Import Exposure and Labor Market Adjustments: Evidence from India

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Abstract

A vast literature has documented the effects of the surge in imports from China on high-income countries, but less is known about its impact on developing nations. In this paper, I causally examine the effects of rising Chinese imports on the Indian labor market by exploiting plausibly exogenous variation in exposure to imports at the district level. I find evidence of a decline in the manufacturing share of employment among working-age men in more exposed districts, primarily driven by a contraction of low-skill occupations in manufacturing across workers of all ages, with young and mid-career workers reallocating to high-skill or mid-skill occupations in services. I also document an increase in upward intergenerational occupational mobility – sons are in "better" occupations relative to their fathers. This upward mobility is higher for sons from disadvantaged social groups and in urban areas. I find that education plays a key role in facilitating upward mobility.

JEL Codes: F14, F16, F66, J24, J62

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1 Introduction

Globalization can lead to significant changes in the labor market. Standard theories of international trade, such as the Heckscher-Ohlin model, predict that a contraction in employment in the import-competing sector from rising import pressure is accompanied by a simultaneous increase in employment in the export-oriented sector. These models typically assume away the presence of labor market frictions, which allows the workers displaced from the import sector to be absorbed by other sectors in the economy. However, frictions in the labor market can affect this reallocation process by impeding mobility across sectors.[1]

Following the seminal work of Autor et al. (2013), a vast literature documents a host of effects of the so-called "China shock" – the large surge of Chinese imports in the early 2000s – on the United States. These range from higher unemployment, lower labor force participation, reduced earnings, and weak overall job growth to decline in marriage and fertility and the welfare of children (Acemoglu et al., 2016; Autor et al., 2019). There is also a substantial body of work on the effects of the China shock on other high-income countries.[2] Less is known about its impact on developing nations, such as India. Chakraborty et al. (2024b) document large manufacturing employment losses between 1999 and 2004 in more exposed districts, although the overall effect on employment is negative and imprecisely estimated. In line with predictions of standard models of trade, it is possible for non-manufacturing (export or non-traded sectors) to expand and absorb these displaced manufacturing workers. Thus, by changing the landscape of industries, import exposure can affect labor mobility and reallocation.

In this paper, I exploit geographic variation in exposure to imports from China across Indian districts based on pre-existing industry composition and explore how the labor market in India adjusted in the decade following China's accession to the World Trade Organization. By using a shift-share instrumental variable where I instrument for imports from China to India by imports from China to a set of Latin American countries, this paper uses plausibly exogenous variation to causally study the effects of the "China shock" on the labor market in India. In particular, I investigate the cross-sectional consequences of import exposure, how those effects vary by age, and how that affects mobility across generations.

A developing nation like India makes for a particularly interesting setting. Firstly, relative to developed countries, the manufacturing sector is small in India, employing only

[1] Standard models also assume balanced trade, but trade shocks can also lead countries to run trade imbalances and this can affect the dynamics of reallocation of labor across sectors (Dix-Carneiro et al., 2023).

[2] See Dorn and Levell (2024) for a review.

about 6.4% of the working-age population in 1999.[3] With almost 35% of its workforce engaged in agriculture, the effects of a manufacturing shock on a predominantly rural economy like India can potentially be different from the effects of the China shock on developed countries. Additionally, India is characterized by high intergenerational persistence in social outcomes. Such strong associations between parental and child outcomes can serve as barriers to labor market adjustment. The centuries-old hereditary social stratification system in India, the caste system, also contributes to impeding mobility by restricting individuals' access to occupations outside their caste's traditional occupation.

Since globalization is believed to have played a significant role in economic growth in many countries across the world, it is natural to ask whether the forces of globalization can challenge existing social structures and help facilitate mobility. Despite the liberalization of the Indian economy in the 1990s raising the returns to white-collar occupations, lower-caste networks continued to channel boys into local language schools that led to the traditional occupation (Munshi and Rosenzweig, 2006).[4] Whether a trade shock can help facilitate labor market mobility in the presence of these barriers is thus an empirical question.

I utilize data from three rounds of a large-scale nationally representative household survey with detailed information on employment status, industry, occupation, as well as a host of demographic characteristics. Data on the district of residence allows me to use a local labor markets approach and stack changes in outcomes at the district level. I find evidence of a null effect on overall employment-to-population ratio for working-age men; however, I do find evidence of reallocation across industries in more affected districts. I document a significant decline in the employment share in manufacturing (and construction), which seems to be offset by an increase in services (and agriculture).

Prior literature has emphasized the important role played by occupational classification in determining who is affected by trade shocks (Ebenstein et al., 2014; Artuç and McLaren, 2015). Thus, looking solely at industries might understate the costs of globalization. Using the reported occupation and level of education of employed individuals, I calculate a human capital score for 90 time-consistent occupations, which I then use to classify occupations into terciles of skill-intensity (low-skill, mid-skill, and high-skill). Furthermore, since trade shocks can affect the mobility of workers of different ages differently (Artuç, 2012), I partition working age-men into three mutually exclusive age groups and investigate the intersection between occupations, industries, and worker subpopulations.

[3]The share of manufacturing employment to working-age population for the United States was 12.6% in 1991 and had fallen to about 11% by 1999 (Autor et al., 2013).

[4]Thus, while economic growth can reduce the influence of old social and economic divisions, caste is an important predictor of economic status (Asher et al., 2024).

I find that the aforesaid decline in manufacturing is driven by a contraction in low-skill occupations in manufacturing and that this decline is common to workers in all age-groups. In more affected districts, young workers and mid-career workers are more likely to be engaged in high-skill and mid-skill occupations in services respectively.

I also investigate how exposure to trade affects intergenerational occupational mobility in India, namely, do sons move up or down the occupational ladder (based on the skill content)? To examine this, I link fathers and sons coresiding in the same household to answer whether import exposure induces sons to move into occupations that are "better" or "worse" than that of their father. The human capital score allows me to rank and compare the occupations of fathers and sons to determine whether a son is upward (downward) mobile; i.e. if the son is in an occupation with a human capital score that is higher (lower) than that of their father.

While intergenerational income mobility may seem to be the natural outcome to study, it is not well suited to this context. Since a vast majority of survey respondents work in the informal sector in India, wage or income data can be noisy and unreliable.[5] Occupation and education levels are measured more accurately in developing countries than income and occupations reflect the nature of a country's specialization and skill demand better (Mitra et al., 2024). On top of that, wage data is not available for the majority of individuals surveyed, as more than 50% were self-employed in 1999.

My findings suggest that a 1 percentage point increase in import exposure from China leads to a 0.476 percentage point increase in the share of upward mobile sons among all father-son dyads in a district. This result is fairly stable across a battery of robustness tests and persists even with a stricter definition of mobility and with coarser occupational classification. This finding indicates that differential exposure to imports explains 23.36% of the variation in the share of upward mobile sons between a district at the 25th percentile and a district at the 75th percentile of import exposure.

I also document heterogeneous effects by social groups: the effect of import exposure on upward mobility is higher for the disadvantaged Scheduled Castes (SC) and Scheduled Tribes (ST).[6] In other words, the share of upward mobile SC/ST sons is significantly higher in districts that are more exposed to imports from China. While I do not observe a similar

[5] It is also difficult to ascribe income to individuals in multigenerational households with joint production (Asher et al., 2024).

[6] Individuals from certain castes, considered lower in the hierarchical system, have been subject to discrimination like being denied access to education and being relegated to working in certain stigmatized occupations and industries. Prolonged discriminatory social norms faced by these groups were so endemic that the Constitution of India recognized them as a disadvantaged group and instituted affirmative action policies in education and public sector employment in the hopes of raising their social and economic mobility.

effect for non-SC/STs, this group is mobile (both upward and downward). Given that manufacturing workers were disproportionately from the non-SC/ST population at the baseline, it is possible that this group was relatively more affected by the China shock. Overall, these results provide some evidence to support the idea that globalization can play a role in breaking down caste-based barriers to socioeconomic mobility. Furthermore, I find stronger effects of import exposure on the share of upward mobile sons residing in urban areas. This result could possibly stem from the availability of a more diverse set of industries and occupations in urban areas.

Finally, I explore a potential mechanism through which sons can move to better occupations than their father: acquiring more education. My results suggest that up-skilling plays a key role in facilitating the movement of sons up the occupational ladder.

Contribution to the literature. First, I contribute to the relatively small body of work exploring the effects of Chinese import competition on India. Prior research on India has focused on firms and documented evidence of reduction in the product scope of small and medium-sized manufacturing firms (Chakraborty and Henry, 2019) and a reduction in firm-product output prices through a decline in markups (Chakraborty et al., 2024a). Chakraborty et al. (2024b) find that Chinese import competition led to an increase in the share of formal manufacturing enterprise employment through a reallocation of employment from the informal to the formal sector. This rise in formal-sector employment is driven by more productive formal firms. I add to this strand of research exploring labor market adjustments following the China shock.

