Foreign Direct Investment and Intergenerational Occupational Mobility: Evidence from China*

Jianpeng Deng† Zibin Huang‡ Qing Shi§ Xin Zhao¶

June 30, 2025

Abstract

This paper analyses the impact of foreign direct investment (FDI) liberalization on intergenerational occupational mobility in China by exploiting exogenous variations in FDI liberalization induced by regulatory relaxation. Using a Shift-share instrument variable strategy and national census data from 2000 to 2005, we find that individuals living in cities with greater exposure to FDI Liberalization exhibit higher likelihood of being in a better occupation than their fathers. The reason is that FDI liberalization leads to greater demand for high-skilled labor and therefore, higher skill premium, which encourages workers in young generations to obtain better education and work in high-skilled occupations. The positive effect is more salient for families with low socioeconomic status and coming from underdeveloped regions.

Keywords: Foreign direct investment, Intergenerational mobility, Occupational choice

JEL Codes: F66, J62

---

*We would like to thank the Shanghai Society of World Economy 2024 Annual Meeting, the International Trade Academic Forum at the School of Economics, Shandong University, and the Siyuan Forum at the School of International Trade and Economics, Shanghai University of International Business and Economics, for their comments and suggestions. Zibin Huang acknowledges financial support from the National Natural Science Foundation of China (72403152). Qing Shi acknowledges financial support from the National Social Science Fund of China (23BJL060) and General Program of Shanghai Philosophy and Social Science Research Projects(2022BJB004). All errors are ours. The first version was released in March 2025.

†College of Business, Shanghai University of Finance and Economics, deng.jianpeng@mail.shufe.edu.cn

‡College of Business, Shanghai University of Finance and Economics, and Shanghai Institute of International Finance and Economics, huangzibin@mail.shufe.edu.cn

§School of Economics, Shanghai University, echoshiqing@126.com

¶College of Business, Shanghai University of Finance and Economics, zhaoxinsoe@stu.sufe.edu.cn

1 Introduction

Many developing countries seek foreign direct investment (FDI) to stimulate economic growth (Alfaro, Chanda, Kalemli-Ozcan, and Sayek, 2010; Alfaro, 2017). While extensive research has examined the economic effects of FDI, a crucial yet underexplored question remains: can FDI foster social mobility? As FDI typically targets non-agricultural sectors and intensifies competitions for talent in host countries, FDI has the potential to enhance intergenerational mobility through new labor market opportunities. However, it may hinder educational mobility by promoting low-skill manufacturing jobs, which could incentivize children from low socioeconomic status (SES) families to drop out of school in favor of factory work (Li, 2018).

Establishing the causal impact of FDI on intergenerational mobility presents significant challenges. First, unobserved factors may simultaneously influence both local labor supply and FDI inflows. For example, cities with a strong initial industrial base may encourage educational investments while also attracting more foreign investment. Second, reverse causality poses a concern: regions with few opportunities for jobs or upward mobility may be less likely to attract FDI. To address these challenges, we exploit exogenous variations in Chinese FDI liberalization, driven by regulatory relaxations.

To identify the causal impact of FDI on intergenerational occupational mobility, we construct a Bartik-style shift-share instrument variable (SSIV). As part of its World Trade Organization (WTO) accession commitments, China relaxed FDI regulations across multiple industries in 2002. This regulatory relaxation, combined with city-level variation in industrial structure, led to heterogeneous FDI shocks across cities. Our research design leverages the 2002 industry-specific FDI regulatory relaxation as the shock (shift) and baseline industry employment shares in each city as the shares to construct a city-level FDI liberalization shock. To assess the impact of this FDI shock on social mobility, we measure intergenerational occupational mobility by comparing the educational intensity (EI) of workers' occupations to that of their fathers' occupations. EI, defined as the average years of education within an occupation, serves as an indicator of social rank, with higher values denoting higher social status. This occupation-based approach offers greater reliability and stability than income-based metrics, providing a more comprehensive measure of socioeconomic status.

Our study integrates multiple datasets, including FDI policy records, industrial surveys, and national census data. First, we compare the 2002 version of the *Catalogue for the Guidance of Foreign Investment Industries* with the 1997 version to identify industries that were liberalized, following the procedure of Lu, Tao, and Zhu (2017). Second, we calculate baseline industry employment shares using the Annual Survey of Industrial Firms (ASIF) from China's National Bureau of Statistics. Third, we use the 2000 and 2005 National Population Censuses of China, which include information on region of residence, household composition, educational attainment, demographic characteristics, employment status, occupation, and industry. To measure intergenerational occupational mobility, we calculate EI using education and occupation data and identify father-child pairs based on household composition information. Additionally, we enrich our empirical analysis with various individual-level variables.

Building on the empirical strategy and data outlined above, we find that a one standard deviation increase in FDI exposure leads to a 2.7% standard deviation increase in intergenerational occupational mobility. Our results indicate that FDI significantly enhances upward mobility. Furthermore, our heterogeneity analysis reveals that workers from low-SES families are more likely to move up the occupational ladder relative to their fathers. FDI particularly benefits individuals from disadvantaged backgrounds, especially those whose fathers have limited education, originate from less developed regions, or are employed in the agricultural sector. These findings suggest that FDI plays a crucial role in fostering intergenerational occupational mobility in China.

We then examine the mechanisms through which FDI influences intergenerational occupational mobility, focusing on three key channels: increased relative demand for skilled labor (demand side), greater educational investment (supply side), and accelerated structural transformation. First, FDI raises the relative demand for high-skilled occupations, increasing the odds a worker can enter a higher EI occupation than their fathers. We find that FDI shocks increase occupations with higher EI in the market. To further explore this effect, we categorize FDI shocks into those affecting more skill-intensive or less skill-intensive industries. Both types of FDI shocks increase high EI occupations, with high-skill FDI having a relatively stronger impact. Second, the rise in skill premiums driven by FDI incentivizes households to invest more in education, encouraging individuals to pursue higher-skilled occupations. We find that in cities experiencing larger FDI shocks individuals are more likely to finish college. Third, we document that FDI growth coincides with a structural shift from agriculture to manufacturing and services, further facilitating occupational mobility.

Finally, we perform two sets of robustness checks. First, we address potential selection bias arising from father-child pairs residing in the same household, as highlighted by Ahsan and Chatterjee (2017).To mitigate this bias, we examine the impact of FDI shocks on the likelihood of father-child co-residence, apply propensity score weighting (PSW), and re-estimate the baseline model across varying age ranges. Second, we assess the validity of the shift-share design following Borusyak, Hull, and Jaravel (2022). This approach relies on the assumption that no simultaneous confounding shocks influence a city's intergenerational occupational mobility in the main market of the industries experiencing FDI liberalization. To validate this assumption, we conduct balance tests to examine FDI liberalization exposure against city and industry characteristics, control for external shocks and other factors, and perform placebo tests.

This paper contributes to three strands of literature. First, by examining intergenerational mobility in response to FDI liberalization, we are the first to empirically demonstrate the social effects of FDI in host countries. The existing literature has primarily focused on the economic impacts of FDI, including its effects on productivity and economic growth (Aitken and Harrison, 1999; Javorcik, 2004; Keller and Yeaple, 2009; Alfaro, Chanda, Kalemli-Ozcan, and Sayek, 2010; Lu, Tao, and Zhu, 2017; Fons-Rosen, Kalemli-Ozcan, Sørensen, Villegas-Sanchez, and Volosovych, 2021), knowledge diffusion and innovation (Abebe, McMillan, and Serafinelli, 2022), and employment (Shi, Tan, Zhao, and Zhu, 2024). Two studies are particularly relevant to our work. Li (2018) finds that a low-skill import shock reduces high school and college enrollment rates in China, while Ahsan and Chatterjee (2017) examines the impact of tariff reductions from India's 1991 trade reforms and finds a positive effect on intergenerational occupational mobility. Our study diverges from these in two ways. First, we focus on the social effects of FDI rather than trade. Second, we find that FDI significantly promotes intergenerational occupational mobility, particularly for low-SES families, highlighting its implications for long-term inequality in China.

Second, our paper contributes to the literature on the determinants of intergenerational mobility. Prior research has emphasized the role of internal family influences (Becker and Tomes, 1976, 1986; Jia, Lan, and Padró I Miquel, 2021), education (Blanden, Gregg, and Macmillan, 2007; Güell, Pellizzari, Pica, and Rodríguez Mora, 2018; Neidhöfer, Serrano, and Gasparini, 2018; Akresh, Halim, and Kleemans, 2023; Lavy, Kott, and Rachkovski, 2022), and migration (Nakamura, Sigurdsson, and Steinsson, 2022; Ward, 2022; Connolly, Corak, and Haeck, 2019) in shaping intergenerational mobility. More recently, external factors have received more attention (Ahsan and

Chatterjee, 2017; Fan, Fang, Huang, and Zhou, 2022; Mocetti, Roma, and Rubolino, 2022; Cesar, Ciaschi, Falcone, and Neidhöfer, 2023). For example, Fan, Fang, Huang, and Zhou (2022) examine how the prevalence of state-owned enterprises (SOEs) affects intergenerational income mobility across Chinese cities, while Mocetti, Roma, and Rubolino (2022) investigate how regulatory changes in professional services in Italy since the 2000s have influenced intergenerational occupational mobility. Both studies focus on how domestic market openness affects mobility. In contrast, our paper, along with others (Ahsan and Chatterjee, 2017; Cesar, Ciaschi, Falcone, and Neidhöfer, 2023), extends this literature by providing new evidence on how international economic conditions shape intergenerational mobility. [1]

Finally, our study contributes to the measurement of intergenerational mobility in China. Estimating intergenerational mobility in developing countries is particularly challenging due to the lack of representative, long-term, and comprehensive administrative data (Elias, 2014; Card, Chetty, Feldstein, and Saez, 2010; Yakun, Haochen, Rudai, and Junjian, 2022). Fan, Yi, and Zhang (2021) were the first to use panel data to estimate changes in intergenerational income mobility in China following economic reforms. However, concerns about the accuracy of income measurement remain. To mitigate data quality issues prevalent in developing countries, we focus on a direct and easily measured notion of intergenerational occupational mobility.

The remainder of the paper is organized as follows. Section 2 covers the background of Chinese FDI deregulation, an overview of the data, and the estimation strategy for the key variables in our regressions. Section 3 examines the effects of FDI entry on occupational intergenerational mobility. Section 4 investigates the mechanism. Section 5 presents various robustness checks. Section 6 concludes.

2 Background, Empirical Strategy and Data

2.1 Policy Background

The *Catalogue for the Guidance of Foreign Investment Industries*, first introduced by the Chinese central government in June 1995, was established to guide and regulate FDI inflows. It classi-

[1] Ahsan and Chatterjee (2017) explore the impact of tariff reductions in India on intergenerational occupational mobility, while Cesar, Ciaschi, Falcone, and Neidhöfer (2023) examine how increased Chinese import competition in Brazilian industries affected employment and wages across generations.

fied industries into four categories - encouraged, permitted, restricted, and prohibited - based on national development strategies and economic objectives. The primary aim was to direct foreign investment toward sectors that supported Chinese technological advancement and economic modernization while restricting investment in industries deemed sensitive or misaligned with national interests. Over time, the *Catalogue* has undergone multiple revisions, reflecting both shifts in the global economic landscape and China's evolving foreign investment policies.

The 2002 revision marked a particularly significant liberalization of China's FDI policy. Closely tied to China's WTO accession in 2001, this revision reflected the country's commitment to expanding market access as part of its deepening integration into the global economy. Compared to the 1997 standards, the 2002 *Catalogue* eased foreign entry into numerous industries that had previously been restricted or closed to foreign firms. This policy shift not only encouraged greater foreign participation in China's economy but also generated new employment opportunities in local labor markets.

2.2 Empirical Strategy

We aim to identify the causal effect of FDI on intergenerational occupational mobility. Obtaining an unbiased estimate is challenging for two main reasons. First, FDI inflows are often endogenous to local economic conditions, meaning that cities attracting more FDI may already possess characteristics-such as higher educational attainment or more developed infrastructure-that promote greater social mobility. Second, there may be a reverse causality issue: areas with limited job opportunities and little upward mobility could be less likely to attract significant FDI inflows. To address these concerns, we employ an SSIV approach. We first establish our approach, then discuss the specific data sources we use.

