



Import shock and local labour market outcomes: A Sino-Indian case study

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Abstract

Focusing on Sino-Indian trade, this paper uses detailed district-level data, exploits India's drastic increase in imports from China since 2001, and uses the instrumental variables approach to examine the impact of trade shock on the local labour market outcomes. Through a matching procedure, the geographical coverage of the paper is significantly improved compared with prior studies. The range of labour market outcome variables examined is also much broader, including wage, residual wage fluctuation, employment, unemployment and underemployment as shares of the working-age population. The paper finds that the import competition from China had a negative impact on the districts' average wages but a positive impact on districts' shares of employment. Moreover, the paper allows heterogeneous effects across consumption, age, gender, occupation and industrial groups. The results confirm that the effect of import shock is not uniformly distributed within the districts. Rather, it varies with respect to specific socio-economic characteristics. The wage effect, for example, is positive for those from the lower consumption basket.

Keywords International trade · Wages · Income inequality · Import shock · Underemployment

JEL Classification F14 · F16 · J16

1 Introduction

The role of international trade is becoming more multifaceted, with many trade policies being designed with developmental purposes in mind, such as boosting labour employment and income. To ensure the efficacy of such policies, it is important to understand if and how international trade can significantly affect labour market outcomes. From the theoretical perspective, the Ricardian model points to Pareto efficiency, while the

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Heckscher–Ohlin model suggests that trade can have a sustained negative impact on certain groups. The argument in the latter is essentially that the abundance of labour available at low cost from developing countries could potentially result in factor reallocation, thus negatively affecting employment and wage of the respective industries in a developed economy and aggravating the level of inequality (Lawrence 2008). Empirically, the evidence of international trade’s labour market impacts has also been mixed. Using the sudden rise in Chinese exports in the early 2000s, Autor et al. (2013, 2016) find that rising import competition and the supply shock it constituted had a detrimental impact on employment in the USA, whereas Choi and Mingzhi (2020) identified 0.52 million new job creations as a result of the import shock in South Korea. Moreover, most models and empirical research focus on the traditional setting of a stylised North–South trade. As the economies develop and integrate, South–South trade is becoming increasingly important. Unlike the traditional North–South assumptions built on clear differences in comparative advantage in production efficiency or endowment, technological and factor endowment differences between South–South trading partners can be ambiguous. It is challenging enough to examine such cases using classical theories, and the limited availability of detailed firm-level data further compounds the problem. Hence, South–South relationships are relatively under-studied. Therefore, it is reasonable to question if South–South trade would result in a “race to the bottom” (Chan 2003) and whether it has any effect on labour market outcomes. As these effects can be highly important for economic development, it is then of interest to adopt an empirical approach and investigate the impact of import competition in a South–South setting.

When looking at large and fast-growing developing economies, China and India share several similarities. Beyond being geographical neighbours, both China and India have rich endowments of labour, and they both have undergone a process of liberalisation post-independence, leading to the opening of markets. Based on classical trade theories, the similarities shared imply fewer incentives to trade. And yet, trade liberalisation still brought closer engagements between China and India. While India’s imports from China were evaluated at 556 million USD in 1999 (Harvard Growth Lab n.d.), by 2008, China, with imports valued at \$ 31,586 million USD (WITS n.d.[b]), had become India’s largest trading partner, making up 10% of Indian trade. The dramatic growth in the Sino-Indian trade relationship thus constitutes a nation-level shock. This created a quasi-experiment setting, making it an interesting South–South case to investigate the labour market impacts of the import surge following China’s accession into the World Trade Organization (WTO) in 2001.

With over 500 districts,¹ India has both geographical differences between regions and industry clusters. This allows the formation of a large number of local labour markets and significant variations in terms of industrial activities and labour compositions. Following the significant external event—China’s accession into the WTO, the high number of districts allowed a quasi-random allocation of shocks. The four variables used to represent different aspects of change in the Indian local labour markets include

¹ The number of districts changes depending on the year due to the splits and merges. For the period of interest, the starting number of districts in 1999 was 511.

district-level average log wage, residual wage variance, and employment and under-employment as shares of the working-age population. To study such relationships, this paper uses detailed trade and Indian labour data from 1999–2012 and focuses on the Sino-Indian trade dynamics. Using the national-level shock to India following China's accession to the WTO, it investigates the impacts of the drastic increase in import exposure on the local labour markets.

To assess the effects of this import shock, the ordinary least squares (OLS) models are first used to look at the relationship between the import per worker index and the districts' labour market outcomes. To account for districts' differentiated and varying characteristics, a series of demographic and socio-economic control variables are included, namely the district's labour market activeness,² district's shares of manufacturing workers, female, youth, rural, educated, Hindu population and share of population defined as from "backward" social groups.³ However, the endogeneity problem stemming from confounding variables is suspected for the OLS estimations. The instrumental variables estimation (IV) is therefore adopted to ensure the exogeneity of the exposure to shocks and to identify the impact of the import shock. In this analysis, the instrument used is the sum of trade values (imports from China) from countries similar to India in terms of stage of development, including Bangladesh, Indonesia, South Korea, Malaysia, Morocco, Pakistan, the Philippines and Zambia. District characteristics are also controlled for through a series of covariates included in the regression model; this further accounts for the potential unobserved heterogeneity that could affect the estimation. In addition to purging out the correlation in the error term, further analyses are also developed from the IV models by allowing heterogeneous effects across socio-economic groups to provide a more comprehensive picture of the import trade impact. While the main specifications of the paper do not make the more nuanced assumption that the industry shares are exogenous, the Bartik shift-share instrument approach with Rotemberg weights (Goldsmith-Pinkham et al. 2020) applied was also used for the analysis. The results, albeit more muted, still correspond to the main findings.

By focusing on South–South trade, this paper contributes to the literature in this under-studied but growing area of international trade and development. It uses local labour market data on the district level and detailed individual-level socio-economic information⁴ to provide a micro-foundation in the examination of trade and competition's labour market impacts. Compared with existing studies, the novelty of the paper concentrates on the significant improvement in data coverage, the inclusion of multiple labour market variables and a wider exercise of potential heterogeneous impact across different socio-economic groups. Firstly, previous studies such as Saha et al. (2021) omitted labour data from many districts due to changes in boundaries. However, as it is possible that the districts which underwent boundary changes share certain socio-economic similarities, it is prudent to include them where possible in the analysis to avoid selection biases. By conducting a matching process with the geographical

² This is defined as districts' shares of full-time workers.

³ This is defined as people from the scheduled tribe, scheduled caste and other backward class (NSSO n.d.).

⁴ Such as age, gender, level of education, religion, social group, wage, employment, industrial class of activity and so on. Detailed information is available in data section and in appendix.

records of the districts, this study increases the data coverage from 366 districts (Saha et al. 2021) to 473. The significantly improved coverage is expected to provide a more complete picture of the Indian district labour market dynamics. Secondly, as the period of interest has a span of twelve years, this investigation also provides a long-term perspective in the investigation. Going further than the existing literature, variables covered in the analysis include wage, residual wage variance, employment share and the under-explored underemployment share, which provides more insights into employment efficiency from the local labour markets. Last but not least, as it is possible that the effect of the import shock could vary depending on individuals' socio-economic characteristics, further analyses by socio-economic groups (including groups divided by level of consumption, age, gender, occupation and industry) also help to fill the gaps in the literature by providing more dimensions in the analysis of the labour market outcomes, giving a more holistic picture of the changing dynamics.

The rest of the paper is divided into six sections. To develop an understanding of the general context, Sect. 2 reviews the existing literature on the relevant international trade models for building a theoretical foundation for the analysis. It also acknowledges the difficulties in applying these theories in some settings of international trade activities today, such as South–South trade. Moving to a different approach, this section then briefly summarises some empirical examinations of the effects of import competition. Section 3 reviews the historical background of India's modern economic liberalisation and its labour market characteristics. This is important in explaining districts' heterogeneous reactions and potentially differentiated levels of resilience against economic shocks. Explanations of the methodology and data used for this paper's investigation are provided in Sect. 4. Section 5 covers the key descriptive statistics and discusses the findings of the investigation. Further discussions on the limitations of this investigation and the topic are covered in Sect. 6, and then, Sect. 7 concludes the paper.

2 Literature review

Trade theorists have developed different arguments and approaches for predicting the directions and compositions of trade once countries open their markets, as well as the potential impact on the labour markets of the trading parties. In order to build a theoretical foundation, this section delivers an overview and a discussion in the context of India's local labour markets according to these classic theories. It also reviews existing studies that use classic trade theories as foundations to examine the impacts of import shocks and their re-distributive powers.

2.1 International trade theories

Classic trade theories largely focus on comparative advantage in motivating trade. To highlight the distinctions in comparative advantages, the modelling of these theories is mostly on North–South trade. The assumption is that the developed countries (North) have better access to capital, whereas developing countries (South), such as India, access cheap and abundant labour more easily. These differences can then result in

different production possibility frontiers, comparative advantages in different sectors, different production factor allocations and price ratios in the state of autarky, and thus also different directions and magnitude of change after the economy opens to international trade.

The Ricardian model, for example, centres on comparative advantage based on relative production cost (Dornbusch et al. 1977), where if one country can produce a good at a lower opportunity cost than its counterpart, it has the comparative advantage in the production of said good and would export it in the setting of free trade. As India has a large labour market and also had noticeable advancement in the sector of pharmaceuticals and information technology (IT), it is likely that it is more mature in the technology of labour-intensive goods, such as minerals, textiles, stones, agriculture and also in chemicals⁵ and IT-related goods. According to the Ricardian model, opening up to trade would then cause specialisation, resulting in differentiated effects on the labours depending on the industry. Matching with empirical observations, the key sectors of exports are largely as expected.

