, with a standard deviation of 0.169. Further, Fig. 2 displays the changes in exposure to trade shocks from other prefectures and intergenerational income mobility across the son's birth cohort. Exposure to trade shocks from other prefectures, averaged by region, rises from 0.53 for the earlier cohort to 1.10 for the later cohort. Correspondingly, the average intergenerational rank-rank slope rises from 0.38 to 0.55. Fig. 2 also shows that the 90th–10th percentile income gap rises from 0.44 to 0.70. Thus, Fig. 2 reveals a positive association between exposure to trade shocks from other prefectures and intergenerational income persistence or income inequality: The higher exposure to trade shocks from other prefectures, the higher are income inequality and intergenerational income persistence.

3. Econometric Model

We conduct a rigorous statistical analysis to examine the effect of globalization on intergenerational mobility. The FE estimation model is specified as follows:

$$Y_{cr} = \alpha_0 + \alpha^{other} Exp_{cr}^{other} + \alpha^{own} Exp_{cr}^{own} + X_{cr}\alpha_X + \mu_r + \lambda_c + \varepsilon_{cr}, \tag{11}$$

where Y_{cr} is one of the three measures of intergenerational income mobility for birth cohort c in region r (the rank-rank slope and mean percentile ranks of sons born to parents at the 25th and 75th percentile ranks). Exp_{cr}^{other} and Exp_{cr}^{own} measure the exposure to trade shocks brought about by China's WTO accession from other prefectures and one's own prefecture, respectively. The vector of the control variables, X_{cr}, includes the logarithm of the population, proportion of people aged under 14, land per capita, number of mobile phones per capita, and Internet penetration. We include region FE, μ_r, to control for the unobserved determinants of intergenerational income mobility, which differ across regions but are common to both cohorts. We also include cohort FE, λ_c, to control for unobserved time shocks, which differ across cohorts but are common to all regions. The error term, ε_{cr}, captures measurement errors. Bootstrapped standard errors are clustered at the region level.

We are interested in the coefficient α^{other}, which measures the effect of exposure to trade shocks from other prefectures on intergenerational mobility through the labour market (Tian, et al., 2020). The coefficient α^{own} measures the effect of exposure to trade shocks from one's own prefecture on intergenerational mobility through a combination of increased income and increased labour demand. We also use this equation to estimate the effect of globalization on income inequality by replacing the dependent variable Y_{cr} with the measure of income inequality (the 90$^{\text{th}}$–10$^{\text{th}}$ percentile income gap in the son's generation). As noted earlier, our identification exploits the cross-region and cross-cohort variations in the trade shocks brought about by China's WTO accession as a quasi-experiment (Han, et al., 2012, Li, 2018, Tian, et al., 2020). The two measures of exposure to trade shocks brought about by WTO accession (i.e. exposure to trade shocks from other prefectures and from one's own prefecture) are thus unlikely to be correlated with other socioeconomic factors that affect intergenerational mobility (Han, et al., 2012, Li, 2018, Tian, et al., 2020).

4. Results

4.1. Baseline

Table 2 reports our FE estimation results for equation (11). This model produces a reasonable fit to the data, with an R-squared value over 0.65 across the four columns. Column (1) shows that the estimated coefficient before exposure to trade shocks from other prefectures is 0.366 (p<0.05). The estimate implies that the rank-rank-slope increases by 0.25, which is equivalent to 0.84 of a standard deviation, as exposure to trade shocks from other prefectures increases from the 25$^{\text{th}}$ percentile (0.38) to the 75$^{\text{th}}$ percentile (1.08). Intergenerational mobility decreases with exposure to trade shocks from other prefectures. Our result suggests that the effect of globalization on intergenerational mobility through the labour market is negative. Column (1) also shows that the estimated coefficient before exposure to trade shocks from one's own prefecture is 0.065, but this is not statistically significant. The result suggests that the labour demand effect and income effect, through which globalization influences intergenerational mobility, are largely cancelled out.

We use the mean percentile rank of sons born to parents at the 25$^{\text{th}}$ percentile rank as the dependent variable in column (2). The FE estimated coefficient before exposure to trade shocks from other prefectures is -20.41 (p<0.05). The estimate implies that the mean percentile rank of sons born to parents at the 25$^{\text{th}}$ percentile rank decreases by 14.21, which is equivalent to 0.74 of a standard deviation, as exposure to trade shocks from other prefectures increases from the 25$^{\text{th}}$

percentile (0.38) to the 75th percentile (1.08). By contrast, column (3), in which the dependent variable is the mean percentile rank of sons born to parents at the 75th percentile rank, shows that the estimated coefficient before exposure to trade shocks from other prefectures is small and not statistically significant. Comparing column (2) with column (3), we conclude that the negative effect of globalization on intergenerational mobility through the labour market is driven by the decrease in the mobility of sons born to bottom-quartile parents.

We also examine the effect of trade shocks on income inequality for the son's generation. Column (4) shows that the estimated coefficient before exposure to trade shocks from other prefectures is 0.167 (p<0.01). The result suggests that globalization raises income inequality in the son's generation through the labour market. By contrast, the estimated coefficient before exposure to trade shocks from one's own prefecture is small and not statistically significant.

4.2. Robustness

We conduct six sets of robust analyses. The first analysis is to use alternative definition of the earlier cohort. In the baseline analysis, the time span for the 1966–1981 cohort is longer than that for the 1982–1994 cohort. To examine whether our results are sensitive to the definition of birth cohort, we thus restrict the earlier cohort to birth years between 1968 and 1981. Previous studies have found that experiencing important historical and political events such as the Cultural Revolution affects the educational attainment of children and intergenerational mobility, especially for children born before 1965 (Chen, et al., 2019, Meng and Zhao, 2021, Xie and Zhang, 2019). The sons in this restricted cohort (i.e. the 1968–1981 cohort) are thus less likely to be influenced by early historical and political events than those in the unrestricted cohort (i.e. the 1966–1981 cohort); therefore, we can isolate the impact of globalization on intergenerational income mobility from other historic events.

The second analysis is to use alternative definition of the later cohort. Our baseline analyses focus on the parent–son pairs with sons aged 19 and above in 2013. One concern is that sons aged around 20 are likely to be at the start of their careers. We thus restrict the later cohort to those born between 1982 and 1992 (i.e. sons are at least 21 years in 2013).

The third analysis is to use different sample provinces. The full sample consists of parent–son pairs from 21 provinces and autonomous regions; however, Zhejiang province is different from other provinces or autonomous regions. For example, disposable income per capita for rural residents in Zhejiang province has been far above that in other provinces in the past several decades.

To test whether our results are sensitive to the inclusion of this province, we drop Zhejiang province from our sample.

The fourth analysis is to control for exposure to pre-WTO trade shocks. To further isolate the causal effect of post-WTO trade shocks, we address the possibility that pre-WTO tariff dynamics might confound our results. We construct two additional measures capturing tariff declines during the 2000–2002 pre-WTO period: exposure to pre-WTO trade shocks from other prefectures and exposure to pre-WTO trade shocks from one's own prefecture. The construction is similar to that of exposure to trade shocks from other prefectures and exposure to trade shocks from one's own prefecture, as detailed in Section 2.2.

The fifth analysis is to control for exposure to other trade shocks. China's WTO accession introduced multifaceted policy changes—including input tariff reductions, FDI liberalization, and removal of quantitative restrictions—that could also affect local outcomes through overlapping industry exposure channels. To mitigate the omitted variable biases, we explicitly control for two additional policy channels: (1) exposure to China's import tariff declines, to address potential spillovers from cheaper imported inputs, and (2) exposure to the U.S. Most Favored Nation (MFN) tariff shocks, to isolate the impact of post-WTO MFN certainty from the direct effect of tariff reductions.

The sixth analysis is to use alternative measures of income inequality. We consider four alternative measures of income inequality: the 95^{th}–5^{th} percentile income gap, 90^{th}–50^{th} percentile income gap, 50^{th}–10^{th} percentile income gap, and Gini coefficient of income. The 90^{th}–50^{th} percentile income gap measures income inequality in the upper half of the income distribution, whereas the 50^{th}–10^{th} percentile income gap measures income inequality in the lower half. Appendix Table B4 reports the summary statistics for all variables in robustness analyses. Table 3 presents the estimation results and shows that our finding that China's accession to the WTO decreases intergenerational income mobility in Chinese villages is robust in all these sensitivity analyses.

5. Mechanisms

We propose that migrant selectivity drives the negative effect of globalization on intergenerational income mobility in Chinese villages through increased labour demand. If sons from wealthy families were more likely to grasp the newly created job opportunities in coastal and urban areas and more capable of competing in the international labour market than sons from less-wealthy families, income inequality persisted across generations, as rural-to-urban migration for jobs led to a large income benefit (Clemens, 2013, Clemens, et al., 2008).