2.2.1 Measuring the Exposure to FDI Liberalization: A Shift-Share Instrument

We construct a SSIV to measure the city-level FDI shock (Goldsmith-Pinkham, Sorkin, and Swift, 2020; Borusyak, Hull, and Jaravel, 2022). This instrument consists of two components. First, we use the exogenous industry-level FDI entry shock from the Chinese government's 2002 revision of the Catalogue for the Guidance of Foreign Investment Industries. Second, we use initial industry employment shares to account for city-specific exposure to these changes. Specifically, the FDI shock at city c in year t, denoted as FDI_Shock_{ct}, is defined as:

$$FDI\_Shock_{ct} = \sum_{j} \Delta FDI_{jt} \times \frac{E_{cj1998}}{E_{c1998}}, \tag{1}$$

where ΔFDI_{jt} is a dummy variable that equals 1 if industry j was liberalized in year t under the FDI entry liberalization reforms, and 0 otherwise; $\frac{E_{cj1998}}{E_{c1998}}$ represents the employment share of industry j in city c in the initial year, 1998, reflecting the relative importance of industry j to the local economy at that time. By weighting the FDI liberalization dummy for each industry by its initial employment share, the SSIV captures the extent of each city's exposure to the exogenous FDI liberalization, based on its pre-liberalization industrial structure.

2.2.2 Measuring Intergenerational Occupational Mobility

We measure intergenerational occupational mobility following Ahsan and Chatterjee (2017), calculating the difference in education intensity between an individual's occupation and that of their father. The degree of intergenerational occupational mobility for individual i is denoted as $|transfer_i|$ and is defined as:

$$|transfer_i| = |EI_i - EI_f| \tag{2}$$

where $|transfer_i|$ represents the absolute value of the difference between the educational intensity of individual i's occupation and that of their father; EI_i is the average years of education associated with individual i's occupation, and EI_f is the average years of education associated with their father's occupation. A larger $|transfer_i|$ indicates a greater degree of intergenerational occupational mobility for individual i. A positive $transfer_i > 0$ indicates upward intergenerational mobility, while $transfer_i < 0$ indicates downward intergenerational mobility.

2.2.3 Baseline Regression

We estimate the effect of FDI liberalization on intergenerational occupational mobility using the following regression:

$$|transfer_{it}| = \beta_0 + \beta_1 FDI\_Shock_{ct} + \beta_2 X_{it} + \beta_3 City_{ct-1} + \phi_c + \phi_{pt} + \phi_{bt} + \epsilon_{it}. \tag{3}$$

$|transfer_{it}|$ represents the realized intergenerational occupational mobility of individual i in city c and year t. The main variable of interest, FDI_Shock_{ct}, measures the city's exposure to FDI liberalization and is set to zero for periods prior to the 2002 revision of the FDI regulation. β_1 is the coefficient of interest, capturing the effect of FDI liberalization on intergenerational mobility. The vector X_{it} includes demographic and socioeconomic controls, such as gender, age, age squared, race, marital status, father's age, father's age squared, and father's years of education. Additionally, we include the individual's *hukou* status, which distinguishes rural from urban residents based on China's government-mandated household registration system. This system plays a crucial role in determining individuals' access to social welfare in different locations (Song, 2014). $City_{c,t-1}$ represents lagged city characteristics, including the log of GDP, the log of average wages, the log of total population, the log of the non-agricultural population, the share of value added from the manufacturing sector, and the share of value added from the service sector.

We account for several fixed effects in the model. City fixed effects, ϕ_c, absorb time-invariant differences across cities. Province-year fixed effects, ϕ_{pt}, capture the influence of macro policies implemented by provincial governments over time, such as the effects of college expansions on local labor market supply.[2] Hence, the identification variation comes from time changes in FDI exposure for cities within the same province. The cohort-year fixed effects, ϕ_{bt}, control for unobserved generational characteristics by dividing the sample into three birth cohorts: before 1970, 1970-1979, and 1980-1989. ϵ_{it} is the error term. Standard errors are clustered at the city level to account for potential correlations in the error term within cities over time.

2.3 Data

2.3.1 City-level FDI Shock

We rely on two data sources to construct the city-level FDI shock resulting from China's 2002 FDI liberalization.

The first data source is the 1997 and 2002 versions of the *Catalogue for the Guidance of Foreign Investment Industries*. By comparing these two verions, we identify the 4-digit industries where restrictions on FDI were either relaxed or eliminated. The details of this process are provided

[2] In China, college admissions is a provincial responsibility. Each province is assigned an enrollment quota for each university (Bao, Chen, Huang, Li, and Wang, 2024).

in Appendix B. Our focus on the 4-digit level is motivated by the fact that policy changes were implemented at this level of industry classification, providing the most granular and precise measure of FDI liberalization. In constructing the city-level FDI shock, we restrict the analysis to the manufacturing sector. The service sector is excluded due to additional ownership restrictions commonly imposed on service industries, which complicate the measurement of liberalization. Furthermore, the absence of employment data at the 4-digit level for service industries further limits our ability to assess the full extent of service FDI liberalization.

The second data source is the Annual Survey of Industrial Firms (ASIF), provided by the National Bureau of Statistics of China. Using the 1998 ASIF data, we calculate the employment shares of 4-digit manufacturing industries for each city. The ASIF dataset covers all domestic and foreign manufacturing firms with annual sales exceeding 5 million RMB (approximately 600,000 USD at the 2002 exchange rate). The ASIF provides detailed firm-level information, including industry classification, geographic location, employment levels, as well as other data such as capital stock, sales, profits, debt, assets, and exports.

2.3.2 Population Census

We calculate occupational education intensity and identify father-child pairs to measure intergenerational occupational mobility using data from the 2000 and 2005 National Population Censuses of China.

The 2000 Census data is a 1‰subsample, yielding 1,180,111 observations, while the 2005 data is a 20% subsample of the 1% Population Sampling Survey, which includes 2,585,481 observations. Both datasets are nationally representative, covering all 31 provinces in mainland China, and were provided by the National Bureau of Statistics. The surveys offer detailed information on individual characteristics, including region of residence, household composition, educational attainment, demographics, employment status, occupation, and industry. We process the Census data as follows. First, we match children and fathers using family codes in the census data and identify father-child pairs based on the "relationship to household head" variable. Our sample includes three types of father-child pairs: (1) the household head and the household head's child, (2) the female household head's husband and the household head's child, and (3) the household head's father and the household head. Second, we restrict the sample to individuals who were employed in the week prior to the survey and who reported their occupation. Finally, to mitigate life-cycle bias and account for the possibility that fathers may have exited the labor market due to old age, we restrict the analysis to children aged 16 to 35. We check the robustness of our results to the age cutoffs in Appendix D.

2.3.3 China City Statistical Yearbook

We include a set of lagged city-level characteristics that may influence social mobility, drawn from the China City Statistical Yearbook. This yearbook provides annual socio-economic data on urban development, compiled by the National Bureau of Statistics of China. Key factors include overall economic development, average income, population size, the non-agricultural population, and the manufacturing and service industry shares.

2.4 Descriptive Statistics

2.4.1 FDI

Table 1 presents descriptive statistics on changes in FDI regulation across 4-digit manufacturing industries between 1997 and 2002. Of the 425 industries, 138 experienced a change in FDI regulations. Within this group, 117 industries were liberalized, 15 were restricted, and 6 underwent mixed changes. The remaining 287 industries exhibited no change in regulatory status. Consistent with the approach in Lu, Tao, and Zhu (2017), our analysis focuses on the 404 industries that were liberalized or remained unchanged. The procedures for defining and classifying these regulatory changes are detailed in Appendix B. Table A1 in Appendix A presents data on the number and proportion of 4-digit industries within each 2-digit industry that experienced FDI liberalization.

Table 1: Changes in FDI Regulation Across Industries Between 1997 and 2002

Type	Number	Percentage (%)
Unchanged	287	67.53
Liberalized	116	27.29
Restricted	15	3.53
Mixed changes	7	1.65
Total	425	100

Notes: This table presents the changes in FDI regulation across 4-digit manufacturing industries between 1997 and 2002.

Table 2: Descriptive Statistics of Main Variables

	Description	Mean	Std. Dev.	Min	Max	Obs.
EI_{it}	Educational Intensity of Occupation	10.31	1.93	6.02	14.57	73
$FDI_{c,2005}$	City-level FDI Shock	0.29	0.13	0.00	0.83	248
$\lvert transfer_{it} \rvert$	Intergenerational Occupational Mobility	0.81	1.36	0.00	8.55	143557
$Gender_{it}$	Gender (Male = 1; Female = 0)	0.66	0.48	0.00	1.00	143557
Age_{it}	Age (Years)	23.43	4.64	16.00	35.00	143557
$Race_{it}$	Ethnicity Dummy (Han ethnicity = 1; Minority ethnicities = 0)	0.06	0.24	0.00	1.00	143557
$Married_{it}$	Marital Status (Married = 1; Unmarried = 0)	0.29	0.45	0.00	1.00	143557
$Hukou_{it}$	Hukou Dummy (Urban Hukou = 1; Rural Hukou = 0)	0.14	0.35	0.00	1.00	143557
Age^{f}_{it}	Father's Age (Years)	51.67	6.90	33.00	97.00	143557
$Eduyear^{f}_{it}$	Father's Years of Education.	7.63	2.91	0.00	19.00	143557

Notes: This table presents descriptive statistics for the key variables used in the analysis. The data originate from the 1997 and 2002 editions of the *Catalogue for the Guidance of Foreign Investment Industries*, the Annual Survey of Industrial Firms, and the 2000 and 2005 China Population Censuses. Individual-level variables are drawn from the China Population Censuses. The City-level FDI shock was constructed using the *Catalogue* and the ASIF Data.

2.4.2 Education Intensity

EI is calculated as average years of education within an occupation and serves as a measure of social rank, with higher values indicating higher social status. We use data from the 2000 census for all EI calculations. Table A2 in Appendix A displays EI scores for 73 different occupations, revealing significant variations in educational requirements across these roles. Occupations with high EI scores, such as Scientific Researchers (EI = 14.57) and Heads of State Agencies and Their Work Institutions (EI = 13.77), are associated with higher educational demands. In contrast, occupations such as Animal Husbandry Production Workers (EI = 6.02), Crop Production Workers (EI = 6.79), and Fishery Production Workers (EI = 7.37) have lower EI scores.

2.4.3 Other Variables

Table 2 reports descriptive statistics for the main variables in our study, with a sample of 143,557 father-child pairs. The Gender variable has a mean of 0.66, indicating a higher proportion of males in the sample reflecting how boys are more likely to live with their parents after reaching adulthood. We will discuss this co-residence bias further in Section 5. Since the sample is restricted to workers aged 16 to 35, the mean age of the sample is 23.43 years, primarily in early adulthood. The Education Year (Eduyear) variable has a mean of 9.18 years, with a standard deviation of 2.23, ranging from 0 to 19 years of education. The minority share is relatively low, with only 6% of the sample belonging to non-Han minority racial groups. 29% of the sample is married. The share of individuals with an urban Hukou is also low, at 14%. Fathers have an average age of 51.67 years and an average of 7.63 years of education, which is notably less than their children's education.

3 Baseline Results

3.1 Main Results

Table 3 presents estimates of the effect of FDI on intergenerational occupational mobility. The dependent variable in each column is $|transfer_{it}|$, which measures the intergenerational occupational mobility of individual i in city c and year t. Columns (1) and (2) report results for the full baseline sample. Column (1) presents estimates without controlling for lagged city characteristics, $City_{ct-1}$. Column (2) includes $City_{ct-1}$, which is our baseline specification. We also include an interaction term between a city's distance to the nearest seaport and a post-2002 time dummy to account for potential confounding effects. The coefficients of FDI_Shock_{ct} in both columns are significantly positive and similar in magnitude. The coefficient in column (2) suggests that a one percentage point increase in FDI exposure raises intergenerational mobility by 0.4 percentage points, or equivalently that a one-standard-deviation increase in FDI exposure results in a 2.7% standard deviation increase in $|transfer_{it}|$.[3] These estimates indicate that individuals in cities more exposed to FDI are more likely to be employed in occupations that differ from their fathers' in terms of education intensity.

The sign of $transfer_{it}$ indicates whether mobility is upward or downward. In columns (3) and (4), we restrict the sample to upwardly mobile individuals ($transfer_{it} > 0$). The estimates show that FDI exposure has a positive and statistically significant effect on upward mobility. In contrast, columns (5) and (6) focus on downwardly mobile individuals ($transfer_{it} < 0$). These coefficients are statistically insignificant, suggesting that FDI does not influence the degree of downward mobility.

To further explore the directional effects of FDI, we replace the continuous dependent variable with binary indicators in Table 4. The dependent variable in columns (1) and (2) is *Upward*, a binary indicator that equals one if an individual's occupation is ranked higher than their father's and zero otherwise. Columns (3) and (4) use *Downward*, a binary variable that equals one if an

[3] The standard deviation of $|transfer_{it}|$ is 1.93, and the standard deviation of FDI_Shock_{ct} is 0.13.