Second, I contribute to the literature studying intergenerational mobility in India. Prior research is largely descriptive and has documented important patterns in intergenerational mobility. Patterns of intergenerational educational mobility are unclear, with Azam and Bhatt (2015) finding a decline in educational persistence and Asher et al. (2024) finding that upward mobility has barely changed from the 1950s to the 1980s birth cohorts. Using the Altham statistic as a measure of distance association of father-son occupations, Azam (2015) found no strong evidence of differences in occupational mobility across birth cohorts. Looking at the disadvantaged Scheduled Caste (SC) and Scheduled Tribe (ST) population from the mid-1980s to the mid-2000s, Hnatkovska et al. (2013) report convergence in the intergenerational mobility rates of SC/STs to non-SC/ST levels in educational attainment and wages. Interestingly, they also find that SC/STs have been switching occupations relative to their parents at a higher rate and have matched non-SC/STs in this regard.

These papers argue that changes in mobility have coincided with structural changes in the Indian economy, but do not attempt to establish causality. To the best of my knowledge, Ahsan and Chatterjee (2017) is the only paper that causally examines the relationship between intergenerational occupational mobility and trade liberalization in India. They find a rise in trade-induced upward mobility in the 1990s following reductions in tariffs. My paper builds on their work by exploring the effects of the China shock on intergenerational mobility in the 2000s.

Finally, I contribute to the nascent literature exploring how globalization affects intergenerational mobility. Studying the effect of a large export shock following the US-Vietnam Bilateral Trade Agreement, Mitra et al. (2024) find evidence of an increase in upward occupational mobility among young sons and daughters. Exploiting variation in exposure to imports from China between 1991 and 2007, Colantone et al. (2024) document a decline in intergenerational income mobility in the United States for the cohort of workers born in 1980-1982.

The rest of the paper is organized as follows. Section 2 introduces the data used and describes the construction of the working sample. Section 3 presents the identification strategy. Section 4 discusses the results and potential mechanisms. Section 5 concludes.

2 Data and Sample Construction

2.1 Data Sources

The primary source of data is the quinquennial Employment and Unemployment Surveys (EUS) conducted by the National Sample Survey Organization (NSSO). I use the 55th round (1999-2000), the 61st round (2004-2005), and the 66th round (2009-2010).[7] The large-scale household-level survey collects information from more than 100,000 households on a host of demographic characteristics of all members of the household along with their principal activity status and the highest completed level of education. For employed individuals, the survey also reports their principal industry (typically at the 5-digit level) and principal occupation code. The data are a repeated cross-section; however, there is a geographic panel dimension at the district level.

Data on imports and exports are sourced from the UN-Comtrade database.[8] All import and export amounts are inflated to 2010 US dollars using the Consumer Price Index from

[7] The surveys run from July to June and correspond to the agricultural year in India. To match with the survey round, I average trade data over the two years. For brevity, I often refer to each survey-round by the starting year.

[8] Import data are reported using the Harmonized System at the product level. This is mapped to ISIC Revision 3 using concordances made available by the World Bank (https://wits.worldbank.org/product_concordance.html).

the World Bank. Manufacturing employment and output information are sourced from the NSSO Unorganized Manufacturing Survey of 1994-1995 (51st round) and the Annual Survey of Industries 1994-1995 (covering the registered manufacturing sector). Tariff data is sourced from the Global Tariff Database (Teti, 2024). Population information comes from the 2001 Population Census of India.

2.2 Sample Construction

I restrict my attention to men in working-age population (ages 16-64).[9] Using the reported industry code, I classify workers into 5 broad sectors: agriculture (includes hunting and forestry), manufacturing, construction, mining (includes quarrying), and services. Similar to Autor et al. (2013), I partition my sample into young workers (ages 16-34), mid-career workers (age 35-49), and older workers (ages 50-64). Summary statistics for this sample are presented in Table 1. I aggregate observations to the district level using sample weights and then take the first difference to create my outcome variables. My analysis sample is a balanced panel with $N = 826$ (413 districts $\times$ 2 first differences) where each observation represents a 5-year change in the outcome of interest for a district.

Ranking occupations. Each employed individual in the data reports an occupation code. The first two rounds of the survey report 3-digit occupations from the 1968 version of the National Classification of Occupations (NCO) whereas the last round reports the same from the 2004 version. I combine the two versions to create 90 time-consistent occupation codes.[10] The survey also reports the highest level of completed education for each respondent. I harmonize these into seven categories: illiterate (1), literate but below primary (2), primary (3), middle (4), secondary (5), higher secondary (6), and post-higher secondary (7). This allows me to assign to each occupation a human capital score as follows:

$$OS_o = \sum_{i=1}^{n_o} \left(\frac{\omega_i}{\sum_{i=1}^{n_o} \omega_i} \right) E_i \tag{1}$$

where o indexes occupations, n_o is the number of individuals in occupation o, $E_i \in \{1, 7\}$ is the education category of individual i as defined above, and ω_i is the sampling weight.

[9] I exclude females from my analysis because of the potential for changes in female labor force participation to confound my results (Hnatkovska et al., 2013; Ahsan and Chatterjee, 2017).

[10] I map the two different versions of occupational classification in three steps. First, I use the available crosswalk to the extent possible; however, the crosswalk maps 5-digit NCO 1968 to 6-digit NCO 2004. This is at a more disaggregated level than is reported in the data and leads to several many-to-one mappings. In the second step, I rely on bigram text matching on occupation titles to find the best match for these many-to-one mappings. In the final step, I perform a manual check.

This measure is similar to the one used by Ahsan and Chatterjee (2017), except that I am able to classify education into 7 categories instead of 6 because newer rounds of the survey report less coarse education codes.[11] However, unlike Ahsan and Chatterjee (2017), I allow the score to vary over time by calculating it for each survey-round using all workers between the age of 25 and 64 (Song et al., 2020). Thus, occupation scores are defined nationally for each survey-round and remain the same across all workers in an occupation.[12]

Working sample for intergenerational mobility. I exploit a special social characteristic of Indian households – coresidence of multiple adult generations to construct my working sample for this part of the analysis. Since the National Sample Survey is a household survey, I am able to link sons coresiding with their fathers (the male head of the households) to construct father-son dyads.[13] Following Ahsan and Chatterjee (2017), I restrict my attention to sons aged between 16 and 35 to maximize chances that the father is not dead or retired. This is particularly important because the survey does not collect retrospective information – I observe occupations for both father and son only if they are both employed.

Since my working sample relies on linking father and sons who coreside in a household, it raises selection issues – it is possible for import exposure to affect coresidence rates of multiple adult generations. Sons can leave households for better employment opportunities elsewhere outside the district. Similarly, facing an import shock in a different district, they may also return to coreside with parents. However, the share of households with multiple adult generations coresiding is fairly stable across survey-rounds at about 52%.[14]

Another potential concern is migration. Migration rates in India are historically low and migration across districts plays no discernible role in Indian labor markets (Topalova, 2010). Intra-district migration is not a cause for concern; in fact, it may be relatively more common for individuals to temporarily migrate to towns and cities within the same district for employment. In 1999, only 1.45% of individuals surveyed (2.2% of sampled house-

[11] The NSSO does not collect information on the years of schooling. However, completion of primary, middle, secondary, and higher secondary would roughly correspond to 5, 8, 10, and 12 years of schooling respectively.

[12] The type of survey data I use does not allow me to calculate occupation scores precisely for each occupation in each birth cohort, like in Song et al. (2020).

[13] Female headed households are few and also special in that they are likely to have undergone special circumstances (Hnatkovska et al., 2013).

[14] To alleviate further concerns, I estimate a specification where I regress the share of households with multiple adult generations coresiding in a district on the import exposure measure. The results, reported in Table A1, do not suggest a cause for concern.

holds) reported not living in the same village or town in the last 6 months.[15]

Outcomes. I define intergenerational occupational mobility as the absence of intergenerational occupational persistence. If the son reports an occupation code that is different from that of the father, the son is "mobile". The human capital score calculated for each occupation further allows me to say whether a son is upward mobile or downward mobile relative to the father. In a survey-round, an upward mobile son is defined as a son whose occupation has a human capital score higher than that of his father. Likewise, a downward mobile son is one whose occupation score is lower than that of his father. Since I use contemporaneous occupation scores, if a father and a son are in the same occupation, the son will not be classified as "mobile". Thus, my outcome variables measure changes in the shares of upward or downward mobile sons among all father-son dyads in a particular district. Tables 2 and 3 present some descriptive statistics of this working sample.

3 Empirical Strategy

Massive internal reforms throughout the last two decades of the previous century led to rapid manufacturing productivity growth in China. Its position as the exporting powerhouse of the world was further cemented by its accession to the World Trade Organization in 2001. Between 1999 and 2009, India experienced an almost 20-fold increase in imports from China, from about \$1.5 billion to \$28.93 billion. Figure 1 plots trade volume (measured in 2010 US dollars) between India and China from 1999 to 2011.[16] Although exports to China also grew during the same period, India experienced a rising trade deficit. Dorn and Levell (2024) find that countries that experienced a rising trade deficit in their goods exchange with China experienced a higher decline in manufacturing employment. As Figure A2 demonstrates, imports to India from China were almost entirely manufacturing goods.