Regarding production factors, the Heckscher–Ohlin model emphasises the comparative advantage in factor endowment (Leamer et al. 1995). The model assumes away differences in technology, and the prediction is that a country exports goods that make extensive use of its comparatively abundant factor and imports goods that do not. India is therefore still more likely to export labour-intensive goods, such as manufacturing, raw material, textiles and agriculture. On factor prices, if in the state of autarky, both goods were produced by both countries, the liberalisation would lead to factor price equalisation. Within an economy, when the relative price of a good rises, the real return to the factor that is used more intensively in its production also rises, such as labour in the case of India. The real return to the other factor, however, is predicted to fall. While this model also explains India's high exports in the aforementioned industries, it still faces limitations in real-world applications. Immigration, for example, can shift factor allocation. The model also assumes away any labour market discrimination, which is very much present, particularly in developing economies (Albuero and Abella 2002; Esteve-Volart 2004; Birdsall and Sabot 1991).

Not only does reality have significant divergence from models' simplified settings, for China and India at the time, both countries were considered developing countries well-endowed in labour and were in the process of modernisation and industrialisation. As argued, it is also possible that, despite the demand for cheaper products, interest to keep the comparative advantage could potentially divert the labour market impacts from the theory predictions, resulting in a “race to the bottom” (Chan 2003). As the comparative advantages are ambiguous, it is challenging to rely solely on a theoretical approach to assess the impact of the China shock on India. Newer trade theories such as the Krugman (1979) model and the Melitz (2003) model step beyond the concept of comparative advantage, and of using the nation as the unit of analysis. However, it is difficult to procure detailed firm-level data and to identify the exact macro-level labour market dynamics in the context of developing countries. Due to these limitations, this

⁵ The general categorisation is according to that in the Atlas of economic complexity from the Harvard Growth Lab (n.d.).

paper draws trade and census data to empirically assess the impact of the import shock on various outcomes.

2.2 Effect of import competition

The magnitude of China's accession to the WTO provides a quasi-experiment setting. Arguably, the higher availability of cheap labour may crowd out labour from partner countries based on cost-effectiveness, resulting in welfare and developmental implications. The classic Autor et al. (2013) paper investigates the effect of China's imports on the US's local labour market. To identify causality, they constructed an import competition exposure index for each commuting zone in the USA. To resolve the endogeneity problem, they instrument China's import to the USA with that to other key partner countries. Exploiting regional differences in exposure between 1990 and 2007, they find that industries with higher exposure to Chinese imports experienced reduced labour force participation, lower wages, a rise in unemployment and longer windows for unemployment. Similarly, Malgouyres (2017) considers the case of France, emphasising spillovers beyond key manufacturing industries. The paper finds that while the impact on the directly affected manufacturing industry seems to be uniformly distributed, the import shock seems to bring a polarising effect on the wages in the non-traded sectors.

However, some studies also find negligible or even positive effects from import competition. Choi and Mingzhi (2020) study trade between South Korea and China between 1993 and 2003. Focusing on industries and firms, the study finds that, in the manufacturing sector, the China shock has actually resulted in the creation of 0.52 million jobs. The argument for this positive impact is that rising Chinese demand for Korean intermediate inputs and capital goods spurred export-led industrial expansion in Korea. Conducting a cross-country level study, Stone and Cepeda (2011) use data between 1988 and 2007 across 93 countries. Following the Feenstra and Hanson (1999) approach,⁶ they find that while tariffs have a significant negative effect on wage, that of imports is positive and significant.

As there is a growing need to focus on South–South trade relationships, which are theoretically ambiguous, some papers take on the empirical approach to this issue. Owing to a growing import surge from China, Deb and Hauk (2020) try to identify changes in wage disparity between skilled and unskilled workers, as well as between male and female workers in India. Keeping with state-level analysis, the authors find import competition has a limited effect on the wage gap between skilled and unskilled labour, but there seems to be a more significant effect on the gender wage gap. More recent studies such as Saha et al. (2021) corroborate these findings using district-level data.

⁶ The method measures the direct impact of structural variables on prices while accounting for the changes in productivity. This is done by using zero-profit condition to derive price regression and the composition of the “mandated changes” in primary factor prices (Feenstra and Hanson 1999).

3 Historical background

3.1 The liberalisation of the Indian economy

Under the overarching anti-colonial theme, the modern economic development of India was initially characterised by protectionism. State-controlled industrialisation and import substitution were used as the key policies to develop and support its infant industries. To develop this form of self-reliance, the government also imposed high tariffs and non-tariff barriers. International trade was thus mostly left on the sideline (Topalova and Khandelwal 2011, p. 996).

It was not until the mid-80s did the sluggish growth motivated the government to slowly reform under the direction of “reforms by stealth” (Panagariya 2005, p. 7) by deregulating the industries. Catalysed by the collapsing Soviet Union and the balance-of-payments crisis of 1991, the Rao government consolidated the liberalisation effort and implemented friendlier policies towards the private sector and international trade (Ganguly and Mukherji 2011). Following the change in policies, the share of products facing quantitative restrictions nearly halved between 1987 and 1995 (Topalova and Khandelwal 2011, p. 996). As the liberalisation pressed on, the implications on India’s economic growth, developmental progress and sector development became visible.

The Indian economy began to experience faster growth post-liberalisation. While the GDP growth from 1970 to 1980 was positive, it remained slow and close to linear. Going from the 1980s to the 1990s, however, the growth rate went from 3.5% to around 5%, reflecting the acceleration during this period (Kotwal et al. 2011). Overall, the GDP increased from around 220 billion USD to 1.2 trillion USD⁷ for the period of 1970 to 2005 (The World Bank n.d.).

When looking at the drivers of growth, the Indian case shows a certain uniqueness in its development path. Unlike many developing countries that emphasised basic manufacturing to foster export-led economic growth, the Indian economic development following liberalisation was led by the growth of the technology sector (Sharma 2006). The information technology (IT) sector experienced tremendous growth in this period (Ganguly and Mukherji 2011). It has been argued that this is due to India continuing to develop its technology sector during the “closed up” period. Local educational institutions also focused on mechanical and civil engineering. Engineering students increased from nearly 0 per million in 1947 to 30 per million in 1980 (Roy 2012). The richer supply of talent coupled with rupee depreciation thus makes Indian products highly competitive in the international market. Both as a pushing factor and a result of liberalisation, the Indian IT industry became a part of the strategy to stimulate high growth via exports, and the sector’s resilience is also argued to withstand the tests of large-scale economic shocks (Barnes 2013).

While it is evident that the IT sector was a key driver in India’s economic development, it is not to say that the other sectors have stagnated. Following the liberalisation, industrial clusters and manufacturing districts began to form in India. Industries such as pharmaceuticals and automobile firms also began to experience growth. By the

⁷ The GDP values are in terms of constant 2010 USD value.

early 2010s, around 10% of the global pharmaceutical production was in India, contributing to roughly 2% of the national GDP, and providing employment to some 29 million people (Akhtar 2013). On automobiles, the city of Pune in Maharashtra state is home to a thriving automobile complex and has attracted major players in the industry like Bajaj Auto and Tata Motors. By the end of the 2000s, the city alone accounted for about 80% of the output of multi-utility vehicles (Roy 2009). Moreover, some labour-intensive traditional sectors and small firms also underwent a period of consolidation and reintegration, such as tea plantations, textile, jewellery and handicraft (Roy 2012). This is also reflected by the growth of India's exports to the world. Banik (2001) records that the years 1995–1996 saw a 63% rise in Indian export of electronic goods and 13.9% in machinery and instruments.

3.2 The labour market of India and the economic reforms

Around the 60s, the Indian labour market was marked by deep-rooted inequality issues, dominated by a form of “dualism” (Holmström and Mark 1984, p. 26), where a clear division can be seen between the labours working in the organised sectors and those in the unorganised sectors. While the organised sectors could grant labour permanent positions with legal recognition and union protection, workers in unorganised sectors were often hired on a temporary basis without protection. When the government started liberalising the economy, adopting the export-led growth approach in the late 80s, certain shifts in the economy became visible.

On the positive side, there were notable rises in employment in certain sectors. The ready-made garments sector in manufacturing, for example, experienced a significant increase in employment growth. The growth rate going from 1977(-78)-1983 to 1987(-88)-1993(-94)⁸ more than five-folded. Moreover, there also was an increase in self-employment in the 1990s (Mitra 2008). As the required skills differ from manufacturing and some traditional industries, the technology sector boom also led to a generally younger workforce and improved female employment (Roy 2012).

On the other hand, there were also some issues in the economy that contradicted standard theory predictions that surfaced following the liberalisation.

In opposition to the fast-paced growth of the economic outputs, there was actually a drop in employment elasticity and a general deterioration in employment. This is particularly apparent in the formal sector, where employment growth was found to be slower than that of the economy as a whole (Sharma 2006). Going from 1987 to 1994, the share of employment in the organised sector actually dropped from 8 to 7% (Chakravarty 1999, p. 165). In particular, the manufacturing industry had a major presence in the formal sector, but its employment elasticity was among the lowest (Chakravarty 1999, p. 165). Without a union, legal protection and compounded with work insecurity, the informalisation of the labour market could have negative implications on the labour market outcomes for Indian workers.