Table 3: Baseline Results

Dependent Variable	$\|transfer_{ict}\|$					
	All		Upward		Downward	
	(1)	(2)	(3)	(4)	(5)	(6)
FDI_Shock_{ct}	0.331***	0.404***	0.842***	0.768***	-0.133	-0.208
	(0.127)	(0.133)	(0.218)	(0.230)	(0.318)	(0.328)
City Lagged Controls		✓		✓		✓
Individual Controls	✓	✓	✓	✓	✓	✓
City FE	✓	✓	✓	✓	✓	✓
Province × Year FE	✓	✓	✓	✓	✓	✓
Cohort× Year FE	✓	✓	✓	✓	✓	✓
$Dist\_Port_c \times Post02_t$		✓		✓		✓
N	143557	143557	37486	37486	19186	19186
adj. R^2	0.110	0.110	0.0265	0.0267	0.158	0.158

Notes: This table presents estimates of the effect of the FDI shock on intergenerational occupational mobility. The dependent variable in all columns is the absolute value of intergenerational occupational mobility. *FDI_Shock*$_{ct}$ represents the city's exposure to FDI liberalization, with a mean of 0.29 and a standard deviation of 0.15. Columns (1) and (2) report results for the full sample. Columns (3) and (4) display results for the upward mobility sample ($transfer_{ict} > 0$), while Columns (5) and (6) present results for the downward mobility sample ($transfer_{ict} < 0$). City Lagged Controls include the logarithm of GDP, average wages, total population, non-agricultural population, the share of secondary industry in value added, and the share of tertiary industry in value added. Individual Controls comprise an individual's gender, age, age squared, race, marital status indicator, father's age, father's age squared, father's years of education, and hukou status. Standard errors are clustered at the city level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

individual's occupation is ranked lower than their father's. In columns (1) and (3), we estimate logit models, while columns (2) and (4) employ linear probability models (LPM). The results indicate that FDI shocks significantly increase upward mobility but do not affect downward mobility. In other words, the positive effect of FDI on occupational mobility stems from children entering more education-intensive occupations than their fathers, rather than the reverse.

3.2 FDI, Family SES, and Mobility

We now examine the heterogeneous effects of FDI-induced mobility across various dimensions of family socioeconomic status (SES), including father's education, hometown economic development, and employment sector.

Father's Educational Attainment Panel A examines the heterogeneity of FDI effects based on father's education, distinguishing between those with at most nine years of education and those with higher levels of attainment. FDI significantly enhances mobility for individuals whose fa-

Table 4: Alternate Baseline Specifications: LPM and Logit

Dependent Variable	*Upward*		*Downward*	
	Logit	LPM	Logit	LPM
	(1)	(2)	(3)	(4)
FDI_Shock_{ct}	0.617*	0.161***	-0.168	-0.0122
	(0.355)	(0.0572)	(0.247)	(0.0232)
City Lagged Controls	✓	✓	✓	✓
Individual Controls	✓	✓	✓	✓
City FE	✓	✓	✓	✓
Province × Year FE	✓	✓	✓	✓
Cohort× Year FE	✓	✓	✓	✓
$Dist\_Port_c \times Post02_t$	✓	✓	✓	✓
N	143557	143557	143557	143557
adj. R^2		0.129		0.103
pseudo R^2	0.115		0.121	

Notes: In the first two columns, the dependent variable is *Upward*, a binary indicator that equals one if an individual has a more educationally-intense occupation than their father's, and zero otherwise. In the last two columns, the dependent variable is *Downward*, which equals one if an individual has a less educationally-intense occupation than their father's. City Lagged Controls include the logarithm of GDP, average wages, total population, non-agricultural population, the share of secondary industry in value added, and the share of tertiary industry in value added. Individual Controls comprise an individual's gender, age, age squared, race, marital status indicator, father's age, father's age squared, father's years of education, and hukou status. Standard errors are clustered at the city level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

thers had lower education levels (column (1)) but has no significant effect for those with more educated fathers (column (2)). For upward mobility (columns (3)-(4)), FDI has a positive and significant effect for individuals from less-educated backgrounds, while neither group exhibits significant effects for downward mobility (columns (5)-(6)). These results suggest that FDI-driven mobility gains are more pronounced for individuals from lower-education backgrounds, likely due to increased labor market opportunities.

Economic Development Level of Father's Hometown Panel B of Table 5 explores heterogeneity by the economic development level of the father's hometown, classified as High GDP or Low GDP based on initial-period median GDP per capita.

FDI significantly increases mobility for individuals whose fathers originated from Low GDP areas (column (2)), while the effect is insignificant for those from High GDP areas (column (1)).

Table 5: Heterogeneity of FDI Impacts by Father Characteristics

Dependent Variable	$\lvert transfer_{ict} \rvert$					
	All		Upward		Downward	
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Father's Years of Education					
	$Edu\_Year^f \leq 9$	$Edu\_Year^f > 9$	$Edu\_Year^f \leq 9$	$Edu\_Year^f > 9$	$Edu\_Year^f \leq 9$	$Edu\_Year^f > 9$
FDI_Shock_{ct}	0.397***	0.218	0.631***	1.019	-0.181	-1.123
	(0.140)	(0.438)	(0.232)	(0.619)	(0.404)	(0.695)
N	126049	17508	32771	4707	13467	5718
adj-R^2	0.114	0.0427	0.0327	0.0499	0.0893	0.217
	Panel B: Economic Development Level of Father's Hometown					
	High GDP	Low GDP	High GDP	Low GDP	High GDP	Low GDP
FDI_Shock_{ct}	0.122	0.598***	0.778**	1.117***	0.331	-0.470
	(0.190)	(0.135)	(0.303)	(0.404)	(0.373)	(0.608)
N	63875	65678	22787	11744	11537	6320
adj-R^2	0.0861	0.0875	0.0214	0.0328	0.127	0.190
	Panel C: Father's Employment					
	Agri	Non-Agri	Agri	Non-Agri	Agri	Non-Agri
FDI_Shock_{ct}	0.567***	0.0578	0.436*	0.366	-0.851	0.0556
	(0.146)	(0.257)	(0.261)	(0.327)	(0.708)	(0.381)
N	112600	30957	26754	10732	5545	13634
adj-R^2	0.149	0.0662	0.0483	0.0773	0.0791	0.194
City Lagged Controls	✓	✓	✓	✓	✓	✓
Individual Controls	✓	✓	✓	✓	✓	✓
City FE	✓	✓	✓	✓	✓	✓
Province × Year FE	✓	✓	✓	✓	✓	✓
Cohort × Year FE	✓	✓	✓	✓	✓	✓
$Dist\_Port_c \times Post02_t$	✓	✓	✓	✓	✓	✓

Notes: The dependent variable in all columns is the absolute value of intergenerational occupational mobility. City Lagged Controls include the logarithm of GDP, average wages, total population, non-agricultural population, the share of secondary industry in value added, and the share of tertiary industry in value added. Individual Controls comprise an individual's gender, age, age squared, race, marital status indicator, father's age, father's age squared, father's years of education, and hukou status. Standard errors are clustered at the city level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

This indicates that FDI disproportionately benefits individuals from less-developed regions. For upward mobility (columns (3)-(4)), FDI significantly enhances mobility for both groups. For downward mobility (columns (5)-(6)), neither coefficient is significant. These findings suggest that FDI expands opportunities particularly in economically disadvantaged regions.

Father's Employment Sector Panel C examines heterogeneity based on father's employment sector (agriculture vs. non-agriculture). FDI significantly increases mobility for individuals whose fathers worked in agriculture (column (1)), while the effect is insignificant for those with fathers in non-agricultural sectors (column (2)). For upward mobility (columns (3)-(4)), FDI has a positive but marginally significant effect for children of agricultural workers (column (3)), whereas the effect is insignificant for those with non-agricultural fathers (column (4)). For downward mobility (columns (5)-(6)), neither coefficient is statistically significant. These results suggest that FDI-driven mobility gains are concentrated among individuals from agricultural backgrounds, likely due to expanded non-agricultural employment opportunities.

In Appendix C, we conduct additional heterogeneity analyses. Our findings indicate that families from hometowns with a higher proportion of ethnic minorities those less influenced by state-owned enterprises (SOEs), and female children are significantly more affected by the FDI shock.

4 Mechanisms of FDI-Induced Occupational Mobility

This section examines the mechanisms through which FDI influences intergenerational occupational mobility. We identify three primary channels. First, FDI increases the demand for high-skilled labor in local markets, as multinational firms employ advanced technologies that require a more educated workforce. This shift raises the skill premium and shifts employment toward higher-skilled occupations. Second, the rising demand for skills and higher returns to education have incentivized greater human capital investment among younger generations. Families are more likely to invest in education when they perceive tangible economic benefits driven by FDI. Third, FDI accelerates the transition from agriculture to manufacturing and services and promotes a more industrialized economic structure.

4.1 Increased Demand for High-skill Occupations

Multinational firms, often by introducing advanced technologies or new management practices, typically require a more educated workforce (Findlay, 1978; Markusen, 1995). We therefore hypothesize that FDI increases the demand for high-skilled labor within local labor markets. To test this, we regress individual occupational education intensity (EI_{it}) on city-level FDI exposure (FDI_Shock_{ct}). Column (1) of Table 6 confirms a positive and significant relationship.

Acknowledging that the skill intensity of FDI varies across industries (Javorcik, 2004), we disaggregate FDI exposure into high-skill ($FDI\_Shock^{H}_{ct}$) and low-skill ($FDI\_Shock^{L}_{ct}$) components,

Table 6: The Impact of FDI on Educational Intensity

Dependent Variable	EI_{it}		$\lvert transfer_{it} \rvert$	
	(1)	(2)	(3)	(4)
FDI_Shock_{ct}	0.497**		0.404***	
	(0.236)		(0.133)	
$FDI\_Shock_{ct}^{H}$		0.549*		0.425***
		(0.315)		(0.156)
$FDI\_Shock_{ct}^{L}$		0.426		0.375**
		(0.269)		(0.188)
City Lagged Controls	✓	✓	✓	✓
Individual Controls	✓	✓	✓	✓
City FE	✓	✓	✓	✓
Province × Year FE	✓	✓	✓	✓
Cohort× Year FE	✓	✓	✓	✓
$Dist\_Port_c \times Post02_t$	✓	✓	✓	✓
F-test p value		0.7395		0.8202
N	143557	143557	143557	143557
adj. R^2	0.388	0.388	0.110	0.110

Notes: The dependent variable in the first two columns is the occupational education intensity, while the dependent variable in the last two columns is intergenerational occupational mobility. City Lagged Controls include the logarithm of GDP, average wages, total population, non-agricultural population, the share of secondary industry in value added, and the share of tertiary industry in value added. Individual Controls comprise an individual's gender, age, age squared, race, marital status indicator, father's age, father's age squared, father's years of education, and hukou status. Standard errors are clustered at the city level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

defined by equations (4) and (5):

$$FDI\_Shock_{ct}^{H} = \sum_j High_{j,2004} \times \frac{E_{cj,1998}}{E_{c,1998}} \times \triangle FDI_{jt} \tag{4}$$

$$FDI\_Shock_{ct}^{L} = \sum_j Low_{j,2004} \times \frac{E_{cj,1998}}{E_{c,1998}} \times \triangle FDI_{jt} \tag{5}$$

where $High_{j,2004}$ ($Low_{j,2004}$) indicates whether industry j was above (below) the median in high-skill (low-skill) labor intensity in 2004, $E_{cj,1998}/E_{c,1998}$ represents industry j's employment share in city c in 1998, and $\triangle FDI_{jt}$ measures FDI liberalization in industry j in year t.

Column (2) of Table 6 shows that both high- and low-skill FDI increase occupational education intensity. FDI, regardless of its skill intensity, promotes a shift toward higher-skilled employment, as even low-skill FDI often demands skilled occupations (e.g., management, supervision).

Columns (3) and (4) confirm that both types of FDI are associated with increased intergenerational occupational mobility, supporting the hypothesis that FDI-driven demand for skill facilitates upward mobility.

4.2 Enhanced Educational Investment

Beyond direct labor market effects, FDI also incentivizes educational investment. As FDI increases the demand for skilled labor, the returns to education rise, leading families to invest more in their children's human capital. This effect is particularly relevant for younger cohorts still making educational decisions.

Table 7 examines this channel. The dependent variable, $College\_Dummy_{it}$, indicates whether an individual completed a college education. Columns (1) and (2) use a broader sample including children (aged 16-35) not living with their parents, while columns (3) and (4) use the baseline sample. Column (1) shows a positive and significant effect of FDI_Shock_{ct} on college attainment. Column (2) reveals that both high- and low-skill FDI promote college completion. The coefficient of FDI_Shock_{ct} in column (3) is positive but insignificant. In column (4), the coefficient for $FDI\_Shock^{H}_{ct}$ (high-skill FDI shock) is statistically significant and positive, while the coefficient for $FDI\_Shock^{L}_{ct}$ (low-skill FDI shock) is negative but not statistically significant. These results suggest that even low-skill FDI can raise the overall skill premium, thus encouraging educational investment. This occurs because the inflow of low-skill FDI often creates demand for complementary high-skill roles (such as management, technical support, and R&D), which require higher levels of education. Therefore, even if FDI is concentrated in low-skill sectors, it can still indirectly increase the overall returns to education, encouraging greater educational investment. Columns (5)-(8) replicate these regressions for a 16-25 age subsample, yielding consistent findings.