Measure of Import Exposure. My key explanatory variable, the measure of import exposure, follows a shift-share structure: it is a within manufacturing employment share weighted sum of industry shifts. Following the tradition in microeconomic studies of In-

[15] The 61st and 66th survey rounds did not ask any questions on migration, but the 64th round (2007-2008) had a questionnaire specifically designed to collect migration information. Only 1.88% of sampled households reported migrating to their place of enumeration during the last 365 days from another district.

[16] Figure A1 plots the same for the United States. Imports from China to the US grew from about \$112.42 billion to \$309.03 billion between 1999 and 2009; however, this is less than a 3-fold increase.

dia, I treat the district as the relevant labor market (Edmonds et al., 2010).[17] I define the import exposure measure for each district as follows:

$$\Delta IP_{dt} = \sum_j \frac{L_{jd,1994}}{L^M_{d,1994}} \frac{\Delta M_{jt}}{Y_{j,1994} + M_{j,1994} - X_{j,1994}} \tag{2}$$

where $L_{jd,1994}$ represents manufacturing employment in industry j in district d in 1994-1995 and $L^M_{d,1994}$ denotes manufacturing employment in district d in 1994-1995. Equation 2 thus leverages between industry variation in exposure to imports from China and variation across Indian districts based on pre-existing within manufacturing employment shares in each district; i.e. it apportions an industry level shift (defined in Equation 3) to each district according to its share within manufacturing employment and aggregates across all manufacturing industries. The industry level shift is given by:

$$\Delta IP_{jt} = \frac{\Delta M_{jt}}{Y_{j,1994} + M_{j,1994} - X_{j,1994}} \tag{3}$$

where ΔM_{jt} is the difference in industry j's imports from China between survey-round t and $t-1$.[18] Imports are normalized by initial Indian market volume. Defined this way, the shift measures the difference in the relative increase in Chinese supply over initial absorption (value of output $Y_{j,1994}$ plus imports $M_{j,1994}$ minus exports $X_{j,1994}$) between two survey-rounds. Thus, the identifying variation comes from the differential exposure to imports from China based on pre-existing within manufacturing industry composition in each district.[19]

Importantly, identification relies on the exogeneity of either the shifts or the shares (Borusyak et al., 2025). The baseline of 1994-1995 is chosen to mitigate concerns of simultaneity bias in the shares: contemporaneous employment can be affected by anticipated trade with China. For the average district in my sample, the measure in Equation 2 increased by about 6.5 percentage points between 1999 and 2009. Table 3 presents summary statistics of this measure. In both time periods, a district at the 75th percentile of import exposure experienced an increase that is about 2.5 times as large as a district at the 25th percentile.

[17] To ensure that the geographic boundaries of each labor market are constant over time, I create a concordance between district codes of the various data sources accounting for district splits. I mostly rely on district creation information from district websites to do this.

[18] I use all manufacturing imports to create this measure and do not draw a distinction between the import of finals goods and intermediate goods.

[19] In Table A3, I add a second source of variation in the shares: differential concentration across manufacturing and non-manufacturing within district employment.

Instrumentation Strategy. A possible concern with Equation 2 is that domestic demand or productivity shocks can influence imports to India from China, making the shifts potentially endogenous. To capture the supply-driven component in Chinese imports to India, I instrument for import exposure by imports to a set of 10 Latin American countries following Chakraborty et al. (2024b) and implement two-stage least squares estimation (2SLS). The Latin American countries are Argentina, Brazil, Chile, Colombia, Costa Rica, Mexico, Paraguay, Peru, Uruguay, and Venezuela. These countries are not major trade partners of India, and so the exclusion restriction is likely to hold.

$$\Delta IP_{dt}^{O} = \sum_{j} \frac{L_{jd,1994}}{L_{d,1994}^{M}} \frac{\Delta M_{jt}^{O}}{Y_{j,1994} + M_{j,1994} - X_{j,1994}} \tag{4}$$

Estimating Equation. I follow the convention in the literature and aggregate the data to the district level (Autor et al., 2013, Acemoglu et al., 2016, Greenland and Lopresti, 2016). I estimate the following specification in stacked first differences:

$$\Delta y_{dt} = \beta \Delta IP_{dt} + \gamma_t + \alpha_s + \Delta \epsilon_{dt} \tag{5}$$

where Δy_{dt} denotes the change in the outcome of interest, typically a share. The coefficient of interest is β, which estimates the causal effect of the change in the import exposure measure for district d. γ_t represents a time fixed effect and α_s is a state fixed effect. I allow for spatial correlation across districts by clustering my standard errors at the state level. Since my outcome variable is a share, each observation is weighted using the district's population share in national population in 1999.

4 Results

4.1 Effects of employment, industry, and occupations

I start by estimating equation 5 by restricting my sample to men in the working-age population (ages 16-64). Results are reported in Panel A of Table 4. The outcome in column 1 is the (change in) employment-to-population ratio. I do not find any significant effect on overall employment to working-age population ratio. In columns 2-6, I restrict my sample to *employed* working-age men to examine the effects of import exposure on reallocation across various sectors: manufacturing, agriculture, construction, mining, and services. I find evidence of significant declines in the share of employment in manufacturing and construction in more affected districts that seem to be offset by increases in services and agriculture.

Sensitivity to tariffs and population controls. To probe the robustness of my findings, I start by controlling for the baseline employment-weighted start-of-period district tariffs. I follow the rich literature studying the effects of Indian tariff liberalization and utilize baseline employment shares to convert national tariffs into district tariffs (Topalova, 2010; Edmonds et al., 2010; Ahsan and Chatterjee, 2017). Explicitly controlling for differences in tariff exposure accounts for a trade channel that can affect imports from China, while also potentially removing any lingering effects of the trade liberalization episode in India.

$$\tau_{d,t-1} = \sum_{j} \frac{L_{jd,1999}}{L_{d,1999}} \tau_{j,t-1} \tag{6}$$

$\tau_{j,t-1}$ measures the average bilateral tariff imposed by India on Chinese manufacturing goods in sector j at the start of each period.

Next, I control for baseline district population characteristics, namely, the share of Scheduled Caste (SC) and Scheduled Tribe (ST) population and the share of literate population.[20] Panel B adds these controls. The estimate in column 1 remains statistically insignificant; in fact, its magnitude is close to zero. This null effect on employment is indicative of a reallocation across industries. The addition of controls attenuates the effects on manufacturing in column 2, but remains statistically significant at the 5% level. A potential explanation for the weak decline in construction (column 4) is that the contraction in manufacturing can reduce the demand for construction workers. Collectively, the findings in this table suggest that the declines in manufacturing (and construction) are offset by increase in services (and agriculture) in more affected districts.

Occupations. I use the human capital score to classify occupations into terciles: low-skill, mid-skill, and high-skill occupations. The goal of this exercise is to categorize occupations into low-skilled (manual) jobs, semi-skilled (or blue collar) jobs, and high-skilled (white collar) jobs.[21] Similar to Autor et al. (2013), I also partition my sample into mutually exclusive age groups: young workers (ages 16-34), mid-career workers (ages 35-49), and older workers (aged 50-64). Table 5 reports results from regressing (changes in) the shares of men in these various age groups and occupation terciles on the import exposure measure. I find a significant increase in the share of young workers in high-skill occupations in col-

[20] The labor market in districts with high share of literate population or high share of SC/ST population can be very different for reasons described in Section 1.

[21] I use the data to perform this classification instead of imposing ad-hoc educational cutoffs.

umn 1 of panel A. Although not significant at conventional levels, younger workers also seem to be less engaged in low-skill occupations.

Interaction between occupations and industries. In Table 6, I explore which industries the workers are engaged in. The estimate in column 3 of panel A suggests that younger workers are less likely to be in low-skill occupations in manufacturing. This is true for mid-career and older workers too, albeit at weaker levels of significance. This result is hardly surprising – China's comparative advantage lay in low-skill labor-intensive manufacturing, and so low-skill occupations in manufacturing shrink in more exposed districts. While low-skill manufacturing jobs contract, access to cheaper intermediate goods and inputs can increase mid-skill or high-skill manufacturing jobs through input-output linkages. There is some weak evidence that this may be true for older workers in mid-skill occupations in manufacturing (panel C, column 2) and younger workers in high-skill occupations in manufacturing (panel A, column 1). Forward and backward linkages can generate spillovers onto other non-manufacturing industries. Indeed, this is what I find – a significantly greater share of young men are engaged in high-skill occupations in services (panel A, column 4) whereas mid-career workers are engaged in mid-skill occupations in services (panel B, column 5).

4.2 Effects on intergenerational occupational mobility

I then turn to the question of intergenerational occupational mobility: are sons in occupations that are "better" than that of their father? The results from estimating equation 5 for the sample of father-son dyads are reported in columns 1–3 of Table 7. The outcome in column 1 is the change in the share of upward mobile sons among all father-son dyads in a district. The point estimate suggests that a 1 percentage point increase in the import exposure measure raises the share of upward mobile sons by 0.491 percentage points.[22] Similarly, column 2 reports the effect on the share of downward mobile sons. Any mobility (column 3) is defined as the absence of persistence; in other words, the son has an occupation that is different from that of his father. I find no evidence of downward mobility and weak evidence of a lack of persistence.