As the “jobless growth” (Mitra 2008) pressed on, inequality rose across India. Examining data from 1970 to 1992, Das and Barua (1996) use a Theil measure to

⁸ The organisation of the statistics in India is closer to that of the financial year rather than the calendar year.

evaluate inequality in the 23 states. With the exception of primary products, they find that regional inequality rose for nearly all sectors, especially agriculture at 4.26%. The observation of the rise in inequality during this period of growth and liberalisation in India, or at least the ambiguous relationship in certain cases, is not a unique finding. Aigbokhan (2000), Lundberg and Squire (2003), Shahbaz (2015), and Rodrik (2014) also suggest against a clear positive relationship between the two. Moreover, while outsourcing and imports tend to utilise developing countries' comparative advantage in unskilled-labour-intensive productions, the varieties themselves compared with other domestic counterparts are shown to be relatively skill-intensive. Therefore, the relevant trading activities could still increase the skilled labour wage premium for both developed and developing countries (Goldberg and Pavcnik 2007), which can worsen the polarisation.

Looking at the characteristics of the Indian labour market, there may be a few explanations for these observations.

Firstly, as an economy opens to trade, it is often expected that the product and price differentials would lead to changes in production patterns. An enabling factor is the mobilisation of factors of production. In comparison with countries where the labour market is more flexible in accommodating industry needs, the Indian labour market was relatively rigid with much less mobility (Sharma 2006). Topalova (2007) focuses on the liberalisation period and finds that, despite the high rate of migration of over 20%, most of the moves were women migrating after marriage. Standard trade models also predict that effective sectors could expect a factor relocation in their favour. In the case of India, however, this prediction was not significantly corroborated by the evidence.

Secondly, the existing social inequality may also play a role in this outcome. Focusing on the gender dimension, the total number of male workers increased by over 22 million from 2004 to 2010, whereas that of women actually shrunk by 21 million (Mazumdar et al. 2011). Despite the minimum wage policy, findings also suggest that firms hiring female workers might have a lower compliance rate towards the policy (Menon and Van Der Meulen Rodgers 2017). Besides gender, Madheswaran and Attewell (2007) show that individuals identified as of the scheduled castes and tribes receive 15% less pay than their higher caste counterparts. The discrimination was particularly severe in the private sector. Therefore, external shocks could disproportionately affect employment opportunities and wages for those who were identified as "lower castes". While these findings are observational, it is prudent to consider the implications of the heterogeneous effects the sudden change had on different socio-economic groups.

4 Method and data

As theories have a limited application in this setting and the evidence from other studies has been mixed, this paper then adopts an empirical approach to investigate the impact of the "China shock" on Indian local labour markets. The following section provides a summary of the key variables of interest, the methodology used and the data sources used in this paper.

4.1 Method

Recent studies (Borusyak et al. 2022; Goldsmith-Pinkham et al. 2020) have expanded the discussions on shift-share instruments, such as those applied in Autor et al. (2013). They furthered the discussion on the dichotomy of exogenous national shocks and exogenous local shares as the two frameworks under which the method's assumptions would hold. Rather than assuming the more nuanced exogeneity of industry shares as in Goldsmith-Pinkham et al. (2020), the fundamental identification strategy of this paper is based on China's accession into the WTO as a significant external event that led to the national-level quasi-randomly assigned import trade shock to the Indian districts' labour markets.⁹ In this case, there is no causal influence from the Indian local labour market on China's access to the WTO. The main regression models are instrumental variable regressions using local shares and statistics to capture local labour markets' exposure and their outcomes' variations following the shock. District-level socio-economic characteristics are also controlled for in the analysis to account for other potential sources of unobserved heterogeneity.

Four key labour market variables are the centre for this investigation, namely the change in district average log wage,¹⁰ average log residual wage variance,¹¹ the share of employed workers¹² against the working-age population and the share of underemployed workers against the working-age population.¹³ In terms of the organisation of the analysis, the OLS estimation is first used to showcase if there exists a general correlation between the trade exposure variable and the labour market outcomes. Then,

⁹ However, to supplement the investigation with stronger industry focus, the relevant Bartik shift-share instrument method is also used and the results with the respective Rotemberg weights applied are provided in appendix section of the paper. The results remain largely consistent with the findings of the study in terms of direction of impact, but the magnitude and level of significance are more muted.

¹⁰ The weekly average wage (nominal) is first divided by the usual number of days spent working in said activity, giving an average daily wage. This is to account for the variation in work intensity throughout the week. The average wage is then adjusted with the real broad effective exchange rate (FRED n.d.) for India to convert to the 2010 dollar value. As the values are low, for ease of analysis, this number is scaled by a thousand. The natural log values of the converted individual average daily wages are then used to derive the district-level average and the analysis.

¹¹ The residual wage is the wage left after controlling for the level of education successfully completed by the individual, work status (controlled by a full-time dummy, which takes the value of one if the total number of days engaging in the said activity is higher or equal to five out of the seven days of the week, and zero otherwise), and general division the individuals' occupations belong to. The weighted variance of this residual wage by district (or socio-economic groups later on) is then used in the analysis.

¹² This is identified by the individuals' usual principal activity status ("The usual activity status relates to the activity status of a person during the reference period of 365 days preceding the date of (the) survey" (NSSO n.d.)).

¹³ Share of underemployment here is defined as the total number of people employed in a field different from their usual field of economic activity in a district as a share of the district's total number of working-age people. Underemployment is often more visible via looking at working hours when a person is working but with hours less than they would like to work. However, this leaves out the invisible kind of underemployment, which captures people working as many hours as they would like to contribute, but in activities with lower productivity, prestige or economic return (Jensen and Slack 2003, p. 23). In this paper, it is presented in the form of people engaging in a field or activity that is not their usual field, thus more likely to be less efficient. This could be of interest to study as it can reflect, to a certain level, the local labour markets' adjustment to the changing dynamics in sectors' profitability and capacity to absorb more factors of production (human capital in this case).

to purge out the endogeneity in the variables, the IV method is adopted, followed by a further investigation into the group-wise analysis results.

The import per worker index (IPW) is constructed accordingly to measure the districts' working-population-adjusted level of exposure to the national-level trade shock; it also represents the districts' levels of susceptibility to the shock. The IPW index's constructions here broadly follow that in the classic study of Autor et al. (2013):

$$\Delta IPW_{dt} = \sum_i \left(\frac{Employment_{dit}}{Employment_{it}} \right) \times \left(\frac{\Delta Import}{Employment_{dt}} \right)$$

where d denotes district, t denotes the year and i denotes the industry. Different from the Autor et al. (2013) paper, in this investigation, the key variables are examined in the form of year-on-year change. This is because the labour data were collected at slightly different intervals, but the variables are often expected to slowly adapt to the changing market. With the year-on-year format, the inclusion of more frequent trade side data is expected to increase the precision of the estimation. $\Delta Import$ is the year-on-year change in the import value, $Employment_{it}$ is the level of employment in India for industry i in year t , $Employment_{dt}$ is the number of people employed in a district d in year t , and $Employment_{dit}$ is the number of people employed in industry i in district d in year t . With these four components, the ΔIPW_{dt} is generated for each district for each according year, namely, for each industry, the per worker import trade values for the district are adjusted by level of exposure, and this value is then summed across all the industries to form IPW to represent districts' level of exposure to the China import trade shock.

To begin, the study first estimates the effect of trade shock on labour market outcomes by using the OLS approach, controlling for district-level characteristics using the aforementioned covariates. The basic econometric model is as follows:

$$\Delta L_{dt} = \beta_0 + \beta_1 \Delta IPW_{dt} + \mathbf{C}'_{it} \beta_2 + \beta_3 Y_t + \epsilon_{dt}$$

where ΔL_{dt} represents the labour market outcome variables for district d in year t . The dependent variables studied include districts' average wage, residual wage variance, employment rate and (invisible) underemployment rate. They are regressed on the import trade exposure indices, a set of district-level characteristics controls \mathbf{C}'_{it} and year dummies. The control matrix includes the district labour market activeness,¹⁴ lagged district share¹⁵ of manufacture workers, females, youth (those between the age of 15 and 24), the share of the rural population, the share of educated workers, Hindu population (the major religious group) and people identified as from certain "backward" social groups. The key coefficient of interest here, however, is β_1 .

Take district average wage as an example, if β_1 is positive, it means that, as the import exposure of a district goes up (either through higher imports or disproportionately more people employed in the import industries), the district's average log

¹⁴ This is the number of full-time workers as a share of the working-age population.

¹⁵ These are shares of the respective sub-populations against the districts' total working-age populations.

wage also increases. Inversely, if β_1 takes a negative value, import exposure rise is thus correlated with a drop in district average log wage, which could negatively affect the workers. For districts' underemployment shares, on the other hand, a negative β_1 means that the more exposed to import competition, the less the share of working-age people of the district would be employed in a field that is different from their usual or chosen field. This could be a reflection of trade competition-induced factor reallocation, which may be a sign of better labour-job skill matching. The inverse could then represent a certain extent of under-utilisation of the local labour force.