4.3 Structural Transformation

The period of significant FDI inflows coincided with a profound structural transformation, characterized by a substantial reallocation of labor from agriculture to manufacturing and services (Erten, Leight, and Zhu, 2023). This subsection examines the role of FDI in facilitating and accelerating this intergenerational occupational shift, specifically the transition from agricultural employment among fathers to non-agricultural employment among their children.

Table 7: The Impact of High- and Low-Skill FDI on College Attainment

Dependent Variable	College_Dummy							
	Age:16-35				Age:16-25			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
FDI_Shock_{ct}	0.0523***		0.0185		0.0723***		0.0250	
	(0.0140)		(0.0136)		(0.0183)		(0.0161)	
$FDI\_Shock^{H}{}_{ct}$		0.0625***		0.0340*		0.0851***		0.0265
		(0.0193)		(0.0174)		(0.0220)		(0.0192)
$FDI\_Shock^{L}{}_{ct}$		0.0393**		-0.00295		0.0554*		0.0230
		(0.0173)		(0.0201)		(0.0302)		(0.0268)
City Lagged Controls	✓	✓	✓	✓	✓	✓	✓	✓
Individual Controls	✓	✓	✓	✓	✓	✓	✓	✓
City FE	✓	✓	✓	✓	✓	✓	✓	✓
Province × Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Cohort× Year FE	✓	✓	✓	✓	✓	✓	✓	✓
$Dist\_Port_c \times Post02_t$	✓	✓	✓	✓	✓	✓	✓	✓
N	783601	783601	143557	143557	338746	338746	99439	99439
adj. R^2	0.235	0.235	0.285	0.285	0.230	0.230	0.272	0.272

Notes: The dependent variable measures whether an individual has completed a college education. Columns (1) - (2) use a broader sample including children (aged 16-35) not living with their parents, while columns (3) - (4) focus on the baseline sample. Columns (5) - (6) use the full census sample of individuals aged 16 to 25, while columns (7) - (8) focus on the baseline sample includes individuals aged 16 to 25. City Lagged Controls include the logarithm of GDP, average wages, total population, non-agricultural population, the share of secondary industry in value added, and the share of tertiary industry in value added. Individual Controls comprise an individual's gender, age, age squared, race, marital status, and hukou status. Standard errors are clustered at the city level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

First, foreign firms usually operate in non-agricultural sectors, creating demand for labor in manufacturing and services. Second, these firms may offer higher wages and better working conditions than traditional agricultural employment, attracting workers away from the agricultural sector. Third, FDI can stimulate the growth of ancillary industries (e.g., suppliers, logistics providers) that further contribute to non-agricultural employment opportunities. Finally, the knowledge spillovers and technological upgrading associated with FDI can increase domestic non-agricultural productivity, attracting workers.

Table 8 investigates this mechanism, focusing on transitions from agricultural employment among fathers to non-agricultural employment among their children. We analyze this transition at both the individual and city levels.

For the individual-level analysis (columns (1) and (2)), we estimate a linear probability model:

$$Trans\_Dummy_{it} = \beta_0 + \beta_1 FDI\_Shock_{ct} + \beta_2 X_{it} + \beta_3 City_{ct-1} + \phi_c + \phi_{pt} + \phi_{bt} + \epsilon_{it} \quad (6)$$

Table 8: The Impacts of FDI on Structural Transformation

Dependent Variable	$Trans\_Dummy_{it}$		$Trans\_Int_{ct}$	
	Industry	Occupation	Industry	Occupation
	(1)	(2)	(3)	(4)
FDI_Shock_{ct}	1.153***	1.041***	0.0930***	0.114***
	(0.372)	(0.387)	(0.0343)	(0.0422)
City Lagged Controls	✓	✓	✓	✓
Individual Controls	✓	✓		
City FE			✓	✓
Province × Year FE	✓	✓	✓	✓
Cohort× Year FE	✓	✓		
$Dist\_Port_c \times Post02_t$	✓	✓	✓	✓
N	143557	143548	392	392
Pseudo R^2	0.0735	0.0807		
adj. R^2			0.641	0.749

Notes: The dependent variable in columns (1) and (2) is a binary indicator that equals 1 if an individual's hukou status transitions from their father's agricultural hukou to a non-agricultural hukou. In columns (3) and (4), the dependent variable represents the proportion of such transitions at the city level. The analysis utilizes data from the 2000 and 2005 Censuses, with columns (1) and (2) estimated at the individual level and columns (3) and (4) at the city level. City Lagged Controls include the logarithm of GDP, average wages, total population, non-agricultural population, the share of secondary industry in value added, and the share of tertiary industry in value added. Individual Controls comprise an individual's gender, age, age squared, race, marital status indicator, father's age, father's age squared, father's years of education, and hukou status. Standard errors are clustered at the city level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

where $Trans\_Dummy_{it}$ is a binary variable equal to one if individual i's father worked in agriculture and individual i works in a non-agricultural sector, and zero otherwise. The positive and statistically significant coefficients on FDI_Shock_{ct} in columns (1) and (2) indicate that FDI significantly increased the individual likelihood of transitioning out of agriculture. This suggests that individuals in areas with greater FDI exposure were more likely to experience upward occupational mobility out of agriculture.

At the city level, we use the proportion of such father-to-child agricultural-to-non-agricultural transitions within a city ($Trans\_Int_{ct}$) as the dependent variable. The estimating equation is:

$$Trans\_Int_{ct} = \beta_0 + \beta_1 FDI\_Shock_{ct} + \beta_2 City_{ct-1} + \phi_c + \phi_{pt} + \epsilon_{ct} \quad (7)$$

The positive and significant coefficient on FDI_Shock_{ct} in columns (3) and (4) demonstrates that cities experienced larger FDI shocks also exhibit a higher rate of structural transformation, as measured by the prevalence of intergenerational occupational shifts from agriculture to non-agricultural sectors.

It is important to acknowledge that other factors, such as government policies promoting industrialization and urbanization, could also contribute to structural transformation. However, the consistent and statistically significant results across both individual and city-level analyses, even after controlling for a range of other factors, strongly suggest that FDI played a distinct and substantial role in shifting the economy away from agricultural employment. The findings align with a broader narrative in which FDI acts as a catalyst for economic modernization, accelerating the transition to a more industrialized economy.

5 Robustness Checks

In this section, we validate the robustness of our findings. First, we address potential sample selection bias by examining the impact of FDI shocks on the likelihood of father-child co-residence, applying propensity score weighting (PSW) to correct for selection bias, and re-estimating the baseline model using different age ranges. Second, we assess the validity of our shift-share IV through industry-level and regional-level balance tests, as recommended by Borusyak, Hull, and Jaravel (2022).

We conduct additional robustness checks, including using alternative measures of occupational status, excluding migrant workers, controlling for the effects of other policies, and performing a placebo test in Appendix D. Overall, these analyses confirm that our conclusions regarding the impact of FDI liberalization on intergenerational occupational mobility are robust and reliable.

5.1 Sample Selection Bias

In our study, we focus on occupational intergenerational mobility for father-child pairs residing in the same household, which introduces potential selection bias. This could introduce bias if the likelihood of co-residing with one's father is influenced by the city's exposure to FDI shocks, which may affect the probabilities of migration or marriage through FDIs labor market effects. The second source of selection bias arises from the age restrictions in our sample. We exclude individuals older than 35 and younger than 16 from the baseline regression, as 16 is the legal working age, and for children older than 35, their parents are likely to be retired. To address these sample selection concerns, we employ the methods proposed by Ahsan and Chatterjee (2017).

To examine selection, we define two datasets. First, we refer to the sample used in the main regression as the "co-resident sample", which applies the following selection criteria: (1) children aged between 16 and 35, and (2) individuals co-residing with their father in the census data, i.e., "co-residing father-child pairs." Second, we define the "complete sample" as the full census dataset for individuals aged 16 to 35, without the co-residence restriction.

If city-level FDI exposure affects the proportion of co-residing father-child pairs, it could confound our results. Thus, we first estimate the following regression using the complete Sample:

$$\text{logit}(P(\text{Coreside}_{it} = 1)) = \beta_0 + \beta_1 \text{FDI\_Shock}_{ct} + \beta_2 \text{X}_{it} + \beta_3 \text{City}_{ct-1} + \phi_c + \phi_{pt} + \phi_{bt} \tag{8}$$

This regression specification is identical to the main regression, except that the dependent variable is replaced with $Coreside_{it}$, a binary indicator equal to 1 if the father and child co-reside (i.e., if the household includes both working-age children and their parents). [4]

The regression results are presented in Table 9, Panel A. In columns (1) and (2), we employ probit and logit models, respectively. The results show that the coefficient of FDI_Shock_{ct} is very small and statistically insignificant. Therefore, we do not find any evidence that the likelihood of individuals co-residing with their fathers is systematically correlated with local exposure to FDI shocks.

To further test for any co-residence bias, we use the propensity score weighting (PSW) method proposed by Francesconi and Nicoletti (2006) to mitigate sample selection bias. Specifically, in the first step, we estimate a probit regression according to equation (9):

$$r^*_{it} = \theta Z_{it} + v_{it} \tag{9}$$

where r^*_{it} represents whether the father and individual are co-residing, and Z_{it} includes a series of individual-level variables that can predict the likelihood of father-child co-residence, such as years of education, marital status, ethnicity, hukou, birth year fixed effects, year fixed effects, and

[4] Note we do not control for father-specific attributes in this regression.

Table 9: Robustness Checks

	Panel A: Sample Selection Bias				
Dependent Variable	$Coreside_{it}$		$\|transfer_{ict}\|$		
	Probit	Logit	All	Upward	Downward
	(1)	(2)	(3)	(4)	(5)
FDI_Shock_{ct}	0.0211	0.0314	0.485**	1.254***	0.208
	(0.100)	(0.173)	(0.220)	(0.469)	(0.472)
City Lagged Controls	✓	✓	✓	✓	✓
Individual Controls	✓	✓	✓	✓	✓
City FE	✓	✓	✓	✓	✓
Province × Year FE	✓	✓	✓	✓	✓
Cohort× Year FE	✓	✓	✓	✓	✓
$Dist\_Port_c \times Post02_t$	✓	✓	✓	✓	✓
N	493498	493498	143557	37486	19186
adj. R^2			0.120	0.0490	0.126
pseudo R^2	0.176	0.177			

	Panel B: Validity of the Reduced-Form Estimation				
Dependent Variable	$\triangle FDI_{jt}$				
Independent Variable	GDP per capita	Ratio of 2nd-industry	Distance to port	Number of university	Teacher-student ratio
	(1)	(2)	(3)	(4)	(5)
	-0.0079	0.0035	0.0196*	0.0018	0.0218
	(0.0153)	(0.0086)	(0.0114)	(0.0106)	(0.0141)
Year FE	✓	✓	✓	✓	✓
N	820	820	820	820	820
adj. R^2	0.144	0.143	0.147	0.143	0.147

Notes: In Panel A, columns (1) and (2) use the indicator of whether an individual lives with their father as the dependent variable. In columns (3) to (5), the dependent variable is the absolute value of intergenerational occupational mobility. In Panel B, the dependent variable is an indicator of whether the industry has experienced FDI liberalization. Data for Panel A are sourced from the 2000 and 2005 Censuses, while Panel B data are derived from the China City Statistical Yearbook and the Annual Survey of Industrial Firms. Panel A is analyzed at the individual level, and Panel B at the city level. City Lagged Controls include the logarithm of GDP, average wages, total population, non-agricultural population, the share of secondary industry in value added, and the share of tertiary industry in value added. Individual Controls comprise an individual's gender, age, age squared, race, marital status indicator, father's age, father's age squared, father's years of education, and hukou status. In columns (1) and (2) of Panel A, we do not control for father characteristics. Standard errors in Panel A are clustered by city. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

city fixed effects. v_{it} is the error term. The predicted values from this regression are the propensity scores.

In the second step, we use weighted least squares to re-estimate the baseline regression model, where the weights are the inverse of the propensity scores from the first step. Lower propensity scores indicate a lower probability of co-residing with one's father based on the child's observable characteristics. In the regression, we assign higher weights to such families so the results reflect potentially non-coresiding families. Columns (3)-(5) in Panel A of Table 9 show the results. The magnitude of the regression coefficients is comparable to our baseline results, supporting the robustness of our main estimation.

To address potential bias from excluding individuals older than 35, we also conduct sensitivity analyses with different age cutoffs. Table D1 in Appendix D presents the results for three alternative age ranges: 25-35, 16-32, and 18-40. The estimated coefficients are consistently positive and similar in magnitude across all age ranges.