Upward mobility can stem from either sons moving up the occupational ladder or fathers moving down the occupational ladder. Facing negative employment outcomes from rising trade pressure, fathers could be moving into occupations with lower educational

[22] Mazumder and Acosta (2015) find that intergenerational mobility estimates are largest when sons are in their mid-career. Since the average son in my sample is about 23 years old and the average father is about 53 years old, I may be understating true upward mobility.

intensities. Unfortunately, I do not observe the occupational history of individuals in the NSSO, and so a direct answer to this question is difficult. In Table A2, I examine the employment industry of sons and fathers to provide some indirect suggestive evidence that the effect on upward mobility is mainly from sons moving into industries that are different from that of their father. None of the estimates are significant at conventional levels, but the point estimates are different in magnitude for fathers and sons. For example, although the coefficient on manufacturing (column 3) is negative for both sons (panel A) and fathers (panel B), it is higher for sons. I find that sons are more likely to be engaged in services (column 4). Collectively, the results in Table A2 seem to suggest that even though sons and fathers are facing the same import exposure (by virtue of residing in the same district), sons are relatively more mobile compared to fathers.

Falsification test. I also conduct a falsification test by regressing future changes in import exposure on changes in current outcomes. I utilize data from the 43rd round of the NSS (1987-88) and 55th round of the NSS (1999-00) for this exercise. Since this is a 12-year difference, the import exposure measure is also a 12-year change between 1999 and 2011.[23] The results are reported in columns 4-6 of Table 7.

Sensitivity to controls. I test the robustness of my finding by controlling for the baseline employment-weighted start-of-period tariffs described earlier. The estimate on upward mobility with this control is reported in column 1 of Table 8. In column 2, I further add baseline population shares and the start-of-period shares of district employment in manufacturing, services, and agriculture to account for changes in the labor market that are unrelated to trade exposure from China. The estimate remains statistically significant at the 5% level, but is slightly lower than the baseline estimate. For every estimate in this table, I also report Adão et al. (2019) standard errors for shift-share variables in square brackets. Allowing for correlations within the shares yields tighter confidence intervals.

Stricter definition of mobility. I also impose a more restrictive definition of mobility. For each survey round, I redefine mobility as a movement across terciles based on the classification into terciles described earlier. In other words, sons are upward mobile relative to fathers if their occupation is in a higher tercile than their father's. Evidently, this measure misses all within-tercile upward movements.

[23] Owing to lack of data, this specification cannot be estimated using stacked first differences, but rather as one first difference. The 43rd round of the NSS EUS is the only round before the 55th round whose public-use files come with district identifiers.

In Figure 2, I present a transition matrix heat map with weighted conditional probabilities. Each cell represents the probability of the son's occupation tercile conditional on the father's occupation tercile. For example, the probability of the son's occupation being in the first tercile given the father's occupation is also in the same tercile is 88.9% in 1999. The principal diagonals, measuring occupational persistence in terciles, typically have the highest probability in each row.[24] Mobility is measured by the off-diagonal elements; upward mobility, specifically, is given by the upper triangle elements. Between 1999 and 2009, the probability of a son born to a tercile 1 father moving to a higher tercile increased by 2.1 percentage points and the probability of a son born to a tercile 2 father moving to tercile 3 increased by 3.9 percentage points.

The results from redefining mobility as described above and re-estimating Equation 5 are presented in Table 9. For comparison, column 1 reports the baseline estimate with controls. The estimate in column 2 suggests that most of the observed effect comes from the son's occupation being in a higher tercile relative to their father's. Column 3-5 further decompose the effect in column 2. I find that almost two-thirds of the movement across terciles is a shift from low-skilled occupations (tercile 1) to mid-skilled occupations (tercile 2).

Human capital score of occupations using Population Census 2001. Instead of relying on the National Sample Survey to create the human capital score for each occupation, I use the 2001 Population Census of India for better representation, which reports coarser 2-digit occupational classifications. I compute the human capital score for each of 28 unique 2-digit occupations using the share of workers in four different education categories: illiterate (1), literate but below secondary (2), secondary but below graduate (3), and diploma/degree (4). This new score has some key differences. First, it keeps the human capital score for each occupation fixed over time. Second, it uses information from all workers rather than those surveyed by the NSSO and in the 25-64 age group.[25]

The results, reported in Table 10, support my main finding. Despite the loss of variation from using coarser occupation groups and coarser education categories, the estimate in column 2 is slightly higher than the baseline estimate.

[24]This does not seem to be the case for sons of tercile 3 fathers, but this is perhaps not surprising given that the average son is 23 years old. Early career occupations might not be representative of their modal or "permanent occupational status" (Mazumder and Acosta, 2015; Ahsan and Chatterjee, 2017).

[25]In future steps, I want to allow this human capital score for each occupation to vary across districts. National occupation scores can fail to capture inequalities that exist across space even within the same occupation (Saavedra and Twinam, 2020; Ward, 2023).

Sensitivity to weights. I test the sensitivity of my estimates to different weights in Table A3. Columns 1-3 report the results from estimating the main specification weighting each observation by district employment share in 1999 within national employment instead of district population share. The estimated coefficient on upward mobility is very similar to the baseline estimate.

Since the Indian economy undertook a massive liberalization episode starting in the early 1990s by lowering tariffs, it is possible that the labor shares in 1994 are not representative employment weights in Equation 2. Therefore, I recalculate my import exposure measure with employment shares from 1999. These weights also add a second source of variation of within district employment across manufacturing and non-manufacturing. I report the estimates from using this new import exposure measure in panel B of Table A3. Although the estimates are qualitatively similar, the magnitudes are considerably larger – a 1 percentage point increase in this new import exposure measure leads to a 3.61 percentage point increase in the share of upward mobile sons.

4.3 Heterogeneity

Social group. In Table 11, I explore heterogeneity by social groups. The Scheduled Castes and the Scheduled Tribes are considered disadvantaged groups due to centuries of social and economic discrimination which kept them economically backward and forced them to stay in low-skill occupations.

In panel A, I restrict my sample to father-son dyads that belong to the Scheduled Caste or Scheduled Tribe social groups. Surprisingly, I find positive and significant effects: among all SC/ST father-son dyads, the share of upward mobile sons is significantly higher in districts more exposed to imports. The estimate in column 2 is more than twice the baseline estimate (with all social groups). For Other Backward Classes and Others (Panel B), there seems to be no effect of import exposure on upward or downward mobility. However, this group is mobile, as captured by the estimate in columns 5 and 6. Sons seem to be moving both up and down the occupational ladder relative to fathers.[26] Collectively, these findings lend support to the idea of structural changes playing a role in breaking down caste-based barriers to socioeconomic mobility (Hnatkovska et al., 2013).

Sector. In Table 12, I explore heterogeneity by sector (rural vs. urban). To do so, I restrict the sample to father-son dyads residing in rural areas (panel A) and urban areas (panel B). I find stronger effects on upward mobility for sons residing in urban areas (columns

[26] Given that almost 80% of working-age manufacturing workers were from the OBC/Others social groups in 1999, it is not unlikely that they were relatively more hard-hit by imports from China.

1-2 of panel B). This result is hardly surprising and possibly stems from the availability of a more diverse set of industries and occupations in urban areas. Rural areas, on the other hand, are mostly agrarian. The coefficient on upward mobility is positive but insignificant for sons in rural areas. This raises the question: is upward mobility restricted to sons of urban non-agricultural fathers? Is it driven by the movement of sons of agricultural fathers out of agriculture? Table A4 explores this by decomposing the baseline estimate by the industry of employment of the father. The coefficient on agriculture and manufacturing are positive but insignificant, whereas services is weakly significant. I cannot rule out that the gains in mobility are shared by sons of fathers from different industries.

4.4 Potential Mechanisms

In this section, I explore potential mechanisms that can allow sons to move up the occupation ladder. One such mechanism is education. The changing nature of the labor market can raise the returns to skill or alter the opportunity cost of schooling – a decline in the opportunity cost of schooling can induce people to stay in school longer.

I test this channel of education playing a facilitating role in upward mobility. Table 13 decomposes the baseline estimate (reported in column 1) into three mutually exclusive groups of sons: those that have the same level of education as the father (column 2), those that are more educated than their father (column 3), and those that are less educated than their father (column 4). I find that almost 85% of the effect is from the group of sons that are more educated than their father. This underscores the importance of education in playing a key role in facilitating movements up the occupational ladder.

5 Conclusion

In this paper, I causally examine the effects of a rise in import exposure on the labor market in India in the 2000s. Exploiting variation in exposure to imports from China across Indian districts, I find evidence of a null effect on the employment-to-population ratio for working-age men. My results suggest reallocation across industries in more affected districts: declines in the manufacturing share of employment are offset by increases in services. This decline in manufacturing is primarily driven by a contraction in low-skill occupations in manufacturing across workers of all ages, but the increase in services stems from an increase in high-skill and mid-skill occupations for young and mid-career workers respectively.

I also provide evidence of upward mobility in sons relative to fathers in more exposed districts – sons are in occupations that are ranked higher in an educational intensity ranking of occupations. This effect is stronger for the socially disadvantaged Scheduled Castes and Scheduled Tribes and for sons residing in urban areas. I find that education plays a key role in facilitating upward occupational mobility.