5.1. Migration and Income

We first conduct an FE estimation at the individual level to examine the association between migration and income using the sample of sons from the RCRE survey in 2003–2013[②]:

$$income_{st} = \gamma_0 + \gamma_1 M_{st} + X_{st}\gamma_s + X_{it}\gamma_i + \mu_s + \lambda_t + \varepsilon_{st}, \tag{12}$$

where $income_{st}$ is the logarithm of the observed income of son s in year t, as calculated in Appendix A, M_{st} is a dummy variable coded 1 if son s is a migrant worker in year t and 0 otherwise. To examine the impact between long-term migration on income, we consider two alternative measures, M_{st}^3 and M_{st}^6, coded 1 if son s migrates to work outside the prefecture for at least 3 months and 6 months in year t, respectively and 0 otherwise. We are interested in the coefficient γ_1, which measures the effects of migrating to work outside the prefecture on individual income. We control for the individual-specific time-varying characteristics X_{st}, including his age and age squared in year t, and a set of prefecture-specific socioeconomic factors X_{it}, including the proportion of the minority, proportion of people aged under 14, proportion of people aged over 60, and proportion of men at the prefecture level. We include individual FE, μ_s, to control for unobserved determinants for income, which differ across people but are common for all years. We also include year FE, λ_t, to control for unobserved time shocks, which differ across years but are common to all sons. The error term, ε_{st}, captures measurement errors. Bootstrapped standard errors are clustered at the individual level. Table 4 reports the summary statistics for the variables in the mechanism analysis.

Table 5 reports the FE estimation results. Column (1) shows that the annual income for the same individual increases by 42.9% if he migrates to work outside the prefecture than works in the prefecture in which his *hukou* is registered. Columns (2) and (3) show that the income benefit is larger if he works outside the prefecture for longer. Our results are thus consistent with those in the literature that find that migration brings about an income benefit that increases with migration duration (Carl, et al., 2001, Li and Sicular, 2014, Zhao, 1999).

5.2. Migrant Selectivity

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② We restrict the estimation sample to sons whose information on migration status was recorded for at least 7 waves and whose age was 16 and 30 years old in 2003–2013.

Using the sample of sons from the RCRE survey in 2003–2013, we then explore migrant selectivity. Specifically, we investigate the heterogeneous impacts of exposure to trade shocks on individuals' migration decisions by household wealth and the mother's education. We first regress the individual's migration status on his exposure to trade shocks, household wealth, and their interactions, controlling for individual- and prefecture-specific time-varying characteristics, individual FE, and survey year FE:

$$M_{st} = \beta_0 + \beta_1^{other} exp_{st}^{other} + \beta_2^{other} exp_{st}^{other} \times hhw_s \quad (13)$$

$$+\beta_1^{own} exp_{st}^{own} + \beta_2^{own} exp_{st}^{own} \times hhw_s + \beta_3 hhw_s + X_{st}\gamma_s + X_{it}\gamma_i + \mu_s + \lambda_t + \varepsilon_{st},$$

where exp_{st}^{other} is son s's exposure to trade shocks from other prefectures in year t, as calculated in equation (8), exp_{st}^{own} is the son's exposure to trade shocks from one's own prefecture, as calculated in equation (7), hhw_s measures the son's household wealth. We use the percentile rank of household income between 1997 and 2002—a period before China's WTO accession—to measure household wealth. We demean the percentile rank of household wealth to interpret the regression coefficients. We intentionally measure household wealth before WTO accession to ensure this measure is not affected by trade shocks and subsequent migration decisions. We are interested in the coefficient, β_2^{other}, which measures the difference in effects of globalization on migration decisions between sons born to wealthy families and those born to less-wealthy families in Chinese villages. The variables M_{st}, X_{st}, and X_{it} are the same as in equation (12). Individual FE, μ_s, and year FE, λ_t, are also controlled for. Bootstrapped standard errors are clustered at the individual level. Table 4 reports the summary statistics for the variables in the mechanism analysis.

Table 6 reports our FE estimation results on the heterogeneous effects of exposure to trade shocks on migration decisions by household wealth. Column (1) shows that the estimated coefficient before the interaction term between individuals' exposure to trade shocks from other prefectures and household wealth is 0.01 (p<0.10). This estimate suggests that when individuals' exposure to trade shocks from other prefectures increases from the 25th percentile (0.058) to the 75th percentile (0.173), the probability of migrating to work outside the prefecture increases by 5.72 percentage points for sons from families at the 75th percentile rank of the provincial household wealth distribution before WTO accession compared with sons from families at the 25th percentile. The estimated coefficients before the interaction term increase to 0.012 and 0.013 (p<0.05) when we use the two alternative measures of migration status in columns (2) and (3), respectively. These statistically significant results suggest that sons from wealthy families in rural areas are more capable of grasping the job opportunities brought about by WTO accession and more likely to be migrant workers than sons from less-wealthy families. By contrast, the estimated coefficients before the interaction term between individuals' exposure to trade shocks from one's own prefecture and household wealth are almost zero and not statistically significant across all three columns.

We then study the heterogeneous effects of exposure to trade shocks on migration decisions by the mother's education. We regress the individual's migration status on his exposure to trade shocks, the mother's schooling years, and their interactions, controlling for individual- and prefecture-specific time-varying characteristics, individual FE, and survey year FE. Specifically, we replace household wealth with maternal schooling years in equation (13). Likewise, we demean schooling years to interpret the regression coefficients. The mother's education is also predetermined from the perspective of the son making the migration decision and is thus unlikely to be influenced by the subsequent migration decision of the son. Column (1) in Table 7 shows that the estimated coefficient before the interaction term between individuals' exposure to trade shocks from other prefectures and the mother's schooling years is 0.121 ($p<0.01$). This estimate suggests that when individuals' exposure to trade shocks from other prefectures increases from the 25th percentile (0.058) to the 75th percentile (0.173), the son's probability of migrating to work outside the prefecture increases by 1.39 percentage points when his mother's schooling years increase by 1. The estimated coefficients before the interaction term change to 0.101 and 0.089 ($p<0.05$) when we use the two alternative measures of migration status in columns (2) and (3), respectively. By contrast, the estimated coefficients before the interaction term between individuals' exposure to trade shocks from one's own prefecture and the mother's education level are small and not statistically significant across all three columns. We also explore the role of the father's education by additionally controlling the father's schooling years, and its interaction term with the son's exposure to trade shocks. The results presented in Appendix Table B5 show that compared to father's education, mother's education exerts a more decisive influence on son's migration decision. These results are in line with established theoretical foundations and empirical evidence (Carneiro, et al., 2015, Carneiro, et al., 2013, Ermisch and Francesconi, 2001, Zou and Ma, 2019).

In sum, our results suggest that migrant selectivity induced by WTO accession may explain the decrease in intergenerational income mobility in Chinese villages. Sons from wealthy and better-educated families in rural areas are more likely to be migrants when facing the increased job opportunities brought about by WTO accession than sons from less-wealthy and less-educated families. Together with the income benefit from migration, income inequality in one generation thus persists into the next generation as globalization advances.

Many factors may drive the observed pattern of migrant selectivity, such as liquidity constraints, information friction, social networks, and human capital. For example, migration requires large upfront costs such as travel costs and foregone earnings during the trip and job search (Abramitzky, et al., 2013, Kleemans, 2015). If rural households are liquidity-constrained (i.e. lack savings and cannot borrow against future earnings in the destination to pay the migration cost (Abramitzky, et al., 2013, Borger, 2010, Fernández-Huertas Moraga, 2013)), potential migrants, especially the less skilled, may be unable to migrate despite the potential to earn a higher income by doing so (Orrenius and Zavodny, 2005, Stark and Taylor, 1991). Migration also includes non-monetary costs such as institutional barriers. In China, for example, the *hukou* system restricts migration, especially for the less-educated.

6. Conclusion

We investigate the effect of China's accession to the WTO on intergenerational income mobility in Chinese villages and our analysis yields three main results. First, intergenerational income mobility has declined in Chinese villages over recent decades. The intergenerational rank-rank slope rises from 0.39 for the earlier cohort to 0.55 for the later cohort. Second, the trade shocks brought about by China's accession to the WTO in 2001 have lowered intergenerational mobility in Chinese villages, especially for poor families. Third, sons from wealthy and better-educated families in rural areas are more likely to grasp the job opportunities brought about by WTO accession and more likely to migrate than sons from less-wealthy and less-educated families. The observed migrant selectivity, coupled with the income benefit from migration, may explain the negative effect of globalization on intergenerational income mobility through the labour market.