5.2 Validity of the Shift-Share IV

In this section, we test the validity of the Bartik shift-share shock. According to Borusyak, Hull, and Jaravel (2022), the assumption for the SSIV is that the shocks are assigned as good as random. That is, shocks to industries cannot be correlated with other local shocks in the primary markets of these industries. For instance, if the car industry is opened to FDI, we should not expect a simultaneous labor supply shock in cities producing cars. To verify the validity of this assumption, we conduct two balance tests.

First, we regress industry-level variables on industry FDI shocks. If the FDI shock is random, it should not have explanatory power for industry-specific characteristics. We choose several industry characteristics including the log of the number of firms in the industry, the log of capital, the log of exports, average firm age, the proportion of state-owned capital, input tariffs, and output tariffs, which reflect the degree of competition level, capital availability, market openness, and the maturity of the industry. Regression results are shown in Appendix Table D2. We find no significant evidence of a correlation between industry characteristics and FDI shocks.

Second, we follow Xu (2022) to convert city-level characteristics to industry-level and regress them on industry FDI shocks. If shocks to industries are random, these weighted average regional characteristics (with high weights for the primary markets of the industry) should not be correlated with industry shocks. The pre-treatment city characteristics include city-level per capita GDP in 1998, the share of secondary industry in GDP, distance to the nearest port, the log of the number of universities plus one, and the student-teacher ratio in primary and secondary schools. We then take the weighted average of these city-level characteristics, X_{ct}, and sum up to the industry level according to equation (10), resulting in $\bar{X}_{jt}$:

$$\bar{X}_{jt} = \frac{\sum_c \frac{E_{cj1998}}{E_{c1998}} \times X_{ct}}{\sum_c \frac{E_{cj1998}}{E_{c1998}}} \tag{10}$$

Next, the standardized $\bar{X}_{jt}$ is used as an explanatory variable, and the regression is performed on

$\triangle FDI_{jt}$. The results are shown in Panel B of Table 9, which indicate that most of the weighted average city characteristics are uncorrelated with our FDI shocks, supporting our identifying assumption. However, one factor is marginally unbalanced: cities closer to ports are more likely to experience FDI shocks, though the point estimate of two percentage points is small. To account for this, we include the interaction between distance to the nearest port and the post-shock year dummy ($Dist\_Port_c \times Post02_t$) as a control in the baseline specifications, ensuring that its potential direct effect on intergenerational mobility is properly adjusted for.

5.3 Other Robustness Checks

We further conduct a series of sensitivity analyses detailed in Appendix D. First, we use an alternative measure of occupational status, the International Socio-Economic Index of Occupational Status (ISEI), which combines both income and education levels across occupations. Second, we test whether our results are influenced by migrant workers, who may have distinct socio-economic characteristics and mobility patterns. Third, we control for other policy changes that occurred concurrently with FDI liberalization, including hukou reform, import trade liberalization, and trade policy uncertainty (TPU). Finally, we conduct a placebo test to verify that our results are not driven by random variations. We randomly assign $FDI\_Shock_{c,2005}$ to different cities and estimate pseudo-treatment effects. By generating 500 placebo estimates and comparing them to our actual estimated coefficient of 0.40, we assess whether our results are statistically meaningful. In general, all robustness checks show that our results are consistent.

6 Conclusion

This study examines the impact of FDI deregulation following China's WTO accession on intergenerational occupational mobility, using a Bartik-style shift-share instrument based on pre-WTO initial industry employment structures. We find that individuals in cities with greater exposure to FDI liberalization are more upwardly mobility, as evidenced by a significant increase in the education intensity of their occupations compared to their fathers. People from low-SES families benefit more from this FDI shock. According to our mechanism analysis, FDI liberalization raises occupational mobility not only by offering more high-skill opportunities (i.e., demand-side mechanism), but also by increasing parental investment in education, which led to higher college enrollment rates (i.e., supply-side mechanism). Our analysis also provides some evidence that FDI has accelerated the transition of the labor force from agricultural to non-agricultural sectors.

Our heterogeneity analysis underscores that the positive effects of FDI liberalization are especially pronounced among disadvantaged socioeconomic groups, such as families with less parental education, agricultural backgrounds, or origins in underdeveloped regions. These findings imply that FDI liberalization can help reduce social inequality by improving access to high-quality employment for disadvantaged groups.

In terms of policy implications, this study suggests that the relaxation of FDI regulations, by allowing children from low-income backgrounds to enter better occupations, can lead to upward intergenerational occupational mobility even if it increases cross-sectional inequality in developing countries (Feenstra and Hanson, 1997). Government should consider these improved intergenerational mobility effects instead of focusing only on enlarged cross-sectional inequality. Indeed, FDI inequality in the long run.

References

Abebe, G, M McMillan, and M Serafinelli. 2022. "Foreign Direct Investment and Knowledge Diffusion in Poor Locations." *Journal of Development Economics* 158:102926.

Ahsan, Reshad N. and Arpita Chatterjee. 2017. "Trade Liberalization and Intergenerational Occupational Mobility in Urban India." *Journal of International Economics* 109:138–152.

Aitken, Brian J. and Ann E. Harrison. 1999. "Do Domestic Firms Benefit from Direct Foreign Investment? Evidence from Venezuela." *American Economic Review* 89 (3):605–618.

Akresh, Richard, Daniel Halim, and Marieke Kleemans. 2023. "Long-Term and Intergenerational Effects of Education: Evidence from School Construction in Indonesia." *The Economic Journal* 133 (650):582–612.

Alfaro, Laura. 2017. "Gains from Foreign Direct Investment: Macro and Micro Approaches." *The World Bank Economic Review* 30:S2–S15.

Alfaro, Laura, Areendam Chanda, Sebnem Kalemli-Ozcan, and Selin Sayek. 2010. "Does Foreign Direct Investment Promote Growth? Exploring the Role of Financial Markets on Linkages." *Journal of Development Economics* 91 (2):242–256.

Bao, Xiaohua, Qin Chen, Zibin Huang, Lei Li, and Mengyuan Wang. 2024. "Defensive Innovation: Technological Rivalry and College Major Choice." *SSRN* .

Becker, G. S. and N. Tomes. 1976. "Child Endowment and the Quality and Quantity of Children." *Journal of Political Economy* 84:S143–S162.

Becker, Gary S. and Nigel Tomes. 1986. "Human Capital and the Rise and Fall of Families." *Journal of Labor Economics* 4 (3, Part 2):S1–S39.

Blanden, Jo, Paul Gregg, and Lindsey Macmillan. 2007. "Accounting for Intergenerational Income Persistence: Noncognitive Skills, Ability and Education." *The Economic Journal* 117 (519):C43–C60.

Blau, Peter M. and Otis Dudley Duncan. 1967. "The American Occupational Structure." *American Sociological Review* 33 (2).

Borusyak, K., P. Hull, and X. Jaravel. 2022. "Quasi-Experimental Shift-Share Research Designs." *Review of Economic Studies* 89 (1):181–213.

Card, David, Raj Chetty, Martin S. Feldstein, and Emmanuel Saez. 2010. "Expanding Access to Administrative Data for Research in the United States." *American Economic Association, Ten Years and Beyond: Economists Answer NSF's Call for Long-Term Research Agendas* .

Cesar, Andres, Matías Ciaschi, Guillermo Falcone, and Guido Neidhöfer. 2023. "Trade Shocks and Social Mobility: The Intergenerational Effect of Import Competition in Brazil." *ZEW - Centre for European Economic Research Discussion Paper* No.42.

Chetty, Raj, Nathaniel Hendren, Patrick Kline, and Emmanuel Saez. 2014. "Where is the land of Opportunity? The Geography of Intergenerational Mobility in the United States." *The Quarterly Journal of Economics* 129 (4):1553–1623.

Connolly, Marie, Miles Corak, and Catherine Haeck. 2019. "Intergenerational Mobility Between and Within Canada and the United States." *Journal of Labor Economics* 37:S595–S641.

Elias, Peter. 2014. "Administrative Data." In *Facing the Future: European Research Infrastructures for the Humanities and Social Sciences*. Berlin: SCIVERO, 47–48.

Erten, Bilge, Jessica Leight, and Lianming Zhu. 2023. "The Effects of FDI Liberalization on Structural Transformation and Demographic Change: Evidence from China."

Fan, Haichao, Zheng Fang, Bihong Huang, and Mohan Zhou. 2022. "Prevalence of SOEs and Intergenerational Income Persistence: Evidence from China." *World Economy* 45 (1):276–291.

Fan, Jingting. 2019. "Internal Geography, Labor Mobility, and the Distributional Impacts of Trade." *American Economic Journal: Macroeconomics* 11 (3):25288.

Fan, Yi, Junjian Yi, and Junsen Zhang. 2021. "Rising Intergenerational Income Persistence in China." *American Economic Journal: Economic Policy* 13 (1):202–230.

Feenstra, Robert C. and Gordon H. Hanson. 1997. "Foreign Direct Investment and Relative Wages: Evidence from Mexico's Maquiladoras." *Journal of International Economics* 42 (3):371–393.

Findlay, Ronald. 1978. "Relative Backwardness, Direct Foreign Investment, and the Transfer of Technology: A Simple Dynamic Model." *The Quarterly Journal of Economics* 92 (1):1–16.

Fons-Rosen, Christian, Sebnem Kalemli-Ozcan, Bent E Sørensen, Carolina Villegas-Sanchez, and Vadym Volosovych. 2021. "Quantifying Productivity Gains from Foreign Investment." *Journal of International Economics* 131:103456.

Francesconi, Marco and Cheti Nicoletti. 2006. "Intergenerational Mobility and Sample Selection in Short Panels." *Journal of Applied Econometrics* 21:1265–1293.

Ganzeboom, Harry B., Paul M. De Graaf, and Donald J. Treiman. 1992. "A Standard International Socio-economic Index of Occupational Status." *Social Science Research* 21 (1):1–56.

Goldsmith-Pinkham, Paul, Isaac Sorkin, and Henry Swift. 2020. "Bartik Instruments: What, When, Why, and How." *American Economic Review* 110 (8):2586–2624.

Güell, Maia, Michele Pellizzari, Giovanni Pica, and José V. Rodríguez Mora. 2018. "Correlating Social Mobility and Economic Outcomes." *The Economic Journal* 128 (612):F353–F403.

Hu, Zhi-An, Jinghong Li, and Zhuo Nie. 2023. "Long Live Friendship? The Long-term Impact of Soviet Aid on Sino-Russian Trade." *Journal of Development Economics* 164:103117.

Javorcik, Beata S. 2004. "Does Foreign Direct Investment Increase the Productivity of Domestic Firms? In Search of Spillovers through Backward Linkages." *American Economic Review* 94 (3):605–627.

Jia, Ruixue, Xiaohuan Lan, and Gerard Padró I Miquel. 2021. "Doing Business in China: Parental Background and Government Intervention Determine Who Owns Busines." *Journal of Development Economics* 151:102670.

Keller, Wolfgang and Stephen R Yeaple. 2009. "Multinational Enterprises, International Trade, and Productivity Growth: Firm-Level Evidence from the United States." *Review of Economics and Statistics* 91:821–831.

Lavy, Victor, Assaf Kott, and Genia Rachkovski. 2022. "Does Remedial Education in Late Childhood Pay Off After All? Long-Run Consequences for University Schooling, Labor Market Outcomes, and Intergenerational Mobility." *Journal of Labor Economics* 40 (1):239–282.

Li, Bingjing. 2018. "Export Expansion, Skill Acquisition and Industry Specialization: Evidence from China." *Journal of International Economics* 114:346–361.

Lu, Y., Z. G. Tao, and L. M. Zhu. 2017. "Identifying FDI Spillovers." *Journal of International Economics* 107:75–90.

Lu, Yi and Linhui Yu. 2015. "Trade Liberalization and Markup Dispersion: Evidence from China's WTO Accession." *American Economic Journal: Applied Economics* 7 (4):22153.

Markusen, James R. 1995. "The Boundaries of Multinational Enterprises and the Theory of International Trade." *Journal of Economic Perspectives* 9 (2):169189.

Mocetti, S., G. Roma, and E. Rubolino. 2022. "Knocking on Parents' Doors Regulation and Intergenerational Mobility." *Journal of Human Resources* 57 (2):525–554.

Nakamura, Emi, Jósef Sigurdsson, and Jón Steinsson. 2022. "The Gift of Moving: Intergenerational Consequences of a Mobility Shock." *The Review of Economic Studies* 89 (3):1557–1592.

Neidhöfer, Guido, Joaquín Serrano, and Leonardo Gasparini. 2018. "Educational Inequality and Intergenerational Mobility in Latin America: A New Database." *Journal of Development Economics* 134:329–349.

Pierce, Justin R. and Peter K. Schott. 2016. "The Surprisingly Swift Decline of US Manufacturing Employment." *American Economic Review* 106 (7):163262.

Rodrigue, Joel, Qing Shi, and Yong Tan. 2024. "Trade Policy Uncertainty & Resource Misallocation." *European Economic Review* 164:104720.