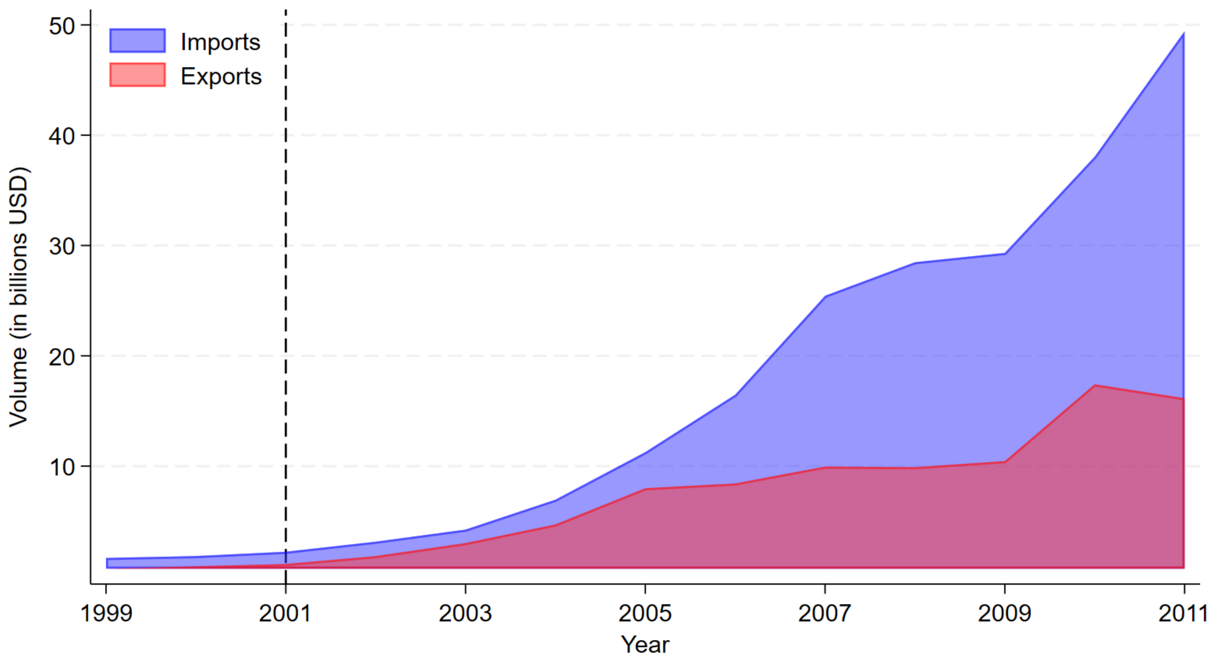

Figure 1: Import and export volume from China to India

Notes: This cumulative area graph shows the total import and export volume from China to India in 2010 US dollars. Data on imports sourced from UN Comtrade.

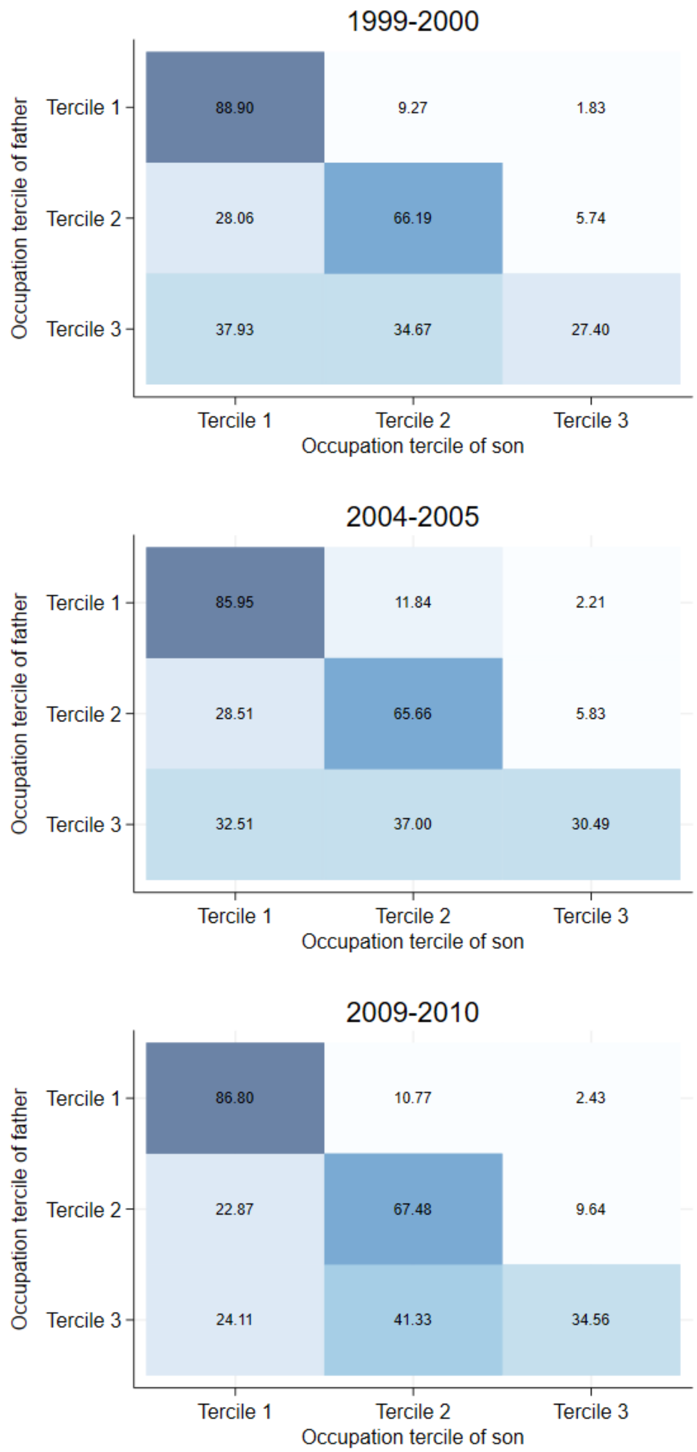

Figure 2: Transition Heat Maps

Notes: This figure shows the (weighted) conditional probabilities. Each cell represents the probability of the son's occupation tercile conditional on the father's occupation tercile. Data sourced from NSSO Employment and Unemployment Surveys (Rounds 55, 61, 66).

Table 1: Summary statistics of working sample

	NSS 55 (1999-00)	NSS 61 (2004-05)	NSS 66 (2009-10)
Working-age men (Ages 16-64)			
Employment-to-population ratio	0.850	0.854	0.832
Employment share among men (Ages 16-64)			
Agriculture	0.534	0.493	0.456
Manufacturing	0.114	0.122	0.114
Services	0.282	0.295	0.301
Construction	0.059	0.078	0.117
Mining & Quarrying	0.007	0.008	0.008
Industry of employment among young workers (Ages 16-34)			
Agriculture	0.526	0.464	0.429
Manufacturing	0.125	0.142	0.133
Services	0.271	0.294	0.294
Industry of employment among mid-career workers (Ages 35-49)			
Agriculture	0.508	0.486	0.445
Manufacturing	0.110	0.112	0.106
Services	0.311	0.312	0.320
Industry of employment among older workers (Ages 50-64)			
Agriculture	0.614	0.593	0.547
Manufacturing	0.089	0.086	0.081
Services	0.252	0.261	0.279

Notes: All values are weighted using survey weights. Data sourced from NSSO Employment and Unemployment Surveys (Rounds 55, 61, 66).

Table 2: Summary statistics of working sample for intergenerational mobility

	NSS 55 (1999-00)	NSS 61 (2004-05)	NSS 66 (2009-10)
Number of father-son dyads	29,299	31,367	21,771
Number of households	20,569	22,181	15,932
Age of son (in years)	23.23	23.44	24.05
Age of father (in years)	53.37	53.09	53.32
Share of SC/ST	0.288	0.281	0.301
Share of non-SC/ST	0.712	0.718	0.699
Share rural	0.809	0.801	0.774
Education of son	3.37	3.61	4.03
Education of father	2.22	2.38	2.57
Share of upward mobile sons	0.189	0.221	0.208
Share of downward mobile sons	0.174	0.172	0.152
Share of sons in same occupation as father	0.637	0.607	0.639
Percent engaged in agriculture			
Sons	0.597	0.527	0.476
Father	0.668	0.634	0.572
Percent engaged in manufacturing			
Son	0.109	0.125	0.120
Father	0.081	0.092	0.088
Percent engaged in services			
Son	0.229	0.260	0.263
Father	0.202	0.213	0.233

Notes: The sample is restricted to sons in the age group 16-35. All values except the number of dyads and the number of households are weighted using survey weights. Education is categorized into 7 broad categories: illiterate (1), literate but below primary (2), primary (3), middle (4), secondary (5), higher secondary (6), and post-higher secondary (7). Data sourced from NSSO Employment and Unemployment Surveys (Rounds 55, 61, 66).