To address the concern that inequality is persisting across generations in Chinese villages as globalization progresses, policies must more equally allocate newly created job opportunities to children from both poor and wealthy families. For example, the government could subsidize the migration cost for poor families or lend them money to cover this cost. It could also reduce institutional barriers by, for instance, relaxing the *hukou* system in China. To reduce information friction, the government is encouraged to use modern technologies to distribute information on job vacancies to people from a range of socioeconomic backgrounds. Finally, and most importantly, the government should heavily subsidize early education for children from poor and rural families (Cunha and Heckman, 2007, Heckman, 2006, Heckman, 2007, Heckman and Raut, 2016). Better-educated children are more capable of reaping the benefit from globalization as they grow up.

The datasets that we use are the best ones available for studying intergenerational income mobility in Chinese villages. For developing countries, rural development and the welfare of rural families remain issues of public concern. More research on rural areas is thus warranted. Additionally, due to limitations in regional/group-level representativeness of the RCRE and the CHIP, our results may not generalize to populations or contexts beyond those captured by the RCRE and the CHIP. However, the relationships we identify remain identified within the studied groups. We explicitly emphasize the need for future research to test the generalizability of our findings across broader populations and institutional contexts, particularly using datasets with enhanced granularity and representativeness.

The world is suffering from the backlash of globalization owing to widening economic inequality and lower intergenerational income mobility, as our study reveals. The resulting political turmoil and global unrest may in turn delay or reverse the process of globalization. To sustain or promote globalization in the future, its benefits should be more equally shared, not only intragenerationally but also intergenerationally.

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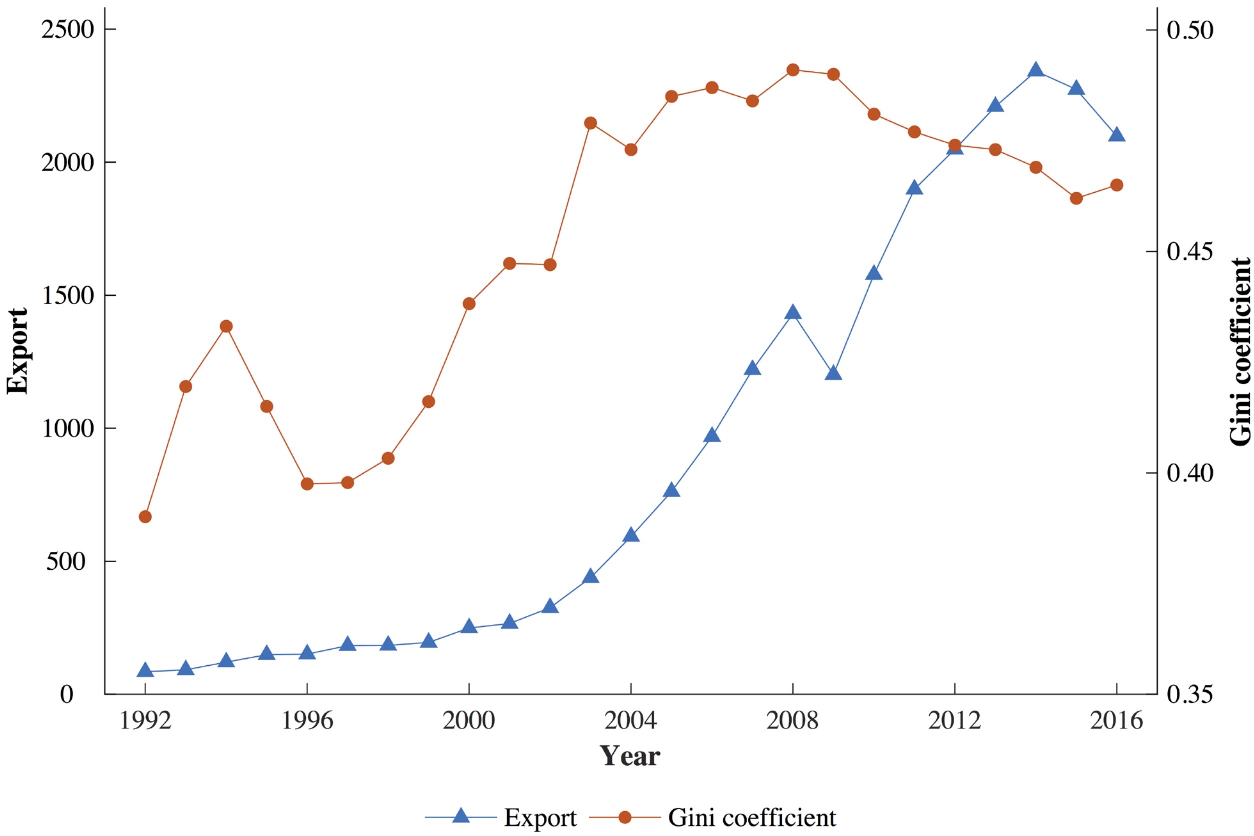

Fig. 1. Export and Gini coefficient in China, 1992–2016

Note: Data on exports are from the World Integrated Trade Solution (1992–2016); Gini coefficients for 1992–2002 are from the United Nations University World Institute for Development Economics Research; and Gini coefficients for 2003–2016 are from the National Bureau of Statistics of China. Exports are measured in billions of U.S. dollars.

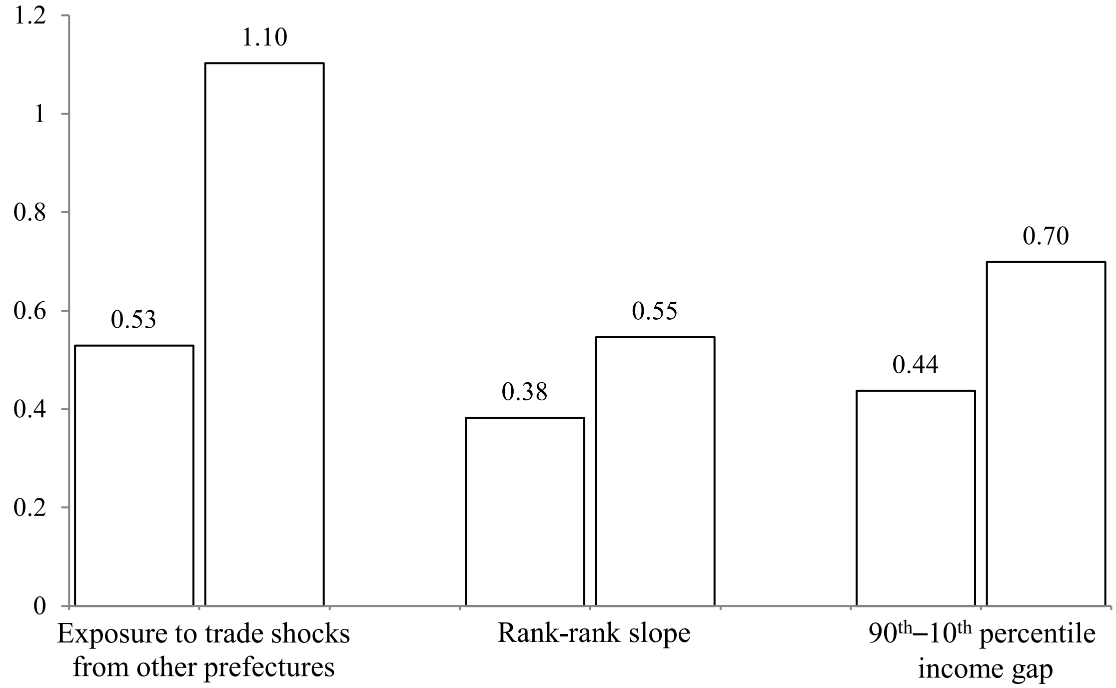

Fig. 2. Changes in exposure to trade shocks from other prefectures, intergenerational income mobility, and income inequality

Note: Exposure to trade shocks from other prefectures, averaged by region, rises from 0.53 for the earlier cohort (1966–1981; left bar) to 1.10 for the later cohort (1982–1994; right bar). The average intergenerational rank-rank slope rises from 0.38 to 0.55. The average 90^{th}–10^{th} percentile income gap rises from 0.44 to 0.70.

Table 1

Summary statistics for variables.

Variable	Obs	Mean	Std.Dev.
Panel A. Intergenerational Income Mobility			
Income rank-rank slope	98	0.464	0.305
Mean income percentile rank of sons born to parents at the 25th income percentile rank	98	39.776	19.174
Mean income percentile rank of sons born to parents at the 75th income percentile rank	98	57.674	15.303
Panel B. Inequality in the Son's Generation			
90th–10th percentile income gap	98	0.568	0.169
Panel C. Exposure to Trade Shocks			
Exposure to trade shocks from other prefectures	98	0.816	0.562
Exposure to trade shocks from one's own prefecture	98	10.231	3.795
Panel D. Control Variables			
Logarithm of population	98	5.837	.614
Land per capita	98	38.71	37.358
Proportion of people aged under 14	98	0.26	0.042
Number of mobile phones per capita	98	0.048	0.069
Internet penetration	98	0.045	0.307

Notes: Data are derived from (i) the RCRE survey in 2003–2013; (ii) CHIP surveys in 1995, 2002, 2007, and 2013; (iii) TRAINS dataset in 2002–2013; (iv) Chinese Industrial Enterprises database in 2000; (v) China's population censuses in 1982, 1990, 2000, 2005, and 2010; and (vi) the China City Statistical Yearbook in 2003–2013.