Shi, Q, Y Tan, X Zhao, and LK Zhu. 2024. "Does Inward FDI Improve the Labour-allocation Efficiency of Local Firms? Evidence from China." *The World Economy* 47 (12):4570–4600.

Song, Yang. 2014. "What Should Economists Know about the Current Chinese Hukou System?" *China Economic Review* 29:200–212.

Ward, Zachary. 2022. "Internal Migration, Education, and Intergenerational Mobility: Evidence from American History." *The Journal of Human Resources* 57 (6):1981–2011.

Xu, C. Z. 2022. "Reshaping Global Trade: The Immediate and Long-Run Effects of Bank Failures." *Quarterly Journal of Economics* 137 (4):2107–2161.

Yakun, Chen, Zhang Haochen, Yang Rudai, and Yi Junjian. 2022. "Economic Opportunity, Intergenerational Mobility, and Common Prosperity: A Survey." *China Center for Economic Research Working Paper Series* No. C2022005.

Appendix

A Additional Tables and Figures

Table A1: Distribution of Industries with Increased FDI Liberalization

2-digit		Increased FDI Liberalization 4-digit	
Code	Name	Number	Ratio(%)
33	Non-Ferrous Metal Smelting and Rolling Industry	13	87
35	General Equipment Manufacturing	12	39
36	Special Equipment Manufacturing	12	29
26	Chemical Raw Materials and Chemical Products Manufacturing	10	33
37	Transportation Equipment Manufacturing	9	39
13	Agricultural and Sideline Food Processing	7	47
40	Communication Equipment, Computer and Other Electronic Equipment Manufacturing	7	44
39	Electrical Machinery and Equipment Manufacturing	7	29
34	Metal Products	5	28
14	Food Manufacturing	4	21
42	Crafts and Other Manufacturing	3	23
41	Instrumentation and Cultural, Office Machinery Manufacturing	3	12
28	Chemical Fiber Manufacturing	2	29
15	Beverage Manufacturing	2	17
31	Non-Metallic Mineral Products	2	7
43	Waste Resources and Used Materials Recycling	1	100
16	Tobacco Products	1	33
25	Petroleum Processing, Coking and Nuclear Fuel Processing	1	25
32	Ferrous Metal Smelting and Rolling	1	25
22	Paper and Paper Products	1	20
29	Rubber Products	1	11
19	Leather, Fur, Feather (Down) and Related Products	1	10
30	Plastic Products	0	0
17	Textile	0	0
20	Wood Processing and Wood, Bamboo, Rattan, Palm, and Straw Products	0	0
27	Pharmaceutical Manufacturing	0	0
23	Printing and Reproduction of Recorded Media	0	0
21	Furniture Manufacturing	0	0
18	Textile Garments, Shoes, and Hats Manufacturing	0	0
24	Cultural and Sports Goods Manufacturing	0	0

Table A1 presents data on the number and proportion of 4-digit industries within each 2-digit industry that experienced increased FDI liberalization. Significant variations are observed across industries, with the number of liberalized 4-digit industries ranging from 0 to 13 and the proportion varying from 0% to 87%. The non-ferrous metal dmelting and rolling industry exhibited the most FDI liberalization, with 13 4-digit industries, representing 87% of the total within this category. This was followed by the general equipment manufacturing industry, which had 12 such 4-digit industries, 39% of its total. The special equipment manufacturing industry also had 12 such 4-digit industries, but with a slightly lower proportion of 29%.

These industries are significant due to their involvement in manufacturing and technology. These counts with the spirit of the*Regulations on Foreign Investment Guidelines*, which aimed to enhance product and firm performance through FDI and facilitate entry into new markets. Conversely, several industries experienced minimal or no FDI liberalization. The sectors with FDI liberalization are often those that do not align with resource conservation and environmental improvement goals, or are legally restricted from foreign investment.

Table A2: EI of Occupations

Rank	Code	Occupation Name	EI
1	12	Scientific Researchers	14.57
2	23	Legal Professionals	14.18
3	27	Journalism, Publishing, and Cultural Workers	14.10
4	2	Heads of State Agencies and Institutions	13.77
5	4	Heads of Public Institutions	13.43
6	13	Engineering Technicians	13.41
7	14	Engineering Technicians	13.38
8	24	Teaching Staff	13.35
9	26	Sports Workers	13.22
10	22	Financial Business Personnel	12.81
11	31	Administrative Staff	12.71
12	1	Leaders of the Communist Party of China	12.66
13	21	Economic Business Personnel	12.39
14	16	Engineering Technicians	12.34
15	19	Health Professionals	12.33
16	15	Engineering Technicians	12.21
17	11	Scientific Researchers	12.01
18	25	Literature and Art Workers	11.86
19	5	Enterprise Leaders	11.56
20	33	Postal and Telecommunications Personnel	11.29
21	17	Agricultural Technicians	11.28
22	29	Other Professional Technicians	11.25
23	46	Medical and Health Support Services Personnel	11.23
24	39	Other Clerical and Related Personnel	11.23
25	18	Aviation and Marine Technicians	11.21
26	84	Broadcast, Film Production, and Cultural Relics Protection Workers	10.87
27	79	Pharmaceutical Production Workers	10.82
28	93	Inspection and Measurement Personnel	10.79
29	3	Leaders of Democratic Parties and Social Organizations	10.61
30	72	Power Equipment Installation, Operation, and Maintenance Personnel	10.50
31	42	Storage Personnel	10.43
32	32	Security and Firefighting Personnel	10.31
33	69	Electromechanical Product Assembly Workers	10.16
34	78	Tobacco and Tobacco Product Processing Workers	10.13
35	64	Chemical Product Production Workers	10.01
36	92	Environmental Monitoring and Waste Treatment Personnel	9.96
37	73	Electronic Components and Equipment Manufacturing, Assembly, and Maintenance Workers	9.92
38	44	Hotel, Tourism, and Entertainment Service Personnel	9.86
39	67	Electromechanical Product Assembly Workers	9.83
40	85	Printing Workers	9.79
41	45	Transportation Service Personnel	9.78
42	71	Mechanical Equipment Repair Personnel	9.68
43	55	Water Conservancy Facility Management and Maintenance Personnel	9.53
44	91	Transportation Equipment Operators and Related Personnel	9.50
45	89	Construction Workers	9.48
46	66	Mechanical Manufacturing and Processing Workers	9.38
47	65	Chemical Product Production Workers	9.34
48	41	Purchasing and Sales Personnel	9.26
49	47	Social Services and Residential Life Service Personnel	9.24
50	62	Metal Smelting and Dairy Personnel	9.22
51	68	Electromechanical Product Assembly Workers	9.01
52	83	Glass, Ceramics, Enamel, and Related Product Manufacturing Workers	8.90
53	87	Cultural, Educational, and Sports Goods Manufacturing Workers	8.84
54	74	Rubber and Plastic Product Manufacturing Workers	8.80
55	49	Other Commercial and Service Industry Personnel	8.74
56	63	Metal Smelting and Dairy Personnel	8.72
57	75	Textile, Knitting, and Dyeing Workers	8.71
58	43	Catering Service Personnel	8.70
59	76	Cutting, Sewing, and Leather Product Manufacturing Workers	8.68
60	61	Surveying and Mineral Extraction Workers	8.59
61	81	Wood Processing, Artificial Board, Wood Products, and Paper Products Manufacturing Workers	8.58
62	88	Construction Workers	8.44
63	59	Other Agriculture, Forestry, Animal Husbandry, Fishery, and Water Conservancy Production Personnel	8.36
64	77	Grain, Oil, Food, Beverage, and Feed Production Workers	8.34
65	99	Other Production and Transportation Equipment Operators and Related Personnel	8.30
66	52	Forestry Production and Wildlife Protection Personnel	8.20
67	86	Craft and Art Product Manufacturing Workers	8.15
68	48	Social Services and Residential Life Service Personnel	8.14
69	82	Building Material Production Workers	8.07
70	28	Religious Professionals	7.97
71	54	Fishery Production Workers	7.37
72	51	Crop Production Workers	6.79
73	53	Animal Husbandry Production Workers	6.02

B Details of Data Cleaning

B.1 National Census Data

We process the Census data as follows. First, we match children and fathers using family codes in the census data and identify father-child pairs based on the "relationship to household head" variable. Our sample includes three types of father-child pairs: (1) the household head and the household head's child, (2) the female household head's husband and the household head's child, and (3) the household head's father and the household head. Second, we restrict the sample to individuals who were employed in the week prior to the survey and who reported their occupation. Finally, to mitigate life-cycle bias and account for the possibility that fathers may have exited the labor market due to old age, we limit the age of sampled children to 16-35 years. Further discussion on sample selection issues is provided in Section 5.

B.2 ASIF Data

We process the ASIF data using the following steps:

First, using a sequential identification method, we perform four rounds of matching to identify firms and assign a new ID to matched firms. The matching criteria are as follows: (1) legal person code, (2) firm name, (3) province-prefecture-county code combined with the legal representative's name, and (4) province-prefecture-county code combined with the telephone number and year of establishment.

Second, starting from 2003, a new Chinese Standard Industrial Classification (CSIC) was implemented. To ensure consistency, we standardize the industry classification by adjusting the industry codes according to the 4-digit industry codes before and after 2002.

Third, we estimate missing "industrial value added" data based on accounting standards and exclude observations with key indicators that do not conform to accounting principles. These anomalies include cases where total assets are less than current assets, total assets are less than fixed assets, total assets are less than the net value of fixed assets, and firms recorded as established later than the reporting year.

Fourth, we exclude firms with negative values for key indicators such as total industrial output, sales, total fixed assets, or exports, as well as firms with fewer than eight employees.

B.3 FDI Regulation

Compared to 1997, the 2002 version of the *Catalogue* introduced significant changes, whereas the 2004 version made only minor adjustments based on the 2002 version. Therefore, we rely on the 2002 *Catalogue* revision relative to the 1997 version to examine the exogenous impact of FDI shocks on occupational intergenerational mobility. We follow Lu, Tao, and Zhu (2017) to process the 1997 and 2002 versions of the *Catalogue*.

First, we match the names of manufacturing industries (products) in both versions of the *Catalogue* with the 4-digit industry codes from the "Chinese Standard Industrial Classification (GB/T4754-2002)" standard. Then, we assign values to industries based on their classification in the *Catalogue*. Industry openness is categorized as *encouraged*, *permitted*, *restricted*, or *prohibited*, which are assigned values of 3, 2, 1, and 0, respectively. After comparing the two versions of the *Catalogue*, industries fall into one of the following four categories:

1. **FDI liberalized**: If an industry's assigned score increased (e.g., it was listed as *prohibited* in the 1997 version of the *Catalogue* but was reclassified as *encouraged*, *permitted*, or *restricted* in the 2002 version), the industry is considered to have experienced FDI liberalization.

2. **FDI unchanged**: If an industry remained in the same category (same score) in both the 1997 and 2002 versions of the *Catalogue*, it is classified as unchanged.

3. **FDI restricted**: If an industry's assigned score decreased (e.g., it was listed as *encouraged* in the 1997 version of the *Catalogue* but was reclassified as *permitted*, *restricted*, or *prohibited* in the 2002 version), the industry is considered to have experienced FDI restriction.

4. **Mixed changes**: If an industry underwent both increases and decreases in the degree of foreign entry liberalization across the two versions of the *Catalogue* (i.e., experiencing both upward and downward changes in scores), it is classified as an industry with mixed FDI changes.

C Additional Heterogeneity

C.1 Ethnic Minority Presence

Literature suggests that cities with a higher proportion of ethnic minorities tend to exhibit lower intergenerational occupational mobility than those with fewer minorities. This disparity may stem from socio-economic factors such as stronger kinship ties due to shared religious beliefs, which can deepen economic dependency and hinder mobility, limited educational resources that restrict access to higher education, or a segmented job market that increases reliance on parental support. To investigate this, we assess the effect of FDI liberalization on intergenerational mobility among individuals from ethnic minority regions. We categorize cities as $minor = 1$ if the ethnic minority ratio exceeds the national median and $minor = 0$ if it falls below. As shown in Table C1 Panel A, both ethnic minority and non-ethnic minority cities demonstrate an upward trend in intergenerational mobility. Our findings indicate that FDI can significantly enhance mobility in ethnic minority cities, despite potential challenges, by creating new economic opportunities and alleviating socio-economic constraints.

C.2 Prevalence of SOEs

Fan, Fang, Huang, and Zhou (2022) show that the prevalence of SOEs in a city negatively affects intergenerational mobility. To investigate this issue, we estimate separate regressions for cities with more and less SOE influence. We proxy SOE influence using the Sino-Soviet *156 Projects* collaboration. The *156 Projects* were a series of technical assistance agreements between China and the Soviet Union in the 1950s, covering 156 locations. Large state-owned factories were established in these selected locations, significantly reshaping China's industrial landscape, particularly inland. Despite China's transition to a market economy after 1978, these project SOEs often remain locally dominant (Hu, Li, and Nie, 2023).