Table 3: Summary statistics of import exposure and intergenerational outcomes

Variable	Mean	SD	25th percentile	75th percentile
Δ import exposure measure				
Δ 1999-2004	0.0594	0.0462	0.0302	0.0727
Δ 2004-2009	0.1482	0.1106	0.0745	0.1979
Δ share of upward mobile sons				
Δ 1999-2004	0.0316	0.1170	-0.0486	0.1088
Δ 2004-2009	-0.0118	0.1446	-0.1070	0.0825
Δ share of downward mobile sons				
Δ 1999-2004	-0.0043	0.1036	-0.0694	0.0569
Δ 2004-2009	-0.0200	0.1243	-0.0991	0.0601

Notes: The sample is restricted to sons in the age group 16-35. Values are weighted using 1999 district population share in national population. Data sourced from NSSO Employment and Unemployment Surveys (Rounds 55, 61, 66) and UN Comtrade.

Table 4: Effect of Chinese import exposure on industry of employment of working-age men

	(1)	(2)	(3)	(4)	(5)	(6)
	Employment	Manufacturing	Agriculture	Construction	Mining	Services
Panel A: No controls						
Δ Import Exposure	0.059	-0.129**	0.162*	-0.123**	-0.010	0.098
	(0.089)	(0.050)	(0.084)	(0.058)	(0.018)	(0.072)
KP F-stat	116.1	116.1	116.1	116.1	116.1	116.1
AR F-stat	0.440	3.391	3.112	3.714	0.322	1.442
Panel B: Controlling for start-of-period tariffs and baseline population shares						
Δ Import Exposure	-0.007	-0.105**	0.077	-0.096*	-0.008	0.129
	(0.088)	(0.047)	(0.087)	(0.050)	(0.022)	(0.080)
KP F-stat	86.84	86.84	86.84	86.84	86.84	86.84
AR F-stat	0.00673	2.874	0.848	3.641	0.124	1.855

Notes: Robust standard errors clustered on state are reported in parentheses. The sample is restricted to men in working-age population (ages 16-64) in column 1 and columns 2-6 restrict to employed men in that age-group. Imports from China to India are instrumented by imports from China to a set of Latin American countries following Chakraborty et al. (2024b). All specifications include a state FE and a time FE. Population controls in panel B include the share of Scheduled Caste and Scheduled Tribe population and the share of literate population. Observations are weighted using 1999 district population share in national population. $N = 826$ (413 districts $\times$ 2 time periods). KP F-stat is the Kleibergen-Paap first stage F-statistic and AR F-stat is the Anderson-Rubin weak-instrument robust F-statistic. Data sourced from NSSO Employment and Unemployment Surveys (Rounds 55, 61, 66) and UN Comtrade. *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Effect of Chinese import exposure on occupations of employed men

	(1)	(2)	(3)
	Occupation		
	High-skill	Mid-skill	Low-skill
Panel A: Young workers (Ages 16-34)			
Δ Import Exposure	0.272**	0.175	-0.351
	(0.131)	(0.181)	(0.239)
AR F-stat	3.391	0.906	2.176
Panel B: Mid-career workers (Ages 35-49)			
Δ Import Exposure	-0.079	0.288	-0.027
	(0.089)	(0.176)	(0.124)
AR F-stat	0.890	2.284	0.0511
Panel C: Older workers (Ages 50-64)			
Δ Import Exposure	-0.066	0.180	0.034
	(0.173)	(0.148)	(0.187)
AR F-stat	0.166	1.312	0.0353

Notes: Robust standard errors clustered on state are reported in parentheses. The sample is restricted to employed men. All specifications include a time FE, a state FE, start-of-period tariff, and population controls, namely the share of Scheduled Caste and Scheduled Tribe population and the share of literate population. Imports from China to India are instrumented by imports from China to a set of Latin American countries following Chakraborty et al. (2024b). Occupations are classified into high, mid, and low skill based on terciles of the occupational human capital score. Observations are weighted using 1999 district population share in national population. $N = 826$ (413 districts $\times$ 2 time periods). KP F-stat = 86.84. KP F-stat is the Kleibergen-Paap first stage F-statistic and AR F-stat is the Anderson-Rubin weak-instrument robust F-statistic. Data sourced from NSSO Employment and Unemployment Surveys (Rounds 55, 61, 66) and UN Comtrade. *** p<0.01, ** p<0.05, * p<0.1.

Table 6: Effect of Chinese import exposure on occupations within industries

	(1)	(2)	(3)	(4)	(5)	(6)
	Manufacturing			Services		
	High-skill	Mid-skill	Low-skill	High-skill	Mid-skill	Low-skill
Panel A: Young workers (Ages 16-34)						
Δ Import Exposure	0.061	0.089	-0.250**	0.205**	0.080	-0.120
	(0.041)	(0.063)	(0.119)	(0.093)	(0.139)	(0.093)
AR F-stat	1.748	2.156	3.206	3.879	0.335	1.631
Panel B: Mid-career workers (Ages 35-49)						
Δ Import Exposure	-0.002	0.079	-0.164*	-0.072	0.238**	-0.036
	(0.030)	(0.120)	(0.090)	(0.076)	(0.097)	(0.064)
AR F-stat	0.00289	0.459	2.329	1.070	3.762	0.309
Panel C: Older workers (Ages 50-64)						
Δ Import Exposure	-0.010	0.181*	-0.126*	0.012	0.078	0.052
	(0.038)	(0.100)	(0.064)	(0.125)	(0.084)	(0.093)
AR F-stat	0.0734	2.586	3.076	0.00937	0.855	0.327

Notes: Robust standard errors clustered on state are reported in parentheses. The sample is restricted to employed men. All specifications include a time FE, a state FE, start-of-period tariff, and population controls, namely the share of Scheduled Caste and Scheduled Tribe population and the share of literate population. Imports from China to India are instrumented by imports from China to a set of Latin American countries following Chakraborty et al. (2024b). Observations are weighted using 1999 district population share in national population. $N = 826$ (413 districts $\times$ 2 time periods). KP F-stat = 86.86. KP F-stat is the Kleibergen-Paap first stage F-statistic and AR F-stat is the Anderson-Rubin weak-instrument robust F-statistic. Data sourced from NSSO Employment and Unemployment Surveys (Rounds 55, 61, 66) and UN Comtrade. *** p<0.01, ** p<0.05, * p<0.1.

Table 7: Effect of Chinese import exposure on intergenerational occupational mobility

	(1)	(2)	(3)	(4)	(5)	(6)
	Upward	Downward	Any	Upward	Downward	Any
Δ Import Exposure	0.491**	0.033	0.524*	-0.003	-0.079	-0.083
	(0.233)	(0.173)	(0.263)	(0.119)	(0.075)	(0.139)
Observations	822	822	822	375	375	375
Time FE	✓	✓	✓			
State FE	✓	✓	✓	✓	✓	✓
KP F-stat	116.1	116.1	116.1	792.4	792.4	792.4
AR F-stat	3.784	0.0370	3.070	0.000765	0.986	0.341

Notes: Robust standard errors clustered on state are reported in parentheses. The sample is restricted to sons in the age group 16-35. Imports from China to India are instrumented by imports from China to a set of Latin American countries following Chakraborty et al. (2024b). Columns 1–3 report estimates from equation 5 whereas columns 4–6 report estimates from a falsification test as described in the text. The human capital score for the falsification test is recomputed with six education categories and observations are weighted by 1987 district population share in national population instead of 1999 district population share. Several states in India undertook district reorganization in the early 1990s. Split districts are merged back to the parent districts to ensure consistent geographic units but this lowers the number of observations (districts) in columns 4-6. KP F-stat is the Kleibergen-Paap first stage F-statistic and AR F-stat is the Anderson-Rubin weak-instrument robust F-statistic. Data sourced from NSSO Employment and Unemployment Surveys (Rounds 43, 55, 61, 66) and UN Comtrade. *** p<0.01, ** p<0.05, * p<0.1.

Table 8: Effect of Chinese import exposure on intergenerational occupational mobility (Robustness)

	(1)	(2)	(3)	(4)	(5)	(6)
	Upward		Downward		Any	
Δ Import Exposure	0.535**	0.476**	0.041	0.123	0.575**	0.599**
	(0.236)	(0.206)	(0.183)	(0.179)	(0.274)	(0.256)
	[0.129]	[0.168]	[0.104]	[0.125]	[0.136]	[0.192]
Observations	822	822	822	822	822	822
Time FE	✓	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓	✓
Start-of-period tariff	✓	✓	✓	✓	✓	✓
Population controls		✓		✓		✓
Start-of-period employment shares		✓		✓		✓
KP F-stat	113.3	76.91	113.3	76.91	113.3	76.91
AR F-stat	4.093	4.679	0.0502	0.456	3.324	4.175

Notes: Robust standard errors clustered on state are reported in parentheses. Shift-share standard errors following Adão et al. (2019) are reported in square brackets. The sample is restricted to sons in the age group 16-35. Imports from China to India are instrumented by imports from China to a set of Latin American countries following Chakraborty et al. (2024b). Population controls include the share of Scheduled Caste and Scheduled Tribe population and the share of literate population. Start-of-period employment shares include the share of employment in manufacturing, services, and agriculture. Observations are weighted using 1999 district population share in national population. KP F-stat is the Kleibergen-Paap first stage F-statistic and AR F-stat is the Anderson-Rubin weak-instrument robust F-statistic. Data sourced from NSSO Employment and Unemployment Surveys (Rounds 55, 61, 66) and UN Comtrade. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 9: Effect of Chinese import exposure on intergenerational occupational mobility (More restrictive definition)