Table 2

Effects of globalization on intergenerational income mobility.

	(1)	(2)	(3)	(4)
	Rank-rank slope	Mean percentile rank of sons born to parents at the 25th percentile rank	Mean percentile rank of sons born to parents at the 75th percentile rank	90th–10th percentile income gap
Exposure to trade shocks from other prefectures	0.366**	-20.41**	-9.381	0.167***
	(0.143)	(8.262)	(7.440)	(0.0504)
Exposure to trade shocks from one's own prefecture	0.0650	-7.507	-3.095	0.0269
	(0.129)	(9.830)	(4.760)	(0.0418)
R-squared	0.685	0.663	0.839	0.918
Other Control variables	YES	YES	YES	YES
Cohort FE	YES	YES	YES	YES
Region FE	YES	YES	YES	YES
Observations	98	98	98	98
Outcome mean	0.464	39.776	57.674	0.568

Notes: Bootstrapped standard errors clustered at the region level are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$ for two-sided t tests.

Table 3

Robustness analyses.

	(1)	(2)	(3)
	Rank-rank slope	Mean percentile rank of sons born to parents at the 25th percentile rank	Mean percentile rank of sons born to parents at the 75th percentile rank
Panel A. Alternative Definition of the Earlier Cohort: Sons Born between 1968 and 1981			
Exposure to trade shocks	0.380**	-21.04*	-9.431
from other prefectures	(0.159)	(9.603)	(7.862)
Exposure to trade shocks	0.0805	-8.623	-3.424
from one's own prefecture	(0.146)	(11.18)	(5.169)
Observations	98	98	98
R-squared	0.689	0.658	0.822
Outcome mean	0.478	39.076	57.578
Panel B. Alternative Definition of the Later Cohort: Sons Born between 1982 and 1992			
Exposure to trade shocks	0.362**	-20.03**	-9.250
from other prefectures	(0.135)	(8.571)	(7.129)
Exposure to trade shocks	0.0914	-7.815	-2.395
from one's own prefecture	(0.163)	(13.08)	(5.748)
Observations	98	98	98
R-squared	0.686	0.628	0.830
Outcome mean	0.472	39.487	57.604
Panel C. Different Sample Provinces: Drop Zhejiang Province			
Exposure to trade shocks	0.299**	-16.99***	-9.561

from other prefectures	(0.136)	(5.389)	(6.242)
Exposure to trade shocks	-0.0307	-1.675	-2.375
from one's own prefecture	(0.0824)	(2.630)	(2.583)
Observations	94	94	94
R-squared	0.752	0.915	0.909
Outcome mean	0.434	41.456	57.691
Panel D. Additional Control Variables: Exposure to Pre-WTO Trade Shocks			
Exposure to trade shocks	0.515*	-40.62*	-19.43
from other prefectures	(0.270)	(21.75)	(12.19)
Exposure to trade shocks	0.0908	-10.58	-4.536
from one's own prefecture	(0.140)	(11.27)	(5.438)
Observations	98	98	98
R-squared	0.707	0.694	0.849
Outcome mean	0.464	39.776	57.674
Panel E. Additional Control Variables: Exposure to Other Trade Shocks			
Exposure to trade shocks	0.367**	-22.52**	-11.56
from other prefectures	(0.164)	(10.48)	(7.905)
Exposure to trade shocks	0.00883	-8.981	-6.190
from one's own prefecture	(0.182)	(13.69)	(6.155)
Observations	98	98	98
R-squared	0.696	0.674	0.860
Outcome mean	0.464	39.776	57.674

Other Control variables	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes
Region FE	Yes	Yes	Yes

VARIABLES	(1) 95th–5th percentile income gap	(2) 90th–50th percentile income gap	(3) 50th–10th percentile income gap	(4) Gini coefficient of income
Panel F. Alternative Measures of Inequality				
Exposure to trade shocks	0.131**	0.0182	0.149***	0.0209**
from other prefectures	(0.0501)	(0.0317)	(0.0423)	(0.00824)
Exposure to trade shocks	0.0430	-0.0256	0.0525	0.00597
from one's own prefecture	(0.0420)	(0.0199)	(0.0443)	(0.00665)
Observations	98	98	98	98
R-squared	0.946	0.871	0.904	0.936
Outcome mean	0.683	0.239	0.329	0.119
Other control variables	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes

Notes: Bootstrapped standard errors clustered at the region level are in parentheses. *** p<0.01, ** p<0.05, * p<0.1 for two-sided t tests.

Table 4

Summary statistics for variables in mechanism analysis.

Variable	Obs	Mean	Std.Dev.
Panel A. Migration and Income			
Individual Income (in logarithmic form)	8,089	9.248	0.604
Migrant workers (going out to work=1)	8,089	0.743	0.437
(going out to work for at least 90 days=1)	8,089	0.731	0.444
(going out to work for at least 180 days=1)	8,089	0.689	0.463
Age	8,089	23.592	3.429
Age squared/100	8,089	5.683	1.613
Proportion of the minority	8,089	0.094	0.281
Proportion of people aged under 14	8,089	0.194	0.196
Proportion of people aged over 60	8,089	0.131	0.139
Proportion of the male	8,089	0.51	0.011
Panel B. Migrant Selectivity			
Migrant workers (going out to work=1)	7,789	0.529	0.499
(going out to work for at least 90 days=1)	7,789	0.512	0.5
(going out to work for at least 180 days=1)	7,789	0.465	0.499
Son's exposure to trade shocks from other prefectures	7,789	0.144	0.294
Son's exposure to trade shocks from one's own prefecture	7,789	0.984	0.552
Household wealth	7,789	-1.019	28.556
Mother's education	7,716	-0.002	2.624
Age	7,789	23.722	3.539
Age squared/100	7,789	5.753	1.665
Proportion of the minority	7,789	0.13	0.299
Proportion of people aged under 14	7,789	0.208	0.21
Proportion of people aged over 60	7,789	0.131	0.149
Proportion of the male	7,789	0.51	0.012

Notes: Data are derived from the RCRE survey in 2003–2013 and China population censuses in 1982, 1990, 2000, 2005, and 2010.

Table 5

Correlations of migration and income.

	Log (individual income)		
VARIABLES	(1)	(2)	(3)
Going out to work	0.429***		
	(0.029)		
Going out to work for at least 90 days		0.433***	
		(0.028)	
Going out to work for at least 180 days			0.453***
			(0.023)
Control variables	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	8,089	8,089	8,089
R-squared	0.579	0.581	0.594
Number of individuals	1,022	1,022	1,022
Individual income mean (in 1,000 yuan)	10.383	10.383	10.383

Notes: Robust standard errors clustered at the individual level are in parentheses. *** p<0.01, ** p<0.05, * p<0.1 for two-sided t tests.

Table 6

Heterogeneous effects of globalization on migration decisions by household wealth.

	Migrant workers		
	(1)	(2)	(3)
VARIABLES	Going out to work	Going out to work for at least 90 days	Going out to work for at least 180 days
Son's exposure to trade shocks from other prefectures	0.122	0.129	0.089
	(0.126)	(0.131)	(0.081)
Son's exposure to trade shocks from other prefectures * household wealth	0.010*	0.012**	0.013**
	(0.006)	(0.006)	(0.006)
Son's exposure to trade shocks from one's own prefecture	0.014	0.032	0.038
	(0.042)	(0.043)	(0.043)
Son's exposure to trade shocks from one's own prefecture * household wealth	0.000	0.000	-0.000
	(0.001)	(0.001)	(0.001)
Other Control variables	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	7,789	7,789	7,789
R-squared	0.520	0.515	0.497
Number of individuals	943	943	943
Outcome mean	0.529	0.512	0.465

Notes: Robust standard errors clustered at the individual level are in parentheses. *** p<0.01, ** p<0.05, * p<0.1 for two-sided t tests.

Table 7

Heterogeneous effects of globalization on migration decisions by the mother's education.

	Migrant workers		
	(1)	(2)	(3)
VARIABLES	Going out to work	Going out to work for at least 90 days	Going out to work for at least 180 days
Son's exposure to trade shocks from other prefectures	-0.014	0.011	-0.012
	(0.090)	(0.095)	(0.098)
Son's exposure to trade shocks from other prefectures * mother's education	0.121***	0.101**	0.089**
	(0.041)	(0.044)	(0.045)
Son's exposure to trade shocks from one's own prefecture	0.019	0.039	0.042
	(0.042)	(0.043)	(0.044)
Son's exposure to trade shocks from one's own prefecture * mother's education	-0.006	-0.008	-0.004
	(0.006)	(0.006)	(0.006)
Other Control variables	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	7,716	7,716	7,716
R-squared	0.518	0.513	0.495
Number of individuals	933	933	933
Outcome mean	0.531	0.513	0.466

Notes: Robust standard errors clustered at the individual level are in parentheses. *** p<0.01, ** p<0.05, * p<0.1 for two-sided t tests.