Table C1 Panel B examines the differential impact of FDI shocks on cities based on their historical involvement in the *156 Projects*. Specifically, we analyze the coefficients of FDI_Shock_{ct} using two samples: cities that were chosen as a location for at least one of the 156 projects during the 1950s ($SOE = 1$) and those that were not ($SOE = 0$).

Our findings indicate that the coefficient of FDI_Shock_{ct} is not statistically significant for cities targeted for SOEs, suggesting that FDI does not have a notable impact on occupational intergenerational mobility in these cities. This can be attributed to the common practice of occupational inheritance among SOE employees, which potentially mitigates the influence of external economic shocks such as FDI. Conversely, in cities where $SOE = 0$, FDI_Shock_{ct} is positive and statistically significant, implying that FDI has a substantial and positive effect on occupational intergenerational mobility in cities less dominated by SOEs.

These results highlight the heterogeneous nature of FDI impacts across different urban contexts in China, influenced by historical economic policies and industrial structures.

C.3 Gender

Chetty, Hendren, Kline, and Saez (2014) find that daughters are less influenced by the intergenerational transmission of income characteristics compared to sons. This finding aligns with China's historical preference than sons, where male children have traditionally been granted greater financial resources and educational opportunities within families (Fan, Yi, and Zhang, 2021).

Table C1, Panel C, shows that the impact of FDI is more pronounced for daughters than for sons. This gender heterogeneity in the effect of FDI on intergenerational occupational mobility underscores the dual role of globalization and capital flows in promoting gender equality. On one hand, FDI creates new career opportunities and advancement pathways for women, helping to narrow the gender gap in occupational mobility. On the other hand, while the impact of FDI on men is smaller, it remains significant, suggesting that men may continue to hold advantages in certain fields.

Table C1: Additional Heterogeneity

Dependent Variable	$\lvert transfer_{ict} \rvert$					
	All		Upward		Downward	
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Ethnic Minority Presence in Father's Hometown					
	Minor=1	Minor=0	Minor=1	Minor=0	Minor=1	Minor=0
FDI_Shock_{ct}	0.478*	0.394**	1.128**	0.724***	0.363	-0.262
	(0.262)	(0.172)	(0.458)	(0.268)	(0.527)	(0.419)
N	48818	94739	11295	26191	6430	12756
adj-R^2	0.127	0.0999	0.0207	0.0301	0.169	0.157
	Panel B: Presence of *156 Project* SOEs					
	SOE=1	SOE=0	SOE=1	SOE=0	SOE=1	SOE=0
FDI_Shock_{ct}	-0.216	0.467***	0.426	0.947***	0.130	-0.329
	(0.389)	(0.132)	(0.366)	(0.263)	(0.624)	(0.412)
N	30749	112808	6973	30513	4274	14912
adj-R^2	0.101	0.113	0.0172	0.0301	0.150	0.160
	Panel C: Gendered Effects					
	Male	Female	Male	Female	Male	Female
FDI_Shock_{ct}	0.336**	0.551***	0.700**	0.955***	-0.651	0.378
	(0.146)	(0.176)	(0.286)	(0.353)	(0.410)	(0.474)
N	94250	49307	23519	13967	11709	7475
adj-R^2	0.107	0.115	0.0206	0.0461	0.160	0.149
City Lagged Controls	✓	✓	✓	✓	✓	✓
Individual Controls	✓	✓	✓	✓	✓	✓
City FE	✓	✓	✓	✓	✓	✓
Province × Year FE	✓	✓	✓	✓	✓	✓
Cohort × Year FE	✓	✓	✓	✓	✓	✓
$Dist\_Port_c \times Post02_t$	✓	✓	✓	✓	✓	✓

Notes: The dependent variable in all columns is the absolute value of intergenerational occupational mobility. City Lagged Controls include the logarithm of GDP, average wages, total population, non-agricultural population, the share of secondary industry in value added, and the share of tertiary industry in value added. Individual Controls comprise an individual's gender, age, age squared, race, marital status indicator, father's age, father's age squared, father's years of education, and hukou status. Standard errors are clustered at the city level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table D1: Age Range Robustness Checks

Dependent Variable	$\|transfer_{ict}\|$		
	Age:25-35	Age:16-32	Age:18-40
	(1)	(2)	(3)
FDI_Shock_{ct}	0.361**	0.354***	0.416***
	(0.141)	(0.131)	(0.133)
City Lagged Controls	✓	✓	✓
Individual Controls	✓	✓	✓
City FE	✓	✓	✓
Province × Year FE	✓	✓	✓
Cohort × Year FE	✓	✓	✓
$Dist\_Port_c \times Post02_t$	✓	✓	✓
N	52902	137175	134243
adj. R^2	0.112	0.109	0.110

Notes: In all columns, the dependent variable is the absolute value of intergenerational occupational mobility. Different age cutoffs are applied across the columns: Column (1) includes individuals aged 25-35, Column (2) those aged 16-32, and Column (3) individuals aged 18-40. City Lagged Controls include the logarithm of GDP, average wages, total population, non-agricultural population, the share of secondary industry in value added, and the share of tertiary industry in value added. Individual Controls comprise an individual's gender, age, age squared, race, marital status indicator, father's age, father's age squared, father's years of education, and hukou status. Standard errors are clustered at the city level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

D Robustness

D.1 Age Sampling

One potential source of sample selection bias arises from the exclusion of individuals over 35 years old from our sample. While this restriction aims to minimize the inclusion of fathers who have retired and lack occupational information, it may introduce selection bias. To assess the impact of this age restriction on our key findings, we conduct sensitivity analyses using alternative age cutoffs, as presented in Table D1. Specifically, we examine three age ranges: 25-35 years (column (1)), 16-32 years (column (2)), and 18-40 years (column (3)). Our results show that the coefficients remain significantly positive across these different age specifications, with magnitudes comparable to our baseline estimates. This consistency suggests that our main findings are robust

Table D2: Correlation between FDI Liberalization and Industry Characteristics

	$Firm\_Num_{jt}$	$Capital_{jt}$	$Export_{jt}$	Ave_Age_{jt}	Soe_Share_{jt}	$Input\_Tariff_{jt}$	$Output\_Tariff_{jt}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\triangle FDI_{j,2005}$	-0.358	0.527	-0.0154	0.847	0.0285	-1.229	-0.407
	(0.265)	(0.370)	(0.415)	(0.957)	(0.0200)	(0.970)	(2.066)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	819	819	819	819	819	819	819
adj. R^2	0.0950	0.0706	0.139	0.291	0.326	0.461	0.184

Notes: The dependent variables include 4-digit industry-level characteristics such as the log of the number of firms in the industry, the log of capital scale , the log of export scale, average firm age, the proportion of state-owned capital , input tariffs , and output tariffs. Data are sourced from the Annual Survey of Industrial Firms. Standard errors are clustered at the city level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

to variations in the age composition of the sample.

D.2 Industry-Level Balance Test

Table D2 presents the results of the industry-level balance test. The dependent variables include industry-level characteristics such as the log of the number of firms in the industry ($Firm\_Num_{jt}$), the log of capital ($Capital_{jt}$), the log of exports ($Export_{jt}$), average firm age (Ave_Age_{jt}), the proportion of state-owned capital (SOE_Share_{jt}), input tariffs ($Input\_Tariff_{jt}$), and output tariffs ($Output\_Tariff_{jt}$). These variables capture the degree of competition level, capital availability, and market openness, and maturity of each industry. The independent variable is $\Delta FDI_{j,2005}$[5]. The results in Table D2 indicate that the FDI shock is not systematically correlated with any industry characteristics during the same period, supporting the as good as random assignment of the FDI shock.

D.3 Other Robustness Check

D.3.1 Other Measures of Occupational Status

We further employ an alternative measure of occupational status, the International Socio-Economic Index of Occupational Status (ISEI), to assess the social status of occupations. The ISEI was initially proposed by Blau and Duncan (1967) and later refined by Ganzeboom, De Graaf, and

[5]Each regression is weighted by the proportion of the industry's labor force relative to the total national labor force.

Treiman (1992). It quantifies the socio-economic status of various occupational groups by weighting the average income and education level associated with each occupation.

We compute realized intergenerational occupational mobility for individual i at time t, denoted as $|transfer_{it}^{ISEI}|$, by taking the absolute difference between the individual's occupational social status and that of their father:

$$|transfer_{it}^{ISEI}| = |ISEI_{it} - ISEI_{ft}| \tag{D1}$$

By using $|transfer_{it}^{ISEI}|$ as the dependent variable in our regression analysis, we aim to more accurately capture the extent of occupational mobility across generations. The regression results, presented in Table D3, show that the coefficients for $|transfer_{it}^{ISEI}|$ align with our previous findings. This suggests that the impact of FDI liberalization on occupational mobility remains significant. The consistency across different measures of occupational status further strengthens the robustness of our conclusions.

D.3.2 Exclusion of Migrants

Table D4 presents the results of our analysis after excluding migrants. This reflects concerns that our findings may be influenced by the inclusion of migrants, who often exhibit distinct socio-economic characteristics and mobility patterns. By restricting our analysis to the non-migrant population, we aim to obtain estimates that more precisely capture the impact of FDI liberalization on intergenerational occupational mobility, minimizing potential biases related to migration. The results indicate that both the statistical significance and magnitude of our estimates remain unchanged. This suggests that migrants are unlikely to be the primary drivers of our findings, reinforcing the robustness of our conclusions.

D.3.3 Excluding Other Policies Occurring Simultaneously

Exclusion of Hukou Reform

The hukou reform aimed to relax the household registration system, facilitating migration and settlement in different cities. Since this reform could potentially influence labor mobility and economic outcomes, it is essential to account for its effects when analyzing the impact of FDI liberalization on intergenerational mobility.

Table D3: Other Measures of Occupational Status

Dependent Variable	$\lvert transfer^{ISEI}_{ict} \rvert$					
	All		Upward		Downward	
	(1)	(2)	(3)	(4)	(5)	(6)
FDI_Shock_{ct}	1.083	1.321*	5.530***	5.278***	-2.622	-3.039
	(0.665)	(0.681)	(1.851)	(1.903)	(2.799)	(3.021)
City Lagged Controls		✓		✓		✓
Individual Controls	✓	✓	✓	✓	✓	✓
City FE	✓	✓	✓	✓	✓	✓
Province × Year FE	✓	✓	✓	✓	✓	✓
Cohort × Year FE	✓	✓	✓	✓	✓	✓
$Dist\_Port_c \times Post02_t$		✓		✓		✓
N	143557	143557	35995	35995	20613	20613
adj. R^2	0.165	0.165	0.109	0.109	0.105	0.105

Notes: In all columns, the dependent variable is the absolute value of intergenerational occupational mobility. We use the International Socio-Economic Index of Occupational Status (ISEI) to measure the social status of occupations. Columns (1) and (2) report results for the full sample. Columns (3) and (4) display results for the intergenerational upward mobility sample ($transfer^{ISEI}_{it} > 0$), while columns (5) and (6) present results for the intergenerational downward mobility sample ($transfer^{ISEI}_{it} < 0$). City Lagged Controls include the logarithm of GDP, average wages, total population, non-agricultural population, the share of secondary industry in value added, and the share of tertiary industry in value added. Individual Controls comprise an individual's gender, age, age squared, race, marital status indicator, father's age, father's age squared, father's years of education, and hukou status. Standard errors are clustered at the city level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Fan (2019) constructed a prefecture-level Hukou Reform Index for the years 1997-2010, where a higher value indicates a greater likelihood of settlement. We include this index in our baseline model, and the coefficients of interest, presented in Table D5, indicate that the inclusion of the Hukou Reform Index does not significantly alter our main estimates. This suggests that our findings regarding the impact of FDI liberalization on occupational intergenerational mobility remain robust even after accounting for the effects of hukou reform.

China's Accession to the WTO and Import Trade Liberalization We incorporate controls for the impact of China's WTO accession and import trade liberalization in our robustness checks to ensure that these events do not bias our core conclusions. This is crucial, as import trade liberalization can significantly influence FDI and intergenerational occupational mobility by altering market dynamics and competitive environments.

Following China's entry into the WTO, industries that were previously protected, with by higher tariffs were liberalized via substantial tariff reductions, leading to greater liberalization.