The usual issue with OLS estimations is that of confounding factors. Potential targeted government policies towards trade-intensive industries, for instance, can lead to a change in the labour market outcome variables as trade shock would. This endogeneity problem could then result in estimation bias. Therefore, the sector-wise values of Chinese exports to other developing countries similar to India at the time are used to instrument for India's imports from China. Theoretically, Chinese imports to these countries are arguably strongly correlated with those to India, but not related to India's labour market outcomes, thus satisfying the IV conditions for correlation and exclusion restriction. Different specifications are then applied accordingly to examine the impact on some key labour market variables. The first-stage estimation of the two-stage least squares estimation is:

$$\widehat{\Delta IPW}_{dt(g)} = \beta_a + \beta_b \Delta IPW_{IV_{dt}} + \mathbf{C}'_{it} \beta_c + \beta_d Y_t + \beta_e S_s + \epsilon_{dt}$$

where, in addition to the OLS specification, $\widehat{\Delta IPW}_{dt(g)}$ is instrumented by $\Delta IPW_{IV_{dt}}$ on the right-hand side using trade values from other countries and S_s is the added dummy to account for the time-invariant state variations.

While often cited, the Gini coefficient provides very limited information on the state of inequality. To have a more detailed view of the inequality issues of a given region, this paper looks to consumption groups as a possible close proxy for the distributional analysis. To move further on the idea of group-wise differences in effects as a result of the trade shock, additional analyses built on the IV model that allow heterogeneity across age groups, gender groups, occupational groups and industry groups are also included¹⁶ in the succeeding subsection.

4.2 Data sources and matching

On the labour side, the National Sample Survey (NSS) Employment and Unemployment Surveys (EUS) (NSSO n.d.) and the Census of India (Government of India n.d.[d]) are the two key sources of data on the Indian labour force. Therefore, in this investigation, both sources are used in order to analyse the impacts on the local labour markets. To alleviate estimation issues that could be caused by particular values, outliers that are located beyond three standard deviations are excluded from the analysis.

¹⁶ Details on the group divisions are available in appendix. The controls stay on the district level while the specification allows the outcome variables to differ across the district group. The weights are also kept accordingly in the regressions.

Firstly, to conduct the desired level of analysis, the Census of India provides high and comprehensive geographic coverage census data by industry from the Indian districts. Therefore, the 2001 and 2011 rounds of the Census are used to construct the relevant district-level variables, particularly the district-level employment¹⁷ by industry, and the ratio of female employment for each district. For the analysis, the data are then used to combine with trade side data to calculate the import per worker indices. Due to the tremendous work required for data collection of this scale, the Census of India is only conducted once in a decade; therefore, the detailed changes for the years between are filled in through a linear calculation. The NSS data provide relatively more rounds of data in the period of interest. As it is sampled survey data, the estimation may be less precise than that of the Census; thus, it is not used for this purpose here.

The NSS data, on the other hand, are a primary source of labour data that includes micro-level records on labours' characteristics, such as weekly wage,¹⁸ age, gender, religion, social group, level of education and region (state and district, and if live in rural or urban area). These variables are included in the analysis because they provide detailed information on the intra-district distribution of labour characteristics. Districts' residual wage variance is also calculated by first identifying the leftover wage after accounting for the level of education successfully completed and work hours and then calculating the weighted district-level variance.

As China's accession took place on December the 11th 2001, the most appropriate rounds of the NSS data for the investigation are the 55th (1999–2000), the 61st (2004–2005), the 66th (2009–2010) and the 68th (2011–2012) round. These rounds of data have also been used in Deb and Hauk (2020) and Saha et al. (2021) for relevant analysis and can be procured from the Indian Ministry of Statistics and Programme Implementation. As the NSS datasets were conducted with multi-stage stratification with randomisation within the final stage, other more detailed district-level characteristics are constructed using these datasets instead, and the gaps are filled in through linear interpolation.

On the control side, the district-level characteristics include the labour market activeness, the share of the highly-educated population, the share of the Hindu population (which is the major religious group in India), the share of identified "backward" social groups and the gender ratio of the districts. On the outcome side, the two aspects of interest are wage and employment. The weekly wage is divided by the total number of days in current activity (per week) to get an estimated average daily wage, which is then adjusted with the inflation rate of the corresponding year (FRED n.d.). The natural log transformation of this wage is then used in the analysis.

Regarding employment, the share of workers in manufacturing, the share of youth workers and the share of underemployment are investigated. Youth worker here is

¹⁷ Investigation in this section is limited to those that were self-employed, employer, regular salaried/wage employee, casual wage labour in public or other types of work for the periods concerned. Unpaid family workers are not used in this analysis as it can bias the wage estimations.

¹⁸ The NSS EUS data are the key source of micro-level data from India. However, it should be noted that the variable used (Wage and salary earnings (received or receivable) for the work done during the week) to derive wage still has a significant count of invalid entries across the rounds, which can affect the accuracy of the average estimation. In the 1999 round of NSS EUS, for example, there were five districts without any entry of wage information for the working-age individuals sampled. Therefore, the observation count in the final district panel is less than those for employment and underemployment.

defined as those that normally engage in paid work as categorised by their usual principal working status,¹⁹ and within the age range of 15 to 24 years old according to the standard classification (Statista n.d.), and underemployment, developed based on the definition in the NSS report (National Sample Survey Office 2014), is the those whose current activity National Industrial Classification code (shortened as NIC) is different from that of their usual activity NIC.

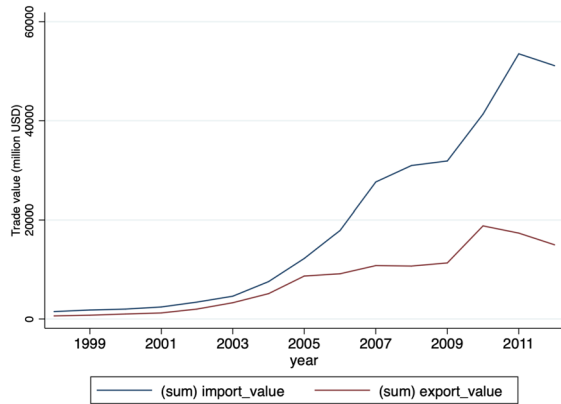
One difficulty in directly merging the two sources of data with each other across the years investigated is that the districts are not consistent over the period of interest. New states have been formed and multiple districts have undergone boundary changes. The approach some existing papers (Saha et al. 2021) have taken is to only keep with the districts that remained unchanged over the years, leaving 366 districts out of over 500 districts based on the division at the time of the earliest round of Survey. While some studies, like Village Dynamics in South Asia (VDSA) (2015), established a track record of some of the district changes, it was not applicable in this investigation because 1) the base year is different; the parent district names can thus differ; 2) not all states and union territories are considered; and 3) the year of change recorded is not always consistent with the listing in the NSS Survey. On the last point, the NSS updates the new districts when the frame details of the new districts are made available to DPD (Data Processing Division, now Data Quality Assurance Division (DQAD)); thus, it is not the case that the list is updated whenever a new district was formed.²⁰ Therefore, only the list of districts presented along with each round of the NSS Survey may be considered as the districts used in that round. Given this challenge, to improve the geographical coverage of this analysis, a matching process has been done (Government of India n.d.[a]) by collapsing the districts split from a single parent district. A total sample of 473 all-apportioned districts are kept and used for this analysis. It should be noted, however, that some districts still remain outside of this sample for two causes. First is that some areas are difficult to conduct the Survey, and thus were beyond the coverage of the NSS Survey. Secondly, the geographical change of some districts is complex, in that one district can be formed by taking various blocks or tehsils from different parent districts. As the block information is unavailable for tracking the detailed changes, these districts with complex separation are then dropped along with the relevant parent districts to avoid introducing biases in the analysis of local labour markets.

On the trade side, product-wise import trade data for the relevant years are available from the United Nations COMTRADE database. These data are then matched with the NIC of the labours in the NSS data in order to identify and control for their associated industries. The first round of NSS data uses the 1998 version of NIC, which is consistent with the ISIC 3 revision of products coding up to a four-digit level (SAARC 2006). In order to use a version with a coding standard most similar to that of the NSS data, the trade data were then procured from the World Integrated Trade Solution (WITS) software with ISIC revision 3 system of product coding.²¹ In order

¹⁹ The categories considered here are consistent with that for district employment.

²⁰ I thank the Indian Ministry of Statistics and Programme Implementation-Data Quality Assurance Division's assistance with confirming the relevant record details.

²¹ When interpreting, the trade values are obtained and are adjusted for inflation in the form of consumer price index at USD 2015 level.

Fig. 1 Sino-Indian Trade Values


to have a meaningful number of observations for each industry, the final grouping of NIC and trade products is generalised based on the one-digit level classification of the industry groups. To construct the instrument, trade data from countries similar to India are obtained for the according years and categories from WITS. This paper uses the trade values from Bangladesh, Indonesia, South Korea, Malaysia, Morocco, Pakistan, the Philippines and Zambia as instruments for India's import trade with China.

5 Results

This section first presents some key summary statistics and stylised facts of the labour market characteristics and trade involved in the analysis. Then, it shows and discusses the empirical analysis results concerning the key labour market outcome variables of interest using OLS, IV and by the key socio-economic groups.