	(1)	(2)	(3)	(4)	(5)
	Upward	Higher tercile	Tercile 1 $\rightarrow$ 2	Tercile 2 $\rightarrow$ 3	Tercile 1 $\rightarrow$ 3
Δ Import Exposure	0.476**	0.440***	0.280**	0.172**	-0.011
	(0.206)	(0.148)	(0.107)	(0.083)	(0.043)
Observations	822	822	822	822	822
Time FE	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓
Start-of-period tariff	✓	✓	✓	✓	✓
Population controls	✓	✓	✓	✓	✓
Start-of-period employment shares	✓	✓	✓	✓	✓
KP F-stat	76.91	76.91	76.91	76.91	76.91
AR F-stat	4.679	6.329	4.415	3.882	0.0686

Notes: Robust standard errors clustered on state are reported in parentheses. The sample is restricted to sons in the age group 16-35. Imports from China to India are instrumented by imports from China to a set of Latin American countries following Chakraborty et al. (2024b). Population controls include the share of Scheduled Caste and Scheduled Tribe population and the share of literate population. Start-of-period employment shares include the share of employment in manufacturing, services, and agriculture. Observations are weighted using 1999 district population share in national population. KP F-stat is the Kleibergen-Paap first stage F-statistic and AR F-stat is the Anderson-Rubin weak-instrument robust F-statistic. Data sourced from NSSO Employment and Unemployment Surveys (Rounds 55, 61, 66) and UN Comtrade. *** p<0.01, ** p<0.05, * p<0.1.

Table 10: Effect of Chinese import exposure on intergenerational occupational mobility (Coarser definition of occupations)

	(1)	(2)	(3)	(4)	(5)	(6)
	Upward		Downward		Any	
Δ Import Exposure	0.592**	0.525**	-0.051	0.057	0.541**	0.583**
	(0.267)	(0.219)	(0.161)	(0.147)	(0.262)	(0.253)
Observations	822	822	822	822	822	822
Time FE	✓	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓	✓
Start-of-period tariff		✓		✓		✓
Population controls		✓		✓		✓
Start-of-period employment shares		✓		✓		✓
KP F-stat	116.1	76.91	116.1	76.91	116.1	76.91
AR F-stat	3.824	3.677	0.107	0.153	3.067	4.099

Notes: Robust standard errors clustered on state are reported in parentheses. Imports from China to India are instrumented by imports from China to a set of Latin American countries following Chakraborty et al. (2024b). Population controls include the share of Scheduled Caste and Scheduled Tribe population and the share of literate population. Start-of-period employment shares include the share of employment in manufacturing, services, and agriculture. Observations are weighted using 1999 district population share in national population. The occupation score is calculated for coarser 2-digit occupations with 4 categories of educated workers from the 2001 Population Census of India. KP F-stat is the Kleibergen-Paap first stage F-statistic and AR F-stat is the Anderson-Rubin weak-instrument robust F-statistic. Data sourced from NSSO Employment and Unemployment Surveys (Rounds 55, 61, 66) and UN Comtrade. *** p<0.01, ** p<0.05, * p<0.1.

Table 11: Effect of Chinese import exposure on intergenerational occupational mobility (Heterogeneity by social group)

	(1)	(2)	(3)	(4)	(5)	(6)
	SC/ST			OBC/Others		
	Upward	Downward	Any	Upward	Downward	Any
Δ Import Exposure	0.994***	0.099	1.093*	0.428	0.204	0.632**
	(0.326)	(0.382)	(0.611)	(0.258)	(0.198)	(0.264)
Observations	774	774	774	788	788	788
KP F-stat	126.4	126.4	126.4	57.95	57.95	57.95
AR F-stat	2.866	0.0670	1.725	3.192	0.976	5.384

Notes: Robust standard errors clustered on state are reported in parentheses. The sample is restricted to sons in the age group 16-35. Imports from China to India are instrumented by imports from China to a set of Latin American countries following Chakraborty et al. (2024b). Population controls include the share of Scheduled Caste and Scheduled Tribe population and the share of literate population. Start-of-period employment shares include the share of employment in manufacturing, services, and agriculture. The number of observations are lower because some districts did not survey individuals that satisfied sample restrictions. Observations in columns 1–3 are weighted using 1999 district SC/ST share in national SC/ST population, whereas observations in columns 4–6 are weighted using 1999 district non-SC/ST share in national non-SC/ST population. KP F-stat is the Kleibergen-Paap first stage F-statistic and AR F-stat is the Anderson-Rubin weak-instrument robust F-statistic. Data sourced from NSSO Employment and Unemployment Surveys (Rounds 55, 61, 66) and UN Comtrade. *** p<0.01, ** p<0.05, * p<0.1.

Table 12: Effect of Chinese import exposure on intergenerational occupational mobility (Heterogeneity by sector)

	(1)	(2)	(3)	(4)	(5)	(6)
	Rural			Urban		
	Upward	Downward	Any	Upward	Downward	Any
Δ Import Exposure	0.121	0.149	0.269	0.681**	0.104	0.786**
	(0.257)	(0.168)	(0.348)	(0.330)	(0.293)	(0.360)
Observations	804	804	804	720	720	720
KP F-stat	56.36	56.36	56.36	111.8	111.8	111.8
AR F-stat	0.232	0.837	0.635	2.549	0.128	2.620

Notes: Robust standard errors clustered on state are reported in parentheses. The sample is restricted to sons in the age group 16-35. Imports from China to India are instrumented by imports from China to a set of Latin American countries following Chakraborty et al. (2024b). Population controls include the share of Scheduled Caste and Scheduled Tribe population and the share of literate population. The number of observations are lower because some districts did not survey individuals that satisfied sample restrictions. Observations in columns 1–3 are weighted using 1999 district rural population share in national rural population, whereas observations in columns 4–6 are weighted using 1999 district urban population share in national urban population. KP F-stat is the Kleibergen-Paap first stage F-statistic and AR F-stat is the Anderson-Rubin weak-instrument robust F-statistic. Data sourced from NSSO Employment and Unemployment Surveys (Rounds 55, 61, 66) and UN Comtrade. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 13: Potential Mechanism – Education (Decomposition)

	(1)	(2)	(3)	(4)
	Upward	Same education	Son more educated	Father more educated
Δ Import Exposure	0.476**	0.066	0.403	0.008
	(0.206)	(0.110)	(0.285)	(0.057)
Observations	822	822	822	822
Time FE	✓	✓	✓	✓
State FE	✓	✓	✓	✓
Start-of-period tariff	✓	✓	✓	✓
Population controls	✓	✓	✓	✓
Start-of-period employment shares	✓	✓	✓	✓
KP F-stat	76.91	76.91	76.91	76.91

Notes: Robust standard errors clustered on state are reported in parentheses. The sample is restricted to sons in the age group 16-35. Imports from China to India are instrumented by imports from China to a set of Latin American countries following Chakraborty et al. (2024b). Observations are weighted using 1999 district population share in national population. KP F-stat is the Kleibergen-Paap first stage F-statistic and AR F-stat is the Anderson-Rubin weak-instrument robust F-statistic. Data sourced from NSSO Employment and Unemployment Surveys (Rounds 55, 61, 66) and UN Comtrade. *** p<0.01, ** p<0.05, * p<0.1.

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Appendix

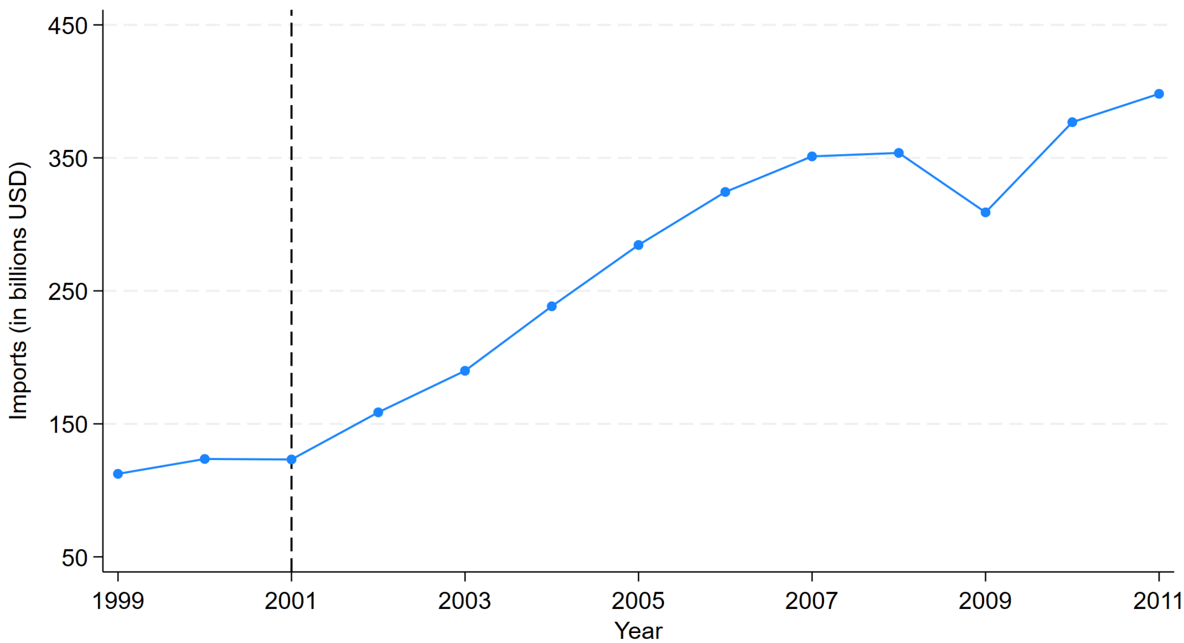

Figure A1: Import volume from China to US

Notes: This figure reports the total import volume from China to the United States in 2010 US dollars. Data on imports sourced from UN Comtrade.