Table D4: Exclusion of Migrant Samples

Dependent Variable	$\lvert transfer_{ict}\rvert$					
	All		Upward		Downward	
	(1)	(2)	(3)	(4)	(5)	(6)
FDI_Shock_{ct}	0.331***	0.404***	0.842***	0.768***	-0.133	-0.208
	(0.127)	(0.133)	(0.218)	(0.230)	(0.318)	(0.328)
City Lagged Controls		✓		✓		✓
Individual Controls	✓	✓	✓	✓	✓	✓
City FE	✓	✓	✓	✓	✓	✓
Province × Year FE	✓	✓	✓	✓	✓	✓
Cohort × Year FE	✓	✓	✓	✓	✓	✓
$Dist\_Port_c \times Post02_t$		✓		✓		✓
N	143557	143557	37486	37486	19186	19186
adj. R^2	0.110	0.110	0.0265	0.0267	0.158	0.158

Notes: The dependent variable in all columns is the absolute value of intergenerational occupational mobility. We exclude migrants from all estimates. Columns (1) and (2) report results for the full sample. Columns (3) and (4) display results for the intergenerational upward mobility sample ($transfer_{ict} > 0$), while Columns (5) and (6) present results for the intergenerational downward mobility sample ($transfer_{ict} < 0$). City Lagged Controls include the logarithm of GDP, average wages, total population, non-agricultural population, the share of secondary industry in value added, and the share of tertiary industry in value added. Individual Controls comprise an individual's gender, age, age squared, race, marital status indicator, father's age, father's age squared, father's years of education, and hukou status. Standard errors are clustered at the city level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Conversely, industries with lower pre-2001 tariffs saw minimal tariff changes and thus experienced less liberalization (Lu and Yu, 2015).

To capture the differential impact of this liberalization at the local level, we construct a city-level import trade liberalization shock measure. We generate this measure by interacting the industry-specific input tariff ($Input_{j,2001}$) or output tariff ($Output_{j,2001}$) in 2001 with the city's baseline industrial structure. Specifically, we use the employment share of industry j in city c in 1998 (calculated as $\frac{E_{cj1998}}{E_{c1998}}$, where E_{cj1998} is employment in industry j, city c, and E_{c1998} is total employment in city c), following the specifications in equations (D2) and (D3). To isolate the effect of liberalization over time, we incorporate an interaction term between this city-level shock measure ($Tariff\_Input_c$ or $Tariff\_Output_c$) and a post-2002 indicator variable into our baseline regression model.

The regression results, presented in Table D6, demonstrate that our findings remain robust even after accounting for the effects of import trade liberalization.

Table D5: Controlling Fo Hukou Reform

Dependent Variable	$\|transfer_{ict}\|$					
	All		Upward		Downward	
	(1)	(2)	(3)	(4)	(5)	(6)
FDI_Shock_{ct}	0.318**	0.392***	0.837***	0.767***	-0.157	-0.213
	(0.122)	(0.129)	(0.217)	(0.230)	(0.320)	(0.329)
Hukou Reform	✓	✓	✓	✓	✓	✓
City Lagged Controls		✓		✓		✓
Individual Controls	✓	✓	✓	✓	✓	✓
City FE	✓	✓	✓	✓	✓	✓
Province $\times$ Year FE	✓	✓	✓	✓	✓	✓
Cohort $\times$ Year FE	✓	✓	✓	✓	✓	✓
$Dist\_Port_c \times Post02_t$		✓		✓		✓
N	143557	143557	37486	37486	19186	19186
adj. R^2	0.110	0.110	0.0264	0.0267	0.158	0.158

Notes: The dependent variable in all columns is the absolute value of intergenerational occupational mobility. We include the city-level Hukou Reform Index for the years provided by Fan (2019) to isolate the effect of hukou reform. Columns (1) and (2) report results for the full sample. Columns (3) and (4) display results for the intergenerational upward mobility sample ($transfer_{ict} > 0$), while Columns (5) and (6) present results for the intergenerational downward mobility sample ($transfer_{ict} < 0$). City Lagged Controls include the logarithm of GDP, average wages, total population, non-agricultural population, the share of secondary industry in value added, and the share of tertiary industry in value added. Individual Controls comprise an individual's gender, age, age squared, race, marital status indicator, father's age, father's age squared, father's years of education, and hukou status. Standard errors are clustered at the city level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

$$Tariff\_Input_c = \sum_j \frac{E_{cj1998}}{E_{c1998}} \times Input_{j,2001} \tag{D2}$$

$$Tariff\_Output_c = \sum_j \frac{E_{cj1998}}{E_{c1998}} \times Output_{j,2001} \tag{D3}$$

Trade Policy Uncertainty and Export Trade Liberalization The decline in trade policy uncertainty (TPU) also affects local labor markets and economies (Rodrigue, Shi, and Tan, 2024). To isolate this effect, we incorporate an interaction between a city-level TPU shock and a post-2002 dummy into our baseline model.

To construct our TPU shock at the city level, we first compute the industry-specific TPU by subtracting the Most Favored Nation (MFN) tariff rates from the Column 2 tariff rates[6] for 1999,

[6] Column 2 tariffs in the U.S. Tariff Schedule are statutory tariff rates originally enacted in the Smoot-Hawley Tariff Act of 1930. These rates were historically applied to countries that did not receive Most Favored Nation (MFN)

Table D6: Controlling For Import Trade Liberalization

Dependent Variable	$\|transfer_{ict}\|$					
	All		Upward		Downward	
	(1)	(2)	(3)	(4)	(5)	(6)
FDI_Shock$_{ct}$	0.359**	0.443***	0.731***	0.730***	-0.302	-0.312
	(0.145)	(0.148)	(0.227)	(0.244)	(0.318)	(0.329)
$Tariff\_Input_c \times Post02_t$	✓	✓	✓	✓	✓	✓
$Tariff\_Output_c \times Post02_t$	✓	✓	✓	✓	✓	✓
City Lagged Controls		✓		✓		✓
Individual Controls	✓	✓	✓	✓	✓	✓
City FE	✓	✓	✓	✓	✓	✓
Province × Year FE	✓	✓	✓	✓	✓	✓
Cohort × Year FE	✓	✓	✓	✓	✓	✓
$Dist\_Port_c \times Post02_t$		✓		✓		✓
N	143557	143557	37486	37486	19186	19186
adj. R^2	0.109	0.110	0.0265	0.0266	0.158	0.158

Notes: The dependent variable in all columns is the absolute value of intergenerational occupational mobility. We include the interaction of the city-level import trade liberalization shock (input tariff or output tariff) with a post-2002 dummy to isolate the effect of import trade liberalization. Columns (1) and (2) show the results for the full sample. Columns (3) and (4) display the results for the intergenerational upward mobility sample ($transfer_{ict} > 0$), while columns (5) and (6) present the results for the intergenerational downward mobility sample ($transfer_{ict} < 0$). City Lagged Controls include the logarithm of GDP, average wages, total population, non-agricultural population, the share of secondary industry in value added, and the share of tertiary industry in value added. Individual Controls include an individual's gender, age, age squared, race, marital status indicator, father's age, father's age squared, father's years of education, and hukou status. Standard errors are clustered by city. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

following Pierce and Schott (2016). For each industry j, this is expressed as:

$$TPU_j = \tau^{Col2}_{j,1999} - \tau^{MFN}_{j,1999} \tag{D4}$$

Next, we calculate the city-level TPU shock by aggregating industry-specific TPU measures, weighted by industry employment within each city. The TPU shock for city c is:

$$TPU\_Shock_c = \sum_j \frac{E_{cj1998}}{E_{c1998}} \times TPU_j \tag{D5}$$

where E_{cj1998} represents employment in industry j in city c in 1998, and E_{c1998} is total employment in city c in 1998. This weighted average captures the TPU shock by reflecting each city's industrial composition, quantifying the impact of trade policy uncertainty on local economies.

status (now referred to as Normal Trade Relations). As such, Column 2 rates are generally higher than MFN rates and represent the maximum tariff the U.S. could legally impose on a country.

Table D7: Controlling For Trade Policy Uncertainty

Dependent Variable	$\lvert transfer_{ict} \rvert$					
	All		Upward		Downward	
	(1)	(2)	(3)	(4)	(5)	(6)
FDI_Shock_{ct}	0.306**	0.379***	0.803***	0.728***	-0.185	-0.253
	(0.132)	(0.137)	(0.218)	(0.237)	(0.325)	(0.338)
$TPU_c \times Post02_t$	✓	✓	✓	✓	✓	✓
City Lagged Controls		✓		✓		✓
Individual Controls	✓	✓	✓	✓	✓	✓
City FE	✓	✓	✓	✓	✓	✓
Province × Year FE	✓	✓	✓	✓	✓	✓
Cohort × Year FE	✓	✓	✓	✓	✓	✓
$Dist\_Port_c \times Post02_t$		✓		✓		✓
N	143557	143557	37486	37486	19186	19186
adj. R^2	0.110	0.110	0.0265	0.0267	0.158	0.158

Notes: The dependent variable in all columns is the absolute value of intergenerational occupational mobility. We incorporate an interaction between the city-level TPU shock and a post-2002 dummy to isolate the effects of the decline in trade policy uncertainty. Columns (1) and (2) show the results for the full sample. Columns (3) and (4) display the results for the intergenerational upward mobility sample ($transfer_{ict} > 0$), while columns (5) and (6) present the results for the intergenerational downward mobility sample ($transfer_{ict} < 0$). City Lagged Controls include the logarithm of GDP, average wages, total population, non-agricultural population, the share of secondary industry in value added, and the share of tertiary industry in value added. Individual Controls include an individual's gender, age, age squared, race, marital status indicator, father's age, father's age squared, father's years of education, and hukou status. Standard errors are clustered by city. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

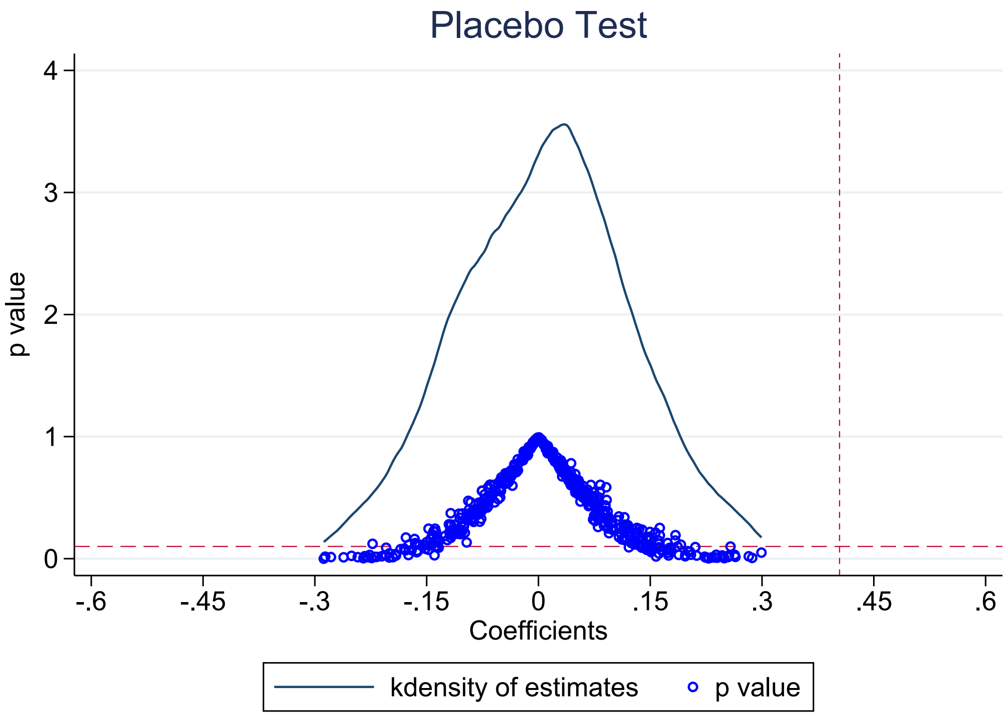
Incorporating this into our baseline model, we find that the inclusion of the TPU shock does not significantly alter the coefficients, as shown in Table D7.

D.3.4 Placebo Test

We further implement a placebo test to verify the robustness of our findings. This test is conducted by randomly assigning FDI shocks to different cities and constructing pseudo-treatment effects $FDI\_Shock_{ct}^{pseudo}$. We then replace the original independent variable in equation (3) with $FDI\_Shock_{ct}^{pseudo}$.

Figure D1 presents the distribution of the pseudo-estimated coefficients and their corresponding p-values based on 500 placebo tests. The horizontal axis represents the regression coefficients of $FDI\_Shock_{ct}^{pseudo}$, while the vertical axis shows the density distribution of these coefficients along with their corresponding p-values. The kernel density distribution of the estimated coeffi-

Figure D1: Placebo Test



cients is depicted by the curve, blue dots indicate the p-values of each estimated coefficient, the vertical red dashed line represents the actual estimated value of 0.404 from the DID model, and the horizontal red dashed line marks the significance threshold of 0.1.

We observe that most of the estimated coefficients cluster around zero, with the majority of p-values exceeding 0.1, indicating that these estimates are not statistically significant. This finding strongly suggests that our empirical results are not driven by randomness or unobserved policy factors. Furthermore, the main coefficients are significantly different from the actual estimated value of 0.404 obtained in our baseline regression. This further confirms that the estimates of the pseudo-treatment effects are not statistically significant, indicating that there is no false positive built into our research design.