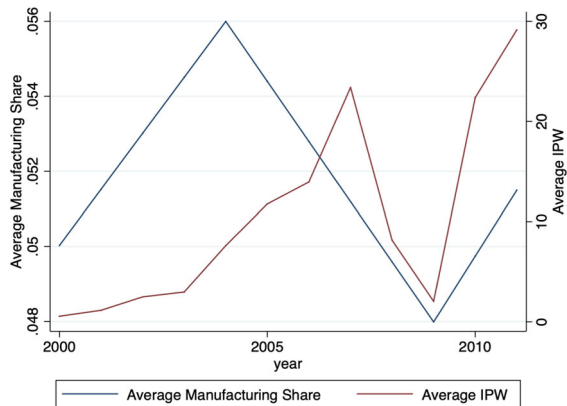
5.1 Descriptive statistics and stylised facts

This paper exploits the effects of the China shock on Indian labour markets. This is possible as bilateral trade increased significantly and accelerated in growth after China's accession to the WTO. This can be seen from India's Chinese imports in Fig. 1.²² Pre-2001, the imports and exports were close in value and showed a similarity in trend. The effect of China's opening was not immediately obvious until after 2004. For the years leading up to the 2008 Global Financial Crisis, import trade visibly accelerated, while export trade stagnated and the growth did not restart until 2009. As the growth is short-lived, by 2011, there is a visible gap between the values of imports and exports. The argument that the competition may affect employment, particularly in the import-intensive sector, seems somewhat plausible to question as in Fig. 2.²³ For each district, the share of the workers employed in the manufacturing industry is calculated for the rounds of surveys available. Then, it is plotted against the average

²² Author's calculation based on trade data from WITS (n.d.[a]).

²³ Author's calculation based on trade data from WITS (n.d.[a]) and labour data from NSSO (n.d.).

Fig. 2 Average District Manufacturing Employment Share and IPW



estimated import per worker²⁴ for the according years. It is visible that, despite both districts' average share of manufacturing employment and average import per worker trending up from 1999–2000 to 2004–2005, the divergence began around 2004–2005 when the average import per worker continued to rise and that average manufacturing employment began to drop.²⁵ Around 2008, most possibly due to the ramifications of the Financial Crisis, both variables experienced a significant decrease, and then the average import per worker was observed to bounce back with higher growth than that of manufacturing employment share.

Regarding the labour market, this investigation primarily concerns working-age people. The age range used in this paper is from the age of 15 to 64 (Organisation for Economic Co-operation and Development 2021). For the variables of interest, the district-level weighted mean log wage and residual are calculated for the according years, as well as the share of employed and underemployed workers as shares of working-age residences in the according year and districts. From Table 1, it is observed that going from 1999 to 2011, the average of districts' mean weighted log wages have increased, and the gap between that at the 10th percentile and that at the 90th percentile has also become smaller. This could be a sign of a shrinking wage gap between the top and bottom earners. Regarding the variance of residual wage, the mean of the districts' variances has largely remained the same over the years, indicating limited fluctuations. But as the mean is slightly higher than the values for 1999 and 2011, this could mean that wage inequality has also increased for the years between when education, work status and occupation are accounted for.

On employment, the mean share of employed workers has actually decreased from 1999 to 2011. This could be because the Indian labour market was still recovering from the 2008 Global Financial Crisis in 2011–12. The 10–90 percentile gap for average share, however, is closing, which could be a sign of convergence among the local labour markets. Underemployment is a concept that has received very limited attention. As the NSS EUS provides data on both usual and current principal activities,

²⁴ The import per worker is calculated with Δ import value and thus should be considered when interpreting.

²⁵ The averages of shares represent district-level average value, which accounts for the weights assigned to households with different characteristics.

Table 1 District-level descriptive statistics

	Wage	Residual Wage Variance	Employment	Underemployment	IPW
1999					
Mean	6.4870	0.4249	0.4238	0.0533	0.8970
p10	5.8511	0.2444	0.3031	0.0145	0.4437
p25	6.1318	0.3324	0.3615	0.0246	0.5871
p50	6.4438	0.4293	0.4186	0.0422	0.7686
p75	6.8299	0.5186	0.4841	0.0641	1.0658
p90	7.1564	0.5909	0.5474	0.1017	1.5177
2011					
Mean	7.5091	0.4249	0.4100	0.0472	29.1438
p10	7.0664	0.2702	0.3111	0.0076	9.7296
p25	7.2127	0.3305	0.3525	0.0158	15.8299
p50	7.4500	0.4214	0.4096	0.0306	23.8297
p75	7.7565	0.5093	0.4631	0.0573	36.8377
p90	8.0707	0.5827	0.5094	0.1167	53.4918
Overall					
Mean	6.9800	0.4252	0.4207	0.0467	9.9279

it is possible to also investigate the changes in districts' share of workers that were underemployed in a normally invisible way. From 1999 to 2011, it is seen that the average district share of underemployment has decreased. This could mean that the labours are being more effectively hired and allocated in the market, and the training they receive is becoming better matched with the sectors' ability to employ workers. The gap between the 10th and 90th percentile, however, has enlarged over the years. This may be a sign of growing differential among districts' levels of hiring or training efficiency. It may be that while some districts provide a more diverse industrial composition, differently trained workers could be employed in their usual field, other districts became more specialised in a few industries, and a higher share of local workers (assuming a high level of immobility) became temporarily employed in fields other than their usual fields. Regarding the main variables of interest, the import from China rose dramatically in value; therefore, it is not surprising to see that the mean import per worker also increased significantly from 1999 to 2011, reflecting the high growth in the local labour markets' exposure to the import shock. Moreover, it is seen that going from the 10th to the 90th percentile, there is a significant difference in the levels of exposure, which can be used to identify the impacts of the import shock.

Looking across regions, the liberation of the economy also brought some variations in the regional pace of industrialisation. Comparing the fractions of people that live in the urban area and work in the manufacturing sector as the principal and (or) subsidiary activity across the 28 states,²⁶ it is observed that the changes across the regions are not uniformly distributed. Gujarat and Himachal Pradesh, for example, have experienced a visible increase, while the fraction of that in Arunachal Pradesh seems to have decreased. As the manufacturing industry is one of the industries with high import trade values, this change could be a result of cluster formation to increase efficiency in competition. An implication can also be diverging levels of exposure to manufacturing trade shocks. This also resonates with the findings in Table 1 (Fig. 3).

On the trade side, the origins and content of India's imports have also evolved in the period of interest. Following China's accession into the WTO, the share of imports from China has increased significantly (Harvard Growth Lab n.d.) for India. In recent years, China has also become one of the largest trading partners of India (Deb and Hauk 2020). Aside from trade values, another aspect is also that of the content of trade. Harvard Growth Lab (n.d.), for example, investigates the product content in countries' trading activities and provides a definition of product complexity, which "captures the amount and sophistication of know-how required to produce a product" (Harvard Growth Lab n.d.). When looking at the Chinese import contents in the case of India, there has been a highly visible transition. As data reflect, in 1999, India's imports from China were more heavily concentrated in the chemical, agriculture and minerals sectors. The top goods imported were raw silk (7.59%) and coke (6.06%). In 2009, on the other hand, the sectors of concentration shifted significantly to electronics and machinery. The most imported goods include telephones (9.37%), transmission

²⁶ The density is measured per 1,000. Telangana formally separated from Andhra Pradesh and became an independent state in 2014. As the data are from the years before the separation, statistics on Telangana and Andhra Pradesh are each shown as half of that of Andhra Pradesh prior to the separation and therefore may not be representative of the intra-region manufacture population distribution. Raw data on this topic are available from NSS EUS Report 1993–94 Table 6.7.2 and NSS EUS Report 2011–12 Table 5.11.1.

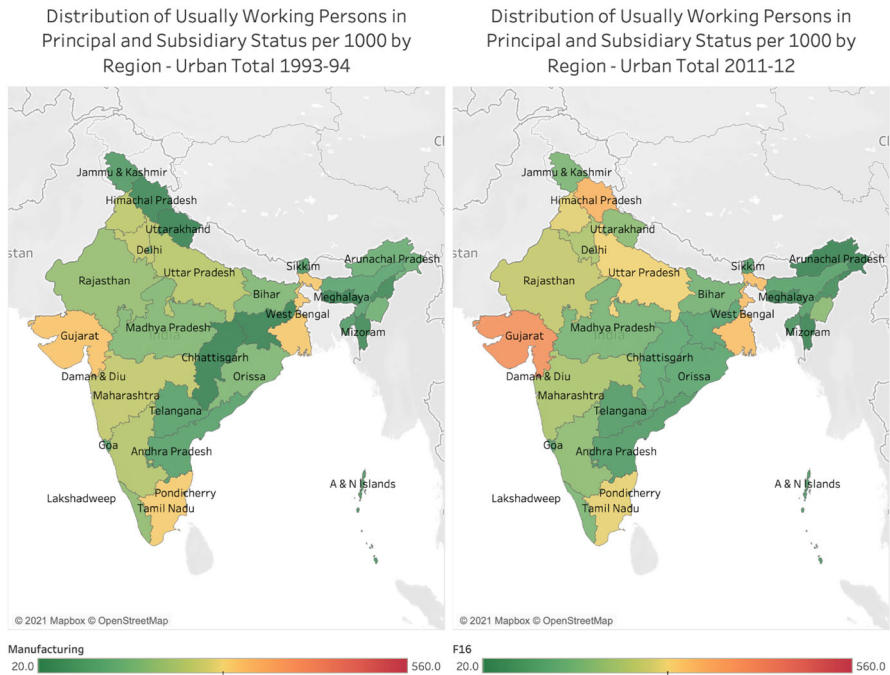


Fig. 3 Regional Distribution of Urban Working Persons in Manufacturing. . Source: Author’s calculation based on data from the Government of India, Development Monitoring and Evaluation Office (NSSO n.d.). Tabulated with Tableau

apparatus for radio, telephone and television(5.82%), computers (4.03%) and steam boilers (2.71%) (Harvard Growth Lab n.d.). An implication of this is also that the level of product complexity has also increased throughout the years examined (Fig. 4).

5.2 Baseline regression results

Following the general econometric model, this subsection presents the results of baseline OLS estimations.²⁷ The data used to generate the variables in the analyses are weighted accordingly using the individual-level multiplier provided in the dataset. For each specification, the standard errors are clustered at the state level, and year dummies are added as specified (Table 2).