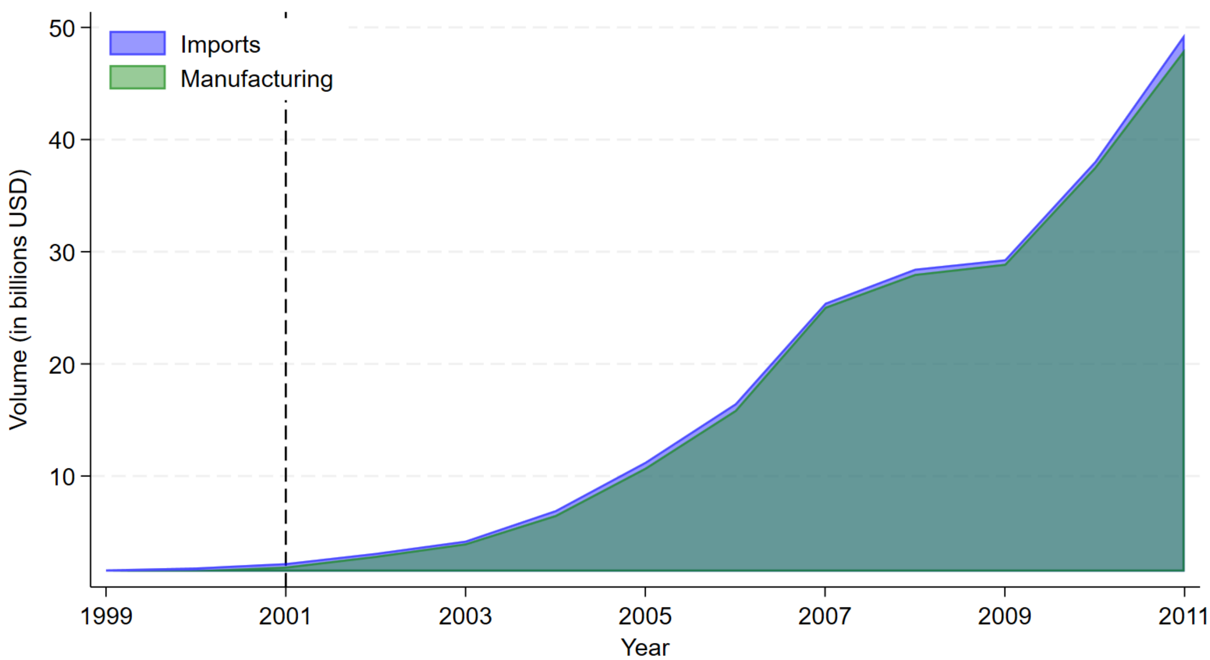

Figure A2: Manufacturing import volume from China to India

Notes: This cumulative area graph shows the total import volume from China to India in 2010 US dollars. Data on imports sourced from UN Comtrade.

Table A1: Effect of Chinese import exposure on share of households with multiple adult generations coresiding

	(1)	(2)	(3)
Δ Import Exposure	0.002	-0.010	0.112
	(0.159)	(0.160)	(0.149)
Observations	822	822	822
Time FE	✓	✓	✓
State FE	✓	✓	✓
Start-of-period tariff		✓	✓
Population controls			✓
Start-of-period employment shares			✓
KP F-stat	139.1	134.4	90
AR F-stat	9.33e-05	0.00373	0.543

Notes: Robust standard errors clustered on state are reported in parentheses. Imports from China to India are instrumented by imports from China to a set of Latin American countries following Chakraborty et al. (2024b). Population controls include the share of Scheduled Caste and Scheduled Tribe population and the share of literate population. Start-of-period employment shares include the share of employment in manufacturing, services, and agriculture. An adult is defined as an individual aged 16 or above. Observations are weighted using 1999 number of households in the district. KP F-stat is the Kleibergen-Paap first stage F-statistic and AR F-stat is the Anderson-Rubin weak-instrument robust F-statistic. Data sourced from NSSO Employment and Unemployment Surveys (Rounds 55, 61, 66) and UN Comtrade. *** p<0.01, ** p<0.05, * p<0.1.

Table A2: Effect of Chinese import exposure on employment industry of sons and fathers

	(1)	(2)	(3)	(4)
	Agriculture	Mining	Manufacturing	Services
Panel A: Sons				
Δ Import Exposure	0.097	0.019	-0.209	0.353
	(0.145)	(0.030)	(0.172)	(0.237)
Observations	822	822	822	822
Time FE	✓	✓	✓	✓
State FE	✓	✓	✓	✓
Start-of-period tariff	✓	✓	✓	✓
Population controls	✓	✓	✓	✓
KP F-stat	86.82	86.82	86.82	86.82
AR F-stat	0.453	0.422	1.289	1.947
Panel B: Fathers				
Δ Import Exposure	0.178	0.046	-0.085	-0.030
	(0.169)	(0.036)	(0.142)	(0.280)
Observations	822	822	822	822
Time FE	✓	✓	✓	✓
State FE	✓	✓	✓	✓
Start-of-period tariff	✓	✓	✓	✓
Population controls	✓	✓	✓	✓
KP F-stat	86.82	86.82	86.82	86.82
AR F-stat	1.045	1.829	0.334	0.0121

Notes: Robust standard errors clustered on state are reported in parentheses. The sample is restricted to sons in the age group 16-35. Imports from China to India are instrumented by imports from China to a set of Latin American countries following Chakraborty et al. (2024b). Population controls include the share of Scheduled Caste and Scheduled Tribe population and the share of literate population. Agriculture includes adjacent sectors like hunting, forestry, and fishing. Mining includes quarrying. Observations are weighted using 1999 district population share in national population. KP F-stat is the Kleibergen-Paap first stage F-statistic and AR F-stat is the Anderson-Rubin weak-instrument robust F-statistic. Data sourced from NSSO Employment and Unemployment Surveys (Rounds 55, 61, 66) and UN Comtrade. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A3: Effect of Chinese import exposure on intergenerational occupational mobility (Sensitivity to weighting)

	(1)	(2)	(3)	(4)	(5)	(6)
	Alternate observation weights			Alternate employment weights		
	Upward	Downward	Any	Upward	Downward	Any
Δ Import Exposure	0.505**	0.128	0.633**	3.613**	1.132	4.744***
	(0.219)	(0.166)	(0.260)	(1.679)	(0.914)	(1.361)
Observations	822	822	822	822	822	822
KP F-stat	92.37	92.37	92.37	606.5	606.5	606.5
AR F-stat	4.360	0.572	4.353	3.082	1.181	4.517

Notes: Robust standard errors clustered on state are reported in parentheses. The sample is restricted to sons in the age group 16-35. Imports from China to India are instrumented by imports from China to a set of Latin American countries following Chakraborty et al. (2024b). Population controls include the share of Scheduled Caste and Scheduled Tribe population and the share of literate population. Start-of-period employment shares include the share of employment in manufacturing, services, and agriculture. Observations are weighted using 1999 district employment share in national employment. The import exposure measure in panel B uses 1999 district employment shares. KP F-stat is the Kleibergen-Paap first stage F-statistic and AR F-stat is the Anderson-Rubin weak-instrument robust F-statistic. Data sourced from NSSO Employment and Unemployment Surveys (Rounds 55, 61, 66) and UN Comtrade. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A4: Effect of Chinese import exposure on intergenerational occupational mobility (Decomposition by father's industry)

	(1)	(2)	(3)	(4)	(5)
	Upward	Agriculture	Mining	Manufacturing	Services
Δ Import Exposure	0.491**	0.116	-0.001	0.041	0.265*
	(0.233)	(0.145)	(0.005)	(0.096)	(0.141)
Observations	822	822	822	822	822
Time FE	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓
KP F-stat	116.1	116.1	116.1	116.1	116.1
AR F-stat	3.784	0.639	0.0293	0.197	2.858

Notes: Robust standard errors clustered on state are reported in parentheses. The sample is restricted to sons in the age group 16-35. Imports from China to India are instrumented by imports from China to a set of Latin American countries following Chakraborty et al. (2024b). Observations are weighted using 1999 district population share in national population. KP F-stat is the Kleibergen-Paap first stage F-statistic and AR F-stat is the Anderson-Rubin weak-instrument robust F-statistic. Data sourced from NSSO Employment and Unemployment Surveys (Rounds 55, 61, 66) and UN Comtrade. *** p<0.01, ** p<0.05, * p<0.1.