Online Supplementary Appendix for
Globalization Raises Intergenerational Inequality Transmission in Chinese Villages

A. Computing Lifetime Income

To estimate the measure of intergenerational income rank-rank slope, we first need to compute lifetime income for both sons and parents of the full sample. The steps are presented as follows.

First, we calculate income for sons based on the RCRE survey. The RCRE survey in each wave collects information on (i) labor time separately allocated to agricultural production and nonagricultural production, (ii) agricultural income and nonagricultural income at the household level, (iii) income when migrating to work outside the village at the individual level, and (iv) other household income (e.g., rent, interest, and dividends). Individual income is the sum of four parts: (i) individual agricultural income, calculated based on household agricultural income and labor time allocated to agricultural work, (ii) individual nonagricultural income, calculated based on household nonagricultural income and labor time allocated to nonagricultural work, (iii) individual income when migrating to work outside the prefecture, and (iv) other individual income, calculated by dividing other household income by the number of household labors. Individual income for 2003–2012 is adjusted by the Consumer Price Index to the 2013 price level. We calculate son's income by averaging individual income across the waves in the RCRE survey to address attenuation bias brought about by measurement errors.

Second, we estimate the following model using the RCRE sample of sons with income:

$$inc_i = \beta_0 + X_i\beta_X + \varepsilon_i, \tag{A1}$$

where inc is the logarithm of the son's income and X is a comprehensive set of demographic and socioeconomic variables including schooling years, age, age squared, age cubed, ethnicity, occupation, coastal dummy, and full interactions with the birth cohort dummy. Educational attainment, which is measured by schooling years, is a key predictor of lifetime income. The son's age is measured in 2003. Ethnicity is a dummy variable equal to 1 if any household member is a *Han* Chinese, and 0 otherwise. Occupation is a vector of dummy variables denoting that the son works either in agriculture, industry, construction, transportation, business, catering, and services, or other industries. The coastal dummy equals to 1 if the household is living in any coastal provinces, which are the most developed areas in China, and 0 otherwise. Column (1) in Table A1 reports the estimates of equation (A1) for sons. The R-squared in column (1) is 0.198.

Third, based on the estimates of equation (A1), we compute lifetime income for all sons from the RCRE and the CHIP surveys using individual characteristics X_i, and the estimated coefficients β_0 and β_X.

We use the predicted lifetime income instead of the observed income for several reasons. First, the predicted lifetime income is less likely to suffer from the attenuation bias arising from transitory income shocks. Second, when estimating equation (A1), the dependent variable of individual income is averaged across multiple years. In addition, we control age, age squared, and age cubed in equation (A1). This practice ensures that the conventional lifecycle bias is mitigated when we use the predicted lifetime income based on equation (A1). Finally, and most importantly, information on income in the CHIP survey is recorded for the survey year only, with which we are not able to compute lifetime income; by contrast, the demographic and socioeconomic information is available in each wave of the CHIP survey. By estimating the lifetime income equation using the RCRE data, we can compute lifetime income for sons in the CHIP surveys based on (i) estimates of equation (A1) and (ii) demographic and socioeconomic information.

We apply a similar procedure to separately compute lifetime income for fathers and mothers of the full sample. Columns (2) and (3) in Table A1 report the estimates of equation (A1) for fathers and mothers of the RCRE sample, respectively. The R-squared in columns (2) and (3) is 0.212 and 0.149, respectively. Parental income is the average of the father's and mother's computed lifetime income. Table B1 summarizes the computed lifetime income for sons, fathers, and mothers separately.

Table A1

Prediction of lifetime income.

VARIABLES	Log (observed income)		
		OLS	
	(1)	(2)	(3)
	Sons	Fathers	Mothers
Schooling years	0.034***	0.013***	0.015***
	(0.004)	(0.004)	(0.004)
Birth cohort (=2)	-4.835	1.672	0.854
	(3.080)	(6.319)	(6.115)
Birth cohort (=2) * schooling years	0.020***	-0.000	0.007
	(0.005)	(0.005)	(0.004)
Age	-0.484	0.172	0.264
	(0.321)	(0.336)	(0.342)
Birth cohort (=2) * age	0.640*	-0.050	-0.009
	(0.357)	(0.348)	(0.353)
Age squared/100	1.762	-0.328	-0.552
	(1.140)	(0.608)	(0.649)
Birth cohort (=2) * age squared/100	-3.015**	0.020	-0.063
	(1.528)	(0.638)	(0.678)
Age cubed/1000	-0.204	0.018	0.036
	(0.133)	(0.036)	(0.041)
Birth cohort (=2) * age cubed/1000	0.497**	0.003	0.009
	(0.252)	(0.039)	(0.043)
Ethnicity	0.127***	0.050	0.084**
	(0.042)	(0.045)	(0.040)
Birth cohort (=2) * ethnicity	-0.082*	-0.011	-0.066
	(0.049)	(0.054)	(0.048)
Occupation (=2)	0.243***	0.219***	0.148**
	(0.024)	(0.040)	(0.062)

(=3)	0.271***	0.235***	0.075
	(0.055)	(0.043)	(0.085)
(=4)	0.336***	0.393***	-0.013
	(0.087)	(0.079)	(0.239)
(=5)	0.266***	0.272***	0.233***
	(0.025)	(0.038)	(0.044)
(=6)	0.166***	0.051*	-0.063*
	(0.025)	(0.031)	(0.035)
Occupation (=2) * birth cohort (=2)	0.019	-0.074	-0.059
	(0.030)	(0.048)	(0.071)
(=3) * birth cohort (=2)	-0.077	0.051	0.029
	(0.072)	(0.048)	(0.109)
(=4) * birth cohort (=2)	0.043	-0.118	-0.141
	(0.113)	(0.087)	(0.272)
(=5) * birth cohort (=2)	-0.023	-0.047	0.047
	(0.031)	(0.047)	(0.053)
(=6) * birth cohort (=2)	0.029	0.155***	0.136***
	(0.031)	(0.039)	(0.046)
Coast	-0.062	0.063	0.011
	(0.043)	(0.043)	(0.043)
Coast * birth cohort (=2)	-0.047**	-0.003	-0.016
	(0.022)	(0.023)	(0.023)
Province fixed effect	Yes	Yes	Yes
Constant	12.789***	6.212	4.778
	(2.974)	(6.167)	(5.972)
Observations	9,387	10,073	9,500
R-squared	0.198	0.212	0.149

Notes: Columns 1–3, OLS estimates of equation (S1) for sons (column 1, n=9,387), fathers (column 2, n=10,073), and mothers (column 3, n=9,500). The dependent variable is the logarithm of observed income; the explanatory variables include schooling years, age, age squared, age cubed, ethnicity, occupation, coastal dummy, and full interactions with the birth cohort dummy; province fixed effects are controlled. Robust standard errors are in parentheses. Data source: the RCRE sample of sons (column 1), fathers (column 2), and mothers (column 3) with income. *** $p<0.01$, ** $p<0.05$, * $p<0.1$ for two-sided t tests.

B. Appendix Tables

Table B1

Summary statistics for the full sample.

Variable	Obs	Mean	Std.Dev.
Panel A. Sons			
Schooling years	26,264	7.901	3.26
Age	26,264	20.332	6.273
Age squared/100	26,264	4.527	2.762
Age cubed/1000	26,264	10.915	9.928
Occupation	26,264	2.994	1.979
Ethnicity (Han=1)	26,264	0.95	0.218
Coast (coastal region = 1)	26,264	0.411	0.492
Computed lifetime income (in logarithmic form)	26,264	9.115	0.305
Panel B. Fathers			
Schooling years	26,264	7.081	2.498
Age	26,264	48.237	7.847
Age squared/100	26,264	23.884	7.724
Age cubed/1000	26,264	121.242	58.766
Occupation	26,264	2.268	1.774
Ethnicity (Han=1)	26,264	0.95	0.218
Coast (coastal region = 1)	26,264	0.411	0.492
Computed lifetime income (in logarithmic form)	26,264	9.264	0.283
Panel C. Mothers			
Schooling years	26,264	5.33	2.847
Age	26,264	46.277	7.394
Age squared/100	26,264	21.962	6.947
Age cubed/1000	26,264	106.751	50.329

Occupation	26,264	1.901	1.681
Ethnicity (Han=1)	26,264	0.95	0.218
Coast (coastal region = 1)	26,264	0.411	0.492
Computed lifetime income (in logarithmic form)	26,264	8.993	0.243

Notes: Panels A–C: The summary statistics for sons (A), fathers (B), and mothers (C) of the full sample. The sample of 26,264 parent–son pairs is generated from the RCRE survey in 2003–2013 (n=10,604) and the CHIP surveys in 1995, 2002, 2007, and 2013 (n=15,660), with sons born between 1966 and 1994 from 21 provinces and autonomous regions in China. We drop Beijing, Tianjin, Inner Mongolia, Shanghai, Hainan, Tibet, Qinghai, and Ningxia because of their limited sample sizes and merge Chongqing municipality with Chengdu prefecture for simplicity.