Firstly, the districts’ change in average log wage is regressed on the import exposure indices. The results from column (1) show that generally there is not a statistically significant relationship. Therefore, from the OLS model, the finding does not provide significant evidence for a negative relationship between the observed surge in import trade exposure and the Indian local labour market average wage. District share of the population from rural areas, however, has a negative significant estimate when all the

²⁷ As the wage data have numbers of invalid entries, the coverage of districts is not comprehensive here for the 473 districts; therefore, the numbers of observations are different for the wage-related investigation and the employment-related investigation.

Table 2 Import exposure and labour market outcomes (OLS)

	(1) Wage	(2) Residual Wage	(3) Employment	(4) Underemployed	(5) Unemployment
Δ IPW	-0.000384 (-1.84)	-0.000133* (-2.22)	0.0000720 (1.69)	-0.0000609 (-1.92)	-0.0000404 (-1.89)
Activeness	0.336** (3.06)	0.106** (3.54)	-0.185*** (-4.97)	-0.138*** (-5.77)	0.000710 (0.07)
Manufacture	-0.380 (-1.49)	0.169 (1.90)	0.302*** (9.26)	-0.0184 (-0.63)	-0.0160 (-1.21)
Female	-0.0175 (-0.12)	0.156* (2.65)	-0.288*** (-6.15)	0.0432* (2.43)	-0.00969 (-1.09)
Youth	-0.135 (-0.84)	0.223*** (6.23)	-0.231*** (-4.94)	0.0159 (0.57)	0.0243* (2.17)
Rural	-0.439*** (-4.67)	-0.0936** (-3.04)	-0.09831 (-0.61)	-0.0150 (-1.65)	-0.00815 (-1.65)
Educated	0.819*** (7.20)	0.278*** (5.39)	-0.0651 (-1.93)	0.00487 (0.25)	0.0287* (2.18)
Hindu	0.164 (1.56)	0.0300 (0.95)	-0.0127 (-0.93)	0.00857 (0.81)	0.00593 (1.12)
Backward	-0.107 (-1.93)	-0.00760 (-0.24)	0.0285 (1.51)	-0.000797 (-0.06)	0.00189 (0.39)
<i>N</i>	5183	5183	5203	5203	5203
r^2	0.219	0.0394	0.114	0.0848	0.0308
Year FE	Yes	Yes	Yes	Yes	Yes

t statistics in parentheses
 * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$
 Using data from 1999–2011

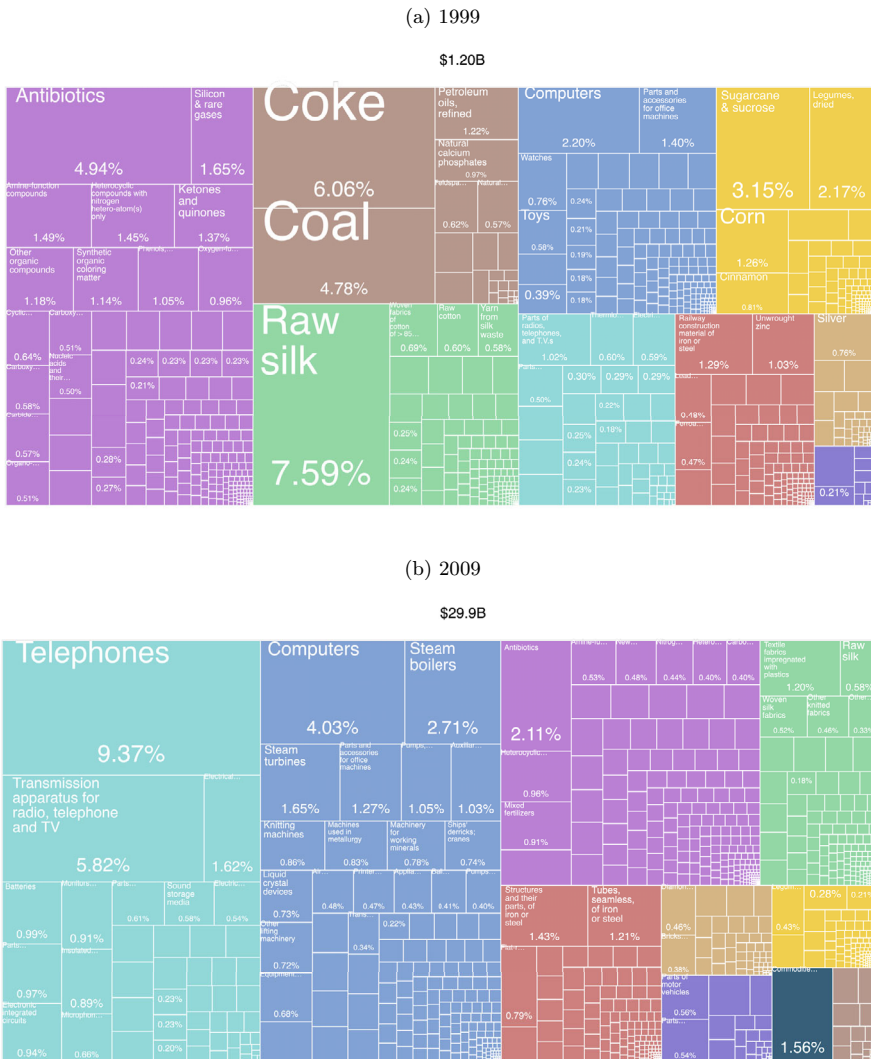


Fig. 4 Change in the Content of India's Imports from China . Source: The Atlas of Economic Complexity, (Harvard Growth Lab n.d.)

control variables are included, reflecting a possible substantive difference between rural and urban incomes.

For the analysis of the district residual wage variances, if the coefficient on the import per worker index is positive, it means that, as the district's exposure to import competition gets higher, the district's residual wage fluctuation is also estimated to increase. This could be an indication of worsening wage inequalities from a variety of socio-economic aspects with higher susceptibility. As shown in column (2), the coefficient estimate for the import per worker index is negative and statistically significant

at 5% level when demographic and socio-economic controls are included. This shows some evidence of a correlation between higher import competition exposure and lower residual wage fluctuations (lower wage inequalities).

For the argument that China's import competition negatively affects other countries' employment, it would mean that, when other sources of variations are controlled for, there is a negative relationship between import per worker and the share of employment. While the OLS estimation cannot identify a causal relationship, it is at least observed that, with the full set of controls, the estimation does not provide evidence for a negative relationship between import exposure and the share of employment on the district level. When all controls are added, the insignificant positive estimate in column (3) shows that there is no significant correlation between import competition and district employment. This is further verified by the insignificant negative estimate in column (5). Therefore, instead of the negative relationship in the "crowding out" case, the most stringent specification under OLS with the full set of controls suggests a limited relationship between districts' import exposure and share of employment.

When looking at the share of people working in fields other than their usual principal fields of activity around the time of the surveys, an increase in the share of this population could be a sign of labour under-utilisation and labour market inefficiency. From the OLS regression result, the coefficient on the import per worker index is not statistically significant here and thus fails to reflect a meaningful correlation between import per worker and underemployment share. The magnitude of the estimates is also quite small, which could be because the shares of the underemployed population, in general, are quite low.

5.3 Instrumental variable results

Using the trade data from Bangladesh, Indonesia, South Korea, Malaysia, Morocco, Pakistan, the Philippines and Zambia, the China-India import trade value is instrumented for the according years. Year dummy, state dummy and clustered standard error are also included in the estimation. The first-stage estimation confirms that the constructed $IPW_{IV_{dt}}$ is a strong instrument for ΔIPW_{dt} for the two-stage least squares analyses. The results of the second stage with the full set of controls are shown in Table 3.

In the first column, the import per worker index is first instrumented for the analysis of the impact on change in average log wage. The estimate is negative and significant at the 1% level. From this sample, a 1,000 USD higher import per worker is found to decrease the district average log wage by 1.37 percentage points. This can be a reflection of the downward pressure coming from the supply side higher availability of goods at a given price level driving up competition, leading to loss of income for those that dropped out of the competition or lower wages to cut costs and stay competitive. For the district-level variance of residual wage in column (2) and underemployment share in column (4), no statistically significant causal relationship was identified. For employment share, however, the estimate is positive and statistically significant at the 5% level. As shown in column (3), a 1,000 USD higher import per worker is found to increase the district share of employment by 0.15 percentage points. Also,

Table 3 District-level labour market outcomes (IV)

	(1) Wage	(2) Residual Wage	(3) Employment	(4) Underemployed	(5) Unemployment
Δ IPW	-0.00137** (-3.17)	-0.000178 (-1.62)	0.000150* (2.29)	-0.0000546 (-0.77)	-0.0000699* (-2.52)
Activeness	0.226* (1.96)	0.108*** (3.51)	-0.165*** (-4.42)	-0.134*** (-5.46)	0.000336 (0.03)
Manufacture	-0.305 (-1.15)	0.145 (1.66)	0.291*** (8.60)	-0.0150 (-0.60)	-0.0143 (-1.14)
Female	0.0109 (0.08)	0.148* (2.51)	-0.295*** (-6.86)	0.0484*** (3.45)	-0.0169 (-1.44)
Youth	-0.154 (-0.97)	0.219*** (6.49)	-0.214*** (-5.33)	0.0256 (1.08)	0.0214* (1.98)
Rural	-0.452*** (-4.86)	-0.0962** (-3.26)	-0.0112 (-0.73)	-0.0175* (-1.99)	-0.00589 (-0.97)
Educated	0.946*** (8.09)	0.268*** (4.82)	-0.0765* (-2.20)	0.0161 (0.84)	0.0286* (2.46)
Hindu	0.155 (1.52)	0.0302 (0.97)	-0.0123 (-0.95)	0.00829 (0.79)	0.00651 (1.28)
Backward	-0.0752 (-1.32)	-0.00578 (-0.18)	0.0248 (1.42)	0.000507 (0.04)	0.00180 (0.38)
<i>N</i>	5183	5183	5183	5183	5183
<i>r</i> ²	0.229	0.0551	0.125	0.105	0.0785
Year FE	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes

t statistics in parentheses
 * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
 Using data from 1999–2011

in column (5), a 1,000 USD higher import per worker is found to decrease the district share of unemployment by 0.0699 percentage points, which is largely in line with the employment investigation. These are usually unexpected outcomes, but it is in line with the finding in Choi and Mingzhi (2020). From speculation, this result may be due to a rise in trade in intermediate goods between India and China, which could also raise the demand for domestic workers in certain sectors (World Trade Organization 2017), or allow businesses to expand with lower input costs. Moreover, as will be shown later in the heterogeneity section of the analysis, it could also be the case that the surge of trade with China also brought opportunities for certain industries and non-tradable sectors, such as the service sector. The positive impact on these sectors thus pushed up employment as an indirect impact of import trade. Therefore, the overall district-level analyses reflect that, while for residual wage fluctuation and for underemployment, the import exposure measure by the import per worker index is not estimated to have statistically significant effects, the wage and employment effects are present and significant.

5.4 Results by socio-economic groups

By looking at district-level outcomes, it is seen that, aside from employment, the import competition had significant wage and employment effects, but limited effects on inequality and underemployment. One possibility is that there exists heterogeneity in the effects of trade shock, which are then averaged out at the district level. Therefore, this section presents the results of estimations that allow the impact of import shock to vary across these groups. The outcome variables in these estimations are the outcomes for the specific group in a given district. At the same time, the controls remain on the district level in line with the settings the groups were situated in. For each specification, year and state controls are added and standard errors are also clustered on state level.²⁸

5.4.1 Consumption group

First, the impact of trade shock is allowed to vary across different consumption groups.²⁹ The results are shown in Table 4.

²⁸ The import per worker and controls remain on the district level to account for the district-varying impacts of these control variables in their settings. It should be noted that the results in the following analysis can be affected by two features. First, as before, since data interpolation was required, the data on labour market fluctuations may be attenuated. Second, in order to identify the impacts across groups, the people identified with a group within a district are clustered into one unit of analysis. As a result, the panel provides equal weight to each estimated district-group-level outcome variable, which can be different from their level of presence in the district-level analysis. This could explain some of the discrepancies with district average results. It should also be noted that when the analysis is with regard to one dimension of the socio-economic groups, attenuation in estimations is still possible from the other dimension of the individuals' characteristics.

²⁹ The district population is divided into three groups. The top-consumption group accounts for individuals who belong to relatively affluent rural households or individuals who belong to households with MPCE within the top 10% in the urban sector. The middle consumption group accounts for rural households, which have non-agricultural activity as their principal source of earning, and urban households with an MPCE in the middle 60%. They are also captured by the *sss2* dummy. The lower consumption group accounts for all

Table 4 Consumption group-level labour market outcomes (IV)

	(1) Wage	(2) Residual Wage Variance	(3) Employment	(4) Underemployment
Δ IPW	-0.00181*** (-6.90)	-0.0000278 (-0.43)	0.000142 (1.92)	-0.0000250 (-1.15)
sss2	0.00142*** (6.80)	-0.0000527 (-0.86)	-0.000133 (-1.74)	-0.0000645* (-2.19)
sss3	0.00292*** (7.59)	0.000141 (1.59)	-0.000267** (-3.02)	0.0000251 (0.69)
group2	-0.105*** (-20.84)	0.000224 (0.21)	0.0104*** (7.30)	0.00179*** (4.83)
group3	-0.211*** (-23.26)	-0.0133*** (-6.38)	0.00825*** (3.31)	0.00395*** (4.04)
<i>N</i>	15,314	15,314	15,314	15,314
<i>r</i> ²	0.214	0.0370	0.0685	0.0594
Year FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes

t statistics in parentheses
 * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$
 Using data from 1999–2011

Focusing on the first row, the import per worker index here estimates the effect on the individuals who belong to relatively affluent rural households or individuals who belong to households with MPCE within the top 10% in the urban sector. The results show that while import per worker has a negative impact on the average change in log wage for the relatively well-off group, it increases the log wage for the individuals from households in the lower consumption spending bracket, possibly due to standardisation requirements when engaging in international trade. On employment share, it seems that the individuals from the lower consumption bracket seem to have lower employment rates following intensified import competition. Regarding underemployment, the import per worker is estimated to have a negative effect on people from the middle bracket, which means that they are less likely to be working in a field that is not their usual principal field. This effect for the other two groups, however, is not statistically different from zero. In other words, the import per worker shock seems to positively affect the employment efficiency for the people in the middle expenditure bracket but has no significant effect on the top and bottom groups.

5.4.2 Age group

This section aims to see if the effects of import shock can also differ across different age groups.³⁰ From Table 5, it is seen that the effect on average wage is largely muted. However, the shock resulted in higher residual wage variance in the youngest age group, indicating a potentially higher level of inequality among the youth. The effect is the opposite for those in the 36–50 age range. The interaction terms in column (3) show that the import shock had a generally positive impact on employment share across the age groups but was more so for the youth at the expense of those in the eldest. The shock is also seen to reduce the level of underemployment for the younger groups.

5.4.3 Gender

When the effects are allowed to vary by gender groups, it is seen that the analysis fails to reject that the average wages for male and female workers are not significantly different. For the result of the variables, there is no visible difference in impact on the gender dimension (Table 6).

5.4.4 Occupation groups

Another dimension through which the impact of import shock may produce heterogeneous effects is occupation groups. This investigation implemented a bifurcation

Footnote 29 continue

the other rural households not yet listed and the urban households with MPCE in the bottom 30% bracket. They are also captured by the *sss3* dummy.

³⁰ According to the division in the survey, four age groups were constructed: Group 1 includes those between 15 and 25, group 2 consists of those between 26 and 35, group 3 includes those between 36 and 50, and group 4 consists of those that are 51 and above. The dummies and the interaction terms were created accordingly and the numbers represent the according groups.

Table 5 Age group-level labour market outcomes (IV)

	(1) Wage	(2) Residual Wage	(3) Employment	(4) Underemployment
Δ IPW	-0.000380 (-1.23)	0.000102* (2.29)	0.000160* (2.49)	-0.000110** (-2.67)
Δ IPW*age2	-0.0000320 (-0.21)	-0.0000366 (-0.65)	-0.0000313 (-0.38)	0.0000765* (2.49)
Δ IPW*age3	0.0000457 (0.18)	-0.000116* (-2.12)	-0.0000298 (-0.51)	0.0000618** (2.91)
Δ IPW*age4	-0.000411 (-1.45)	-0.000139 (-1.51)	-0.000129* (-2.19)	0.0000681 (1.58)
group2	-0.0104*** (-5.05)	0.00378*** (4.54)	0.00263* (2.09)	0.000153 (0.46)
group3	-0.0126*** (-5.26)	0.00495*** (5.49)	0.00488*** (4.52)	0.000209 (0.62)
group4	-0.00309 (-0.76)	0.00669*** (5.05)	0.00769*** (7.89)	0.00150** (2.97)
<i>N</i>	20,543	20,543	20,543	20,543
r^2	0.0882	0.0198	0.0450	0.0584
Year FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes

t statistics in parentheses
 * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$
 Using data from 1999–2011

Table 6 Gender group-level labour market outcomes (IV)

	(1) Wage	(2) Residual Wage	(3) Employment	(4) Underemployment
Δ IPW	-0.000402 (-1.25)	-0.000120 (-1.81)	0.000115 (1.29)	-0.00000179 (-0.03)
Δ IPW*Female	0.0000348 (0.14)	0.0000837 (1.96)	-0.0000311 (-0.44)	-0.0000337 (-1.02)
sexbinary	0.00780 (1.63)	-0.000876 (-1.20)	-0.00269* (-2.38)	0.0000728 (0.12)
<i>N</i>	10,278	10,278	10,278	10,278
r^2	0.108	0.0306	0.0639	0.0723
Year FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes

t statistics in parentheses
 * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$
 Using data from 1999–2011

Table 7 Occupation group-level labour market outcomes (IV)

	(1) Wage	(2) Residual Wage	(3) Employment	(4) Underemployment
Δ IPW	0.000639*** (4.12)	0.0000602 (0.74)	-0.000122** (-2.62)	-0.00000682 (-0.11)
Δ IPW*Production	-0.00204*** (-7.88)	-0.0000232 (-0.30)	0.000364*** (7.16)	-0.0000686 (-1.48)
Production	0.120*** (12.09)	0.00251 (1.13)	-0.0205*** (-11.63)	0.00194 (1.01)
<i>N</i>	10,274	10,274	10,274	10,274
r^2	0.179	0.0537	0.186	0.0481
Year FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes

t statistics in parentheses

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

Using data from 1999–2011

of occupations—those that are directly related to production, such as farmers, services and sales, labourers and production workers, and those that are not, such as professionals, administrative and managerial workers, clerical workers and those that were not classified. The impact of import per worker on the average log wage for production- and sales-related workers is significantly negative. This could be a result of competition in the production of imported goods. For the group not directly related to production, the impact of import per worker is less negative and highly significant. This result may be because of the relative increase in importance and return for trained labour. For employment, however, the import per worker has a significant positive effect on the employment share of production- and sales-related workers, but a negative effect for the other group. A 1,000 USD rise in import per worker is estimated to increase the production- and sales-related group's employment share by 0.242 percentage points. This could be because, as the imports from China surged, the trade in intermediate goods also rose, thus increasing the hiring of Indian workers in the production chain. This positive estimate overall also mirrors the OLS and IV findings on import exposure's positive effect on employment. And for underemployment, the results are generally insignificant (Table 7).