Table B2

Tabulation of the sample size by the son's birth cohort and region (by group) (to be continued).

Group	Birth cohort		
	Earlier (1966–1981)	Later (1982–1994)	Total
Type-1 regions			
Guangdong	220	384	604
Guangxi	88	110	198
Hebei	89	133	222
Heilongjiang	63	91	154
Jiangxi	91	105	196
Jilin	107	148	255
Shandong	85	86	171
Shaanxi	84	150	234
Sichuan	80	84	164
Type-2 regions (to be continued)			
Anhui	150	174	324
Fujian	133	180	313
Gansu	82	133	215
Guangdong	291	382	673
Guangxi	81	203	284
Guizhou	61	111	172
Hebei	64	74	138
Heilongjiang	112	144	256
Henan	178	506	684
Hubei	282	678	960
Hunan	309	572	881
Jiangsu	150	103	253
Jiangxi	276	466	742
Jilin	195	359	554

Table B2

Tabulation of the sample size by the son's birth cohort and region (by group) (continued and to be continued).

Group	Birth cohort Earlier (1966–1981)	Later (1982–1994)	Total
Type-2 regions (continued)			
Liaoning	271	357	628
Shandong	204	328	532
Shaanxi	355	640	995
Shanxi	182	414	596
Sichuan	191	201	392
Yunnan	56	101	157
Zhejiang	149	143	292
Type-3 regions (to be continued)			
Anhui	531	906	1,437
Fujian	133	187	320
Gansu	293	566	859
Guangdong	510	808	1,318
Guangxi	184	422	606
Hebei	427	557	984
Henan	475	800	1,275
Hubei	216	378	594
Hunan	137	352	489
Jiangsu	599	587	1,186
Jiangxi	265	341	606
Jilin	146	186	332
Liaoning	279	362	641
Shandong	381	565	946
Shaanxi	60	161	221

Table B2

Tabulation of the sample size by the son's birth cohort and region (by group) (continued).

Group	Birth cohort Earlier (1966–1981)	Later (1982–1994)	Total
Type-3 regions (continued)			
Shanxi	251	419	670
Sichuan	285	400	685
Yunnan	152	226	378
Zhejiang	264	214	478
Total	10,267	15,997	26,264

Notes: This table presents the sample size of parent–son pairs by the son's birth cohort and region (n=26,264). We first divide the sample into two cohorts by the son's birth year: 1966–1981 and 1982–1994. Second, we divide the prefectures in each province into three regions. Type-1 regions denote provincial capitals, type-2 regions denote all prefectures neighbouring provincial capitals, and type-3 regions denote other prefectures. We should have 126 groups by birth cohort and region because the data cover two birth cohorts and 21 provinces, with three regions per province. By dropping those groups with fewer than 50 parent–son pairs, our analysis sample includes 98 groups.

Table B3

Correlation analyses.

	Income rank-rank slope	Mean income percentile rank of sons born to parents at the 25th income percentile rank	Mean income percentile rank of sons born to parents at the 75th income percentile rank
Income rank-rank slope	1.0000		
Mean income percentile rank of sons born to parents at the 25th income percentile rank	-0.5606 (p=0.0000)	1.0000	
Mean income percentile rank of sons born to parents at the 75th income percentile rank	0.1473 (p=0.1479)	0.7141 (p=0.0000)	1.0000

Table B4

Summary statistics for variables in robustness checks.

Variable	Obs	Mean	Std.Dev.
Panel A. Alternative Definition of the Earlier Cohort: Sons Born between 1968 and 1981			
Intergenerational Mobility			
Income rank-rank slope	98	0.478	0.333
Mean income percentile rank of sons born to parents at the 25^{th} income percentile rank	98	39.076	21.127
Mean income percentile rank of sons born to parents at the 75^{th} income percentile rank	98	57.578	15.254
Exposure to Trade Shocks			
Exposure to trade shocks from other prefectures	98	0.82	0.561
Exposure to trade shocks from one's own prefecture	98	10.231	3.797
Control Variables			
Logarithm of population	98	5.838	0.614
Land per capita	98	38.681	37.168
Proportion of people aged under 14	98	0.259	0.042
Number of mobile phones per capita	98	0.048	0.068
Internet penetration	98	0.039	0.255
Panel B. Alternative Definition of the Later Cohort: Sons Born between 1982 and 1992			
Intergenerational Mobility			
Income rank-rank slope	98	0.472	0.326
Mean income percentile rank of sons born to parents at the 25^{th} income percentile rank	98	39.487	20.937
Mean income percentile rank of sons born to parents at the 75^{th} income percentile rank	98	57.604	15.465
Exposure to Trade Shocks			

Exposure to trade shocks from other prefectures	98	0.82	0.568
Exposure to trade shocks from one's own prefecture	98	10.225	3.774
Control Variables			
Logarithm of population	98	5.834	0.613
Land per capita	98	38.795	37.772
Proportion of people aged under 14	98	0.26	0.042
Number of mobile phones per capita	98	0.04	0.06
Internet penetration	98	0.044	0.307
Panel C. Different Sample Provinces: Drop Zhejiang Province			
Intergenerational Mobility			
Income rank-rank slope	94	0.434	0.235
Mean income percentile rank of sons born to parents at the 25th income percentile rank	94	41.456	14.806
Mean income percentile rank of sons born to parents at the 75th income percentile rank	94	57.691	14.865
Exposure to Trade Shocks			
Exposure to trade shocks from other prefectures	94	0.818	0.57
Exposure to trade shocks from one's own prefecture	94	9.863	3.152
Control Variables			
Logarithm of population	94	5.838	0.627
Land per capita	94	39.39	37.973
Proportion of people aged under 14	94	0.262	0.041
Number of mobile phones per capita	94	0.046	0.067
Internet penetration	94	0.046	0.313
Panel D. Additional Control Variables: Exposure to Pre-WTO Trade Shocks			
Exposure to pre-WTO trade shocks from other prefectures	98	-0.084	0.051

Exposure to pre-WTO trade shocks from one's own prefecture	98	-1.008	1.012
Panel E. Additional Control Variables: Exposure to Other Trade Shock			
Exposure to U.S. MFN tariff shocks from other prefectures	98	-0.110	0.084
Exposure to U.S. MFN tariff shocks from one's own prefecture	98	-3.036	5.169
Exposure to import trade shocks from one's own prefecture	98	43.234	6.030
Panel F. Alternative Measures of Inequality			
95^{th}–5^{th} percentile income gap	98	0.683	0.184
90^{th}–50^{h} percentile income gap	98	0.239	0.069
50^{th}–10^{h} percentile income gap	98	0.329	0.136
Gini coefficient of income	98	0.119	0.031

Notes: Panels A–F: The summary statistics for variables when the earlier cohort is restricted to sons born between 1968 and 1981 (A), for variables when the later cohort is restricted to sons born between 1982 and 1992 (B), for variables when the parent–son pairs from Zhejiang province are dropped (C), for variables measuring exposure to pre-WTO trade shocks (D), for variables measuring exposure to other trade shocks (E), and for alternative measures of inequality (F).

Table B5

Mechanism: Paternal characteristics.

	Migrant workers		
	(1)	(2)	(3)
VARIABLES	Going out to work	Going out to work for at least 90 days	Going out to work for at least 180 days
Son's exposure to trade shocks from other prefectures	-0.044	0.003	-0.009
	(0.110)	(0.115)	(0.121)
Son's exposure to trade shocks from other prefectures * mother's education	0.141***	0.103*	0.083[1]
	(0.054)	(0.057)	(0.061)
Son's exposure to trade shocks from one's own prefecture	0.021	0.041	0.045
	(0.045)	(0.047)	(0.047)
Son's exposure to trade shocks from one's own prefecture * mother's education	-0.004	-0.004	0.001
	(0.008)	(0.008)	(0.008)
Son's exposure to trade shocks from other prefectures * father's education	-0.034	-0.004	0.010
	(0.053)	(0.055)	(0.057)
Son's exposure to trade shocks from one's own prefecture * father's education	-0.004	-0.007	-0.010
	(0.008)	(0.008)	(0.008)
Other Control variables	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes

[1] This insignificant estimate may be attributed to multicollinearity, given the high correlation between father's and mother's education.

Year FE	Yes	Yes	Yes
Observations	7,709	7,709	7,709
R-squared	0.519	0.514	0.496
Number of individuals	932	932	932
Outcome mean	0.531	0.513	0.466

Notes: Robust standard errors clustered at the individual level are in parentheses. *** p<0.01, ** p<0.05, * p<0.1 for two-sided t tests.

Online Supplementary Appendix for

Globalization Raises Intergenerational Inequality Transmission in Chinese Villages

A. Computing Lifetime Income

To estimate the measure of intergenerational income rank-rank slope, we first need to compute lifetime income for both sons and parents of the full sample. The steps are presented as follows.

First, we calculate income for sons based on the RCRE survey. The RCRE survey in each wave collects information on (i) labor time separately allocated to agricultural production and nonagricultural production, (ii) agricultural income and nonagricultural income at the household level, (iii) income when migrating to work outside the village at the individual level, and (iv) other household income (e.g., rent, interest, and dividends). Individual income is the sum of four parts: (i) individual agricultural income, calculated based on household agricultural income and labor time allocated to agricultural work, (ii) individual nonagricultural income, calculated based on household nonagricultural income and labor time allocated to nonagricultural work, (iii) individual income when migrating to work outside the prefecture, and (iv) other individual income, calculated by dividing other household income by the number of household labors. Individual income for 2003–2012 is adjusted by the Consumer Price Index to the 2013 price level. We calculate son's income by averaging individual income across the waves in the RCRE survey to address attenuation bias brought about by measurement errors.

Second, we estimate the following model using the RCRE sample of sons with income:

$$inc_i = \beta_0 + X_i\beta_X + \varepsilon_i, \tag{A1}$$

where inc is the logarithm of the son's income and X is a comprehensive set of demographic and socioeconomic variables including schooling years, age, age squared, age cubed, ethnicity, occupation, coastal dummy, and full interactions with the birth cohort dummy. Educational attainment, which is measured by schooling years, is a key predictor of lifetime income. The son's age is measured in 2003. Ethnicity is a dummy variable equal to 1 if any household member is a *Han* Chinese, and 0 otherwise. Occupation is a vector of dummy variables denoting that the son works either in agriculture, industry, construction, transportation, business, catering, and services, or other industries. The coastal dummy equals to 1 if the household is living in any coastal provinces, which are the most developed areas in China, and 0 otherwise. Column (1) in Table A1 reports the estimates of equation (A1) for sons. The R-squared in column (1) is 0.198.

Third, based on the estimates of equation (A1), we compute lifetime income for all sons from the RCRE and the CHIP surveys using individual characteristics X_i, and the estimated coefficients β_0 and β_X.

We use the predicted lifetime income instead of the observed income for several reasons. First, the predicted lifetime income is less likely to suffer from the attenuation bias arising from transitory income shocks. Second, when estimating equation (A1), the dependent variable of individual income is averaged across multiple years. In addition, we control age, age squared, and age cubed in equation (A1). This practice ensures that the conventional lifecycle bias is mitigated when we use the predicted lifetime income based on equation (A1). Finally, and most importantly, information on income in the CHIP survey is recorded for the survey year only, with which we are not able to compute lifetime income; by contrast, the demographic and socioeconomic information is available in each wave of the CHIP survey. By estimating the lifetime income equation using the RCRE data, we can compute lifetime income for sons in the CHIP surveys based on (i) estimates of equation (A1) and (ii) demographic and socioeconomic information.

We apply a similar procedure to separately compute lifetime income for fathers and mothers of the full sample. Columns (2) and (3) in Table A1 report the estimates of equation (A1) for fathers and mothers of the RCRE sample, respectively. The R-squared in columns (2) and (3) is 0.212 and 0.149, respectively. Parental income is the average of the father's and mother's computed lifetime income. Table B1 summarizes the computed lifetime income for sons, fathers, and mothers separately.

Table A1

Prediction of lifetime income.

VARIABLES	Log (observed income)		
	OLS		
	(1)	(2)	(3)
	Sons	Fathers	Mothers
Schooling years	0.034***	0.013***	0.015***
	(0.004)	(0.004)	(0.004)
Birth cohort (=2)	-4.835	1.672	0.854
	(3.080)	(6.319)	(6.115)
Birth cohort (=2) * schooling years	0.020***	-0.000	0.007
	(0.005)	(0.005)	(0.004)
Age	-0.484	0.172	0.264
	(0.321)	(0.336)	(0.342)
Birth cohort (=2) * age	0.640*	-0.050	-0.009
	(0.357)	(0.348)	(0.353)
Age squared/100	1.762	-0.328	-0.552
	(1.140)	(0.608)	(0.649)
Birth cohort (=2) * age squared/100	-3.015**	0.020	-0.063
	(1.528)	(0.638)	(0.678)
Age cubed/1000	-0.204	0.018	0.036
	(0.133)	(0.036)	(0.041)
Birth cohort (=2) * age cubed/1000	0.497**	0.003	0.009
	(0.252)	(0.039)	(0.043)
Ethnicity	0.127***	0.050	0.084**
	(0.042)	(0.045)	(0.040)
Birth cohort (=2) * ethnicity	-0.082*	-0.011	-0.066
	(0.049)	(0.054)	(0.048)
Occupation (=2)	0.243***	0.219***	0.148**
	(0.024)	(0.040)	(0.062)

(=3)	0.271***	0.235***	0.075
	(0.055)	(0.043)	(0.085)
(=4)	0.336***	0.393***	-0.013
	(0.087)	(0.079)	(0.239)
(=5)	0.266***	0.272***	0.233***
	(0.025)	(0.038)	(0.044)
(=6)	0.166***	0.051*	-0.063*
	(0.025)	(0.031)	(0.035)
Occupation (=2) * birth cohort (=2)	0.019	-0.074	-0.059
	(0.030)	(0.048)	(0.071)
(=3) * birth cohort (=2)	-0.077	0.051	0.029
	(0.072)	(0.048)	(0.109)
(=4) * birth cohort (=2)	0.043	-0.118	-0.141
	(0.113)	(0.087)	(0.272)
(=5) * birth cohort (=2)	-0.023	-0.047	0.047
	(0.031)	(0.047)	(0.053)
(=6) * birth cohort (=2)	0.029	0.155***	0.136***
	(0.031)	(0.039)	(0.046)
Coast	-0.062	0.063	0.011
	(0.043)	(0.043)	(0.043)
Coast * birth cohort (=2)	-0.047**	-0.003	-0.016
	(0.022)	(0.023)	(0.023)
Province fixed effect	Yes	Yes	Yes
Constant	12.789***	6.212	4.778
	(2.974)	(6.167)	(5.972)
Observations	9,387	10,073	9,500
R-squared	0.198	0.212	0.149

Notes: Columns 1–3, OLS estimates of equation (S1) for sons (column 1, n=9,387), fathers (column 2, n=10,073), and mothers (column 3, n=9,500). The dependent variable is the logarithm of observed income; the explanatory variables include schooling years, age, age squared, age cubed, ethnicity, occupation, coastal dummy, and full interactions with the birth cohort dummy; province fixed effects are controlled. Robust standard errors are in parentheses. Data source: the RCRE sample of sons (column 1), fathers (column 2), and mothers (column 3) with income. *** $p<0.01$, ** $p<0.05$, * $p<0.1$ for two-sided t tests.

B. Appendix Tables

Table B1

Summary statistics for the full sample.

Variable	Obs	Mean	Std.Dev.
Panel A. Sons			
Schooling years	26,264	7.901	3.26
Age	26,264	20.332	6.273
Age squared/100	26,264	4.527	2.762
Age cubed/1000	26,264	10.915	9.928
Occupation	26,264	2.994	1.979
Ethnicity (Han=1)	26,264	0.95	0.218
Coast (coastal region = 1)	26,264	0.411	0.492
Computed lifetime income (in logarithmic form)	26,264	9.115	0.305
Panel B. Fathers			
Schooling years	26,264	7.081	2.498
Age	26,264	48.237	7.847
Age squared/100	26,264	23.884	7.724
Age cubed/1000	26,264	121.242	58.766
Occupation	26,264	2.268	1.774
Ethnicity (Han=1)	26,264	0.95	0.218
Coast (coastal region = 1)	26,264	0.411	0.492
Computed lifetime income (in logarithmic form)	26,264	9.264	0.283
Panel C. Mothers			
Schooling years	26,264	5.33	2.847
Age	26,264	46.277	7.394
Age squared/100	26,264	21.962	6.947
Age cubed/1000	26,264	106.751	50.329

Occupation	26,264	1.901	1.681
Ethnicity (Han=1)	26,264	0.95	0.218
Coast (coastal region = 1)	26,264	0.411	0.492
Computed lifetime income (in logarithmic form)	26,264	8.993	0.243

Notes: Panels A–C: The summary statistics for sons (A), fathers (B), and mothers (C) of the full sample. The sample of 26,264 parent–son pairs is generated from the RCRE survey in 2003–2013 (n=10,604) and the CHIP surveys in 1995, 2002, 2007, and 2013 (n=15,660), with sons born between 1966 and 1994 from 21 provinces and autonomous regions in China. We drop Beijing, Tianjin, Inner Mongolia, Shanghai, Hainan, Tibet, Qinghai, and Ningxia because of their limited sample sizes and merge Chongqing municipality with Chengdu prefecture for simplicity.

Table B2

Tabulation of the sample size by the son's birth cohort and region (by group) (to be continued).

Group	Birth cohort		
	Earlier (1966–1981)	Later (1982–1994)	Total
Type-1 regions			
Guangdong	220	384	604
Guangxi	88	110	198
Hebei	89	133	222
Heilongjiang	63	91	154
Jiangxi	91	105	196
Jilin	107	148	255
Shandong	85	86	171
Shaanxi	84	150	234
Sichuan	80	84	164
Type-2 regions (to be continued)			
Anhui	150	174	324
Fujian	133	180	313
Gansu	82	133	215
Guangdong	291	382	673
Guangxi	81	203	284
Guizhou	61	111	172
Hebei	64	74	138
Heilongjiang	112	144	256
Henan	178	506	684
Hubei	282	678	960
Hunan	309	572	881
Jiangsu	150	103	253
Jiangxi	276	466	742
Jilin	195	359	554

Table B2

Tabulation of the sample size by the son’s birth cohort and region (by group) (continued and to be continued).

Group	Birth cohort Earlier (1966–1981)	Later (1982–1994)	Total
Type-2 regions (continued)			
Liaoning	271	357	628
Shandong	204	328	532
Shaanxi	355	640	995
Shanxi	182	414	596
Sichuan	191	201	392
Yunnan	56	101	157
Zhejiang	149	143	292
Type-3 regions (to be continued)			
Anhui	531	906	1,437
Fujian	133	187	320
Gansu	293	566	859
Guangdong	510	808	1,318
Guangxi	184	422	606
Hebei	427	557	984
Henan	475	800	1,275
Hubei	216	378	594
Hunan	137	352	489
Jiangsu	599	587	1,186
Jiangxi	265	341	606
Jilin	146	186	332
Liaoning	279	362	641
Shandong	381	565	946
Shaanxi	60	161	221

Table B2

Tabulation of the sample size by the son's birth cohort and region (by group) (continued).

Group	Birth cohort Earlier (1966–1981)	Later (1982–1994)	Total
Type-3 regions (continued)			
Shanxi	251	419	670
Sichuan	285	400	685
Yunnan	152	226	378
Zhejiang	264	214	478
Total	10,267	15,997	26,264

Notes: This table presents the sample size of parent–son pairs by the son's birth cohort and region (n=26,264). We first divide the sample into two cohorts by the son's birth year: 1966–1981 and 1982–1994. Second, we divide the prefectures in each province into three regions. Type-1 regions denote provincial capitals, type-2 regions denote all prefectures neighbouring provincial capitals, and type-3 regions denote other prefectures. We should have 126 groups by birth cohort and region because the data cover two birth cohorts and 21 provinces, with three regions per province. By dropping those groups with fewer than 50 parent–son pairs, our analysis sample includes 98 groups.

Table B3

Correlation analyses.

	Income rank-rank slope	Mean income percentile rank of sons born to parents at the 25th income percentile rank	Mean income percentile rank of sons born to parents at the 75th income percentile rank
Income rank-rank slope	1.0000		
Mean income percentile rank of sons born to parents at the 25th income percentile rank	-0.5606 (*p*=0.0000)	1.0000	
Mean income percentile rank of sons born to parents at the 75th income percentile rank	0.1473 (*p*=0.1479)	0.7141 (*p*=0.0000)	1.0000

Table B4

Summary statistics for variables in robustness checks.

Variable	Obs	Mean	Std.Dev.
Panel A. Alternative Definition of the Earlier Cohort: Sons Born between 1968 and 1981			
Intergenerational Mobility			
Income rank-rank slope	98	0.478	0.333
Mean income percentile rank of sons born to parents at the 25th income percentile rank	98	39.076	21.127
Mean income percentile rank of sons born to parents at the 75th income percentile rank	98	57.578	15.254
Exposure to Trade Shocks			
Exposure to trade shocks from other prefectures	98	0.82	0.561
Exposure to trade shocks from one's own prefecture	98	10.231	3.797
Control Variables			
Logarithm of population	98	5.838	0.614
Land per capita	98	38.681	37.168
Proportion of people aged under 14	98	0.259	0.042
Number of mobile phones per capita	98	0.048	0.068
Internet penetration	98	0.039	0.255
Panel B. Alternative Definition of the Later Cohort: Sons Born between 1982 and 1992			
Intergenerational Mobility			
Income rank-rank slope	98	0.472	0.326
Mean income percentile rank of sons born to parents at the 25th income percentile rank	98	39.487	20.937
Mean income percentile rank of sons born to parents at the 75th income percentile rank	98	57.604	15.465
Exposure to Trade Shocks			

Exposure to trade shocks from other prefectures	98	0.82	0.568
Exposure to trade shocks from one's own prefecture	98	10.225	3.774
Control Variables			
Logarithm of population	98	5.834	0.613
Land per capita	98	38.795	37.772
Proportion of people aged under 14	98	0.26	0.042
Number of mobile phones per capita	98	0.04	0.06
Internet penetration	98	0.044	0.307
Panel C. Different Sample Provinces: Drop Zhejiang Province			
Intergenerational Mobility			
Income rank-rank slope	94	0.434	0.235
Mean income percentile rank of sons born to parents at the 25th income percentile rank	94	41.456	14.806
Mean income percentile rank of sons born to parents at the 75th income percentile rank	94	57.691	14.865
Exposure to Trade Shocks			
Exposure to trade shocks from other prefectures	94	0.818	0.57
Exposure to trade shocks from one's own prefecture	94	9.863	3.152
Control Variables			
Logarithm of population	94	5.838	0.627
Land per capita	94	39.39	37.973
Proportion of people aged under 14	94	0.262	0.041
Number of mobile phones per capita	94	0.046	0.067
Internet penetration	94	0.046	0.313
Panel D. Additional Control Variables: Exposure to Pre-WTO Trade Shocks			
Exposure to pre-WTO trade shocks from other prefectures	98	-0.084	0.051

Exposure to pre-WTO trade shocks from one's own prefecture	98	-1.008	1.012
Panel E. Additional Control Variables: Exposure to Other Trade Shock			
Exposure to U.S. MFN tariff shocks from other prefectures	98	-0.110	0.084
Exposure to U.S. MFN tariff shocks from one's own prefecture	98	-3.036	5.169
Exposure to import trade shocks from one's own prefecture	98	43.234	6.030
Panel F. Alternative Measures of Inequality			
95^{th}–5^{th} percentile income gap	98	0.683	0.184
90^{th}–50^{h} percentile income gap	98	0.239	0.069
50^{th}–10^{h} percentile income gap	98	0.329	0.136
Gini coefficient of income	98	0.119	0.031

Notes: Panels A–F: The summary statistics for variables when the earlier cohort is restricted to sons born between 1968 and 1981 (A), for variables when the later cohort is restricted to sons born between 1982 and 1992 (B), for variables when the parent–son pairs from Zhejiang province are dropped (C), for variables measuring exposure to pre-WTO trade shocks (D), for variables measuring exposure to other trade shocks (E), and for alternative measures of inequality (F).

Table B5

Mechanism: Paternal characteristics.

	Migrant workers		
	(1)	(2)	(3)
VARIABLES	Going out to work	Going out to work for at least 90 days	Going out to work for at least 180 days
Son’s exposure to trade shocks from other prefectures	-0.044	0.003	-0.009
	(0.110)	(0.115)	(0.121)
Son’s exposure to trade shocks from other prefectures * mother’s education	0.141***	0.103*	0.083[1]
	(0.054)	(0.057)	(0.061)
Son’s exposure to trade shocks from one’s own prefecture	0.021	0.041	0.045
	(0.045)	(0.047)	(0.047)
Son’s exposure to trade shocks from one’s own prefecture * mother’s education	-0.004	-0.004	0.001
	(0.008)	(0.008)	(0.008)
Son’s exposure to trade shocks from other prefectures * father’s education	-0.034	-0.004	0.010
	(0.053)	(0.055)	(0.057)
Son’s exposure to trade shocks from one’s own prefecture * father’s education	-0.004	-0.007	-0.010
	(0.008)	(0.008)	(0.008)
Other Control variables	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes

[1] This insignificant estimate may be attributed to multicollinearity, given the high correlation between father’s and mother’s education.

Year FE	Yes	Yes	Yes
Observations	7,709	7,709	7,709
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