5.4.5 Industrial groups

Four groups were identified to see if the impact of import competition varies. These include people working in hospitality and sales (Sales), manufacturing, agriculture and mining (Blue), storage, communication and financial services (Services) and others (Others).³¹ For people working in sales, it is seen that a surge in import competition drives down their average wages but increases their employment that a 1,000 USD

³¹ Details are provided in appendix.

Table 8 Industrial group-level labour market outcomes (IV)

	(1) Wage	(2) Residual Wage	(3) Employment	(4) Underemployment
Δ IPW	-0.000139 (-0.82)	-0.0000674 (-1.09)	0.0000221 (1.06)	-0.0000549 (-1.95)
Δ IPW*Sales	-0.000891** (-2.77)	0.000165 (1.06)	0.000144** (2.59)	-0.0000722 (-1.29)
Δ IPW*Others	-0.000703 (-1.39)	0.000203 (1.34)	-0.0000350 (-0.92)	0.0000611 (0.95)
Δ IPW*Blue	-0.000609 (-1.79)	0.00000744 (0.00)	-0.000254** (-2.85)	0.000494*** (3.40)
Sales	0.0116 (1.83)	-0.00547** (-2.76)	-0.00351*** (-5.44)	0.00149 (1.66)
Others	-0.00318 (-0.72)	-0.00668*** (-4.40)	0.000131 (0.20)	0.000310 (0.41)
Blue	0.0257*** (3.98)	-0.00613** (-2.83)	0.00392** (3.08)	-0.000213 (-0.18)
<i>N</i>	19,457	19,457	19,457	19,457
r^2	0.0901	0.00998	0.0145	0.0214
Year FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes

t statistics in parentheses

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

Using data from 1999–2011

increase in import per worker increases the average employment share by 0.144 percentage points. For the blue-collar group, it is seen that intensified import competition drives down their employment and results in some displacement in the job market as reflected by the estimate for underemployment. It is estimated that a 1,000 USD increase in import per worker raises the share of underemployment for the “blue” industrial group by 0.494 percentage points, significant at 0.1% level. For people working in other industries, the effect of important competition seems to be largely muted (Table 8).

6 Discussion

By looking at data on labour characteristics and industry trade statistics, this paper is relevant for both the field of labour economics and international trade. As it focuses on South–South trade, the developmental impact can also contribute to informing the understanding of such trade relations and relevant policy-making. Taking China’s accession into the WTO as a trade side economic shock, the impact assessment not only pays attention to a series of labour market outcomes in the Indian local labour markets;

it also explores the heterogeneity across the socio-economic groups. The finding suggests that an increase in import exposure had a significant negative impact on average wages for certain groups and a positive impact on the share of employment in the Indian districts. The paper also finds that socio-economic factors, such as the level of consumption expenditure, age, gender, occupation and industry of work, can contribute to heterogeneous impacts of import shock on the labour market outcomes. On the external value of this investigation, it may be of interest for research on detailed socio-economic impacts of South–South trade's local labour market impacts, particularly regarding the presence of spatial differences, and heterogeneity across sub-population groups. As the question remains largely empirical, the results can be compared against other analyses with different types of economies to draw comparisons. The district-level observations can also provide some information on the micro-regions' levels of resilience to withstand the sudden growth in imports, which could highlight the policy space for further improvements. Moreover, as the findings reflect, the impact of trade shock differs depending on the population characteristics. This could be helpful for painting a fuller picture of trade's impact on the labour markets. Even though competition intensified, the potential increased activities in intermediate goods and in certain industries still resulted in a positive impact on the employment for people working in production and sales and the employment efficiency for young people. Also, when competition intensifies, there is also an indication that people may be extending to subsidiary work to diversify their income streams.

Regarding areas of improvement for further investigation, similar analysis can benefit from richer and more comprehensive data. On the labour side, the Census of India and the NSS surveys have comprehensive geographical coverage and constitute the primary sources of the investigation. However, due to the tremendous effort required to collect data, the Census is only conducted once in a decade and the NSS EUS is conducted mostly at five-year intervals. On the detailed variables, the available wage data consistent across the rounds of Employment and Unemployment Surveys are only on a weekly basis and have a significant number of invalid entries. As seen from the variable "total number of days in each activity", while most of the workers dedicate five days and above to their principal activity, there is still a certain portion of people that spend fewer days working in their principal job. The method this paper adopted is to adjust with regard to the total number of days in activity and inflation. This approach can, to some extent, ameliorate the differences in work intensity and thus the actual wage for work, as the smallest unit of statistic is 0.5 days, these data still do not fully account for the differences in levels of work intensity, and the effectiveness to infer is thus limited. For future research, more comprehensive district-level information with shorter intervals could contribute to more precise estimation in the investigations. Moreover, China and India also participate significantly in the trade of intermediate goods. The re-import and re-export of goods could also contribute to estimating trade's impact on labour market variables. As the NSS EUS has been discontinued after the 68th round, it may not be possible to include more recent data in the analysis.

7 Conclusion

Stepping beyond the usual North–South framework, this paper investigates the effects of import shocks in South–South trade. The empirical investigation of this type of trade relations can also allow more understanding of this more ambiguous area of trade’s developmental impacts.

By using the occasion of China’s accession to the WTO and exploiting the differences across the Indian districts, this investigation focuses on Sino-Indian trade as a case of South–South trade and examines the impacts of the sudden rise in imports on the local labour markets. The matching of districts improves the geographical coverage as compared with prior works, the detailed labour data used provided the analysis with micro-foundation. In addition, by using the long coverage period, the paper allows for a long-run perspective in the analysis. Using the import per worker index to measure exposure and susceptibility to import shocks at the district level, the paper considers the effect of trade shock on district average log wage, residual wage variance, employment share, unemployment share and the effects by groups.

In order to estimate the impact, labour and trade side data are used in this analysis. While the product-specific trade data are available on an annual basis, the labour data are much more limited. The two key sources of labour data used were collected at large and different intervals. The majority of the data used as covariates in the analysis were taken from the NSS data, which was conducted at 2–4-year intervals, while the Census data are only available at 10-year intervals. To remedy the missing data limitation and to harmonise different intervals of available data, the study adopted the method of interpolation. An implication of this is that data used in the regressions are not only actual statistics but also estimated data. This, however, allows more actual variations from the trade side and more precise industry- and gender-specific labour data from the Census to be accounted for.

From the district-level analysis, the paper finds a negative impact of import trade shock on the change in average log wage, limited impact on the residual wage variance and the share of underemployment. However, the estimate for employment points strongly to a positive relationship with import per worker across specifications that a 1,000 USD rise in import per worker increases employment by 0.15 percentage points. When examining by groups, it is also seen that this effect is particularly significant for the younger population and for people working in sales. Overall, the results of the investigation reflect that there is limited evidence for “race to the bottom” in the case of the Sino-India bilateral trade. From the analyses by consumption groups, age groups, gender groups and occupation groups, it is also seen that the impacts of import competition on the labour market outcomes examined could have been attenuated by the district-level averages. As the estimated impacts seem to differ based on the socio-economic groups, these findings could contribute to informing policy-making in terms of targeting particularly affected groups as a result of similar economic shocks.

8 Appendix

8.1 Group divisions in the further analyses

1. For the analysis by consumption groups, the groups are divided according to the second-stage strata of the NSS EUS sampling (details available at NSSO n.d.)
2. For the analysis by age groups, the ages are divided into four groups: 15–25, 26–35, 36–50 and 51 above
3. For the analysis by occupation groups, the occupations are divided into two groups: production- and sales-related (Production And Related Workers, Transport Equipment Operators And Labourers & Craft And Related Trades Workers Farmers, Fishermen, Hunters, Loggers And Related Workers Service Workers And Sales Workers) and others (Professional, Technical And Related Workers & Administrative, Executive And; Managerial Workers Clerical And Related Workers; Workers Not Classified By Occupations).
4. For the analysis by industrial groups, the industries: are divided into four groups: (1) Sales (Hotels and restaurants, Wholesale and retail trade; repair of motor vehicles, motorcycles and personal and household goods); (2) Blue (Manufacturing, Agriculture, hunting and forestry & Fishing, Mining and quarrying); (3) Service (Transport storage and communications, Real estate, renting, business activities and financial intermediation); and Others (Extra-territorial, private households with employed persons, other community, social, personal services, health, education, and public administration, Electricity, gas and water supply and Construction). The divisions are in accordance with the harmonised version of the NCO (Government of India n.d.[b], [c]).

8.2 Full output tables from the OLS analyses by outcome variable

This subsection presents the full OLS result tables from the analyses by outcome variables (Tables 9, 10, 11, 12, 13).³²

³² This notes that the district counts are different and certain districts may be absent; thus, the numbers of observations are not necessarily constant throughout the analyses.

Table 9 Chinese imports and district average wage (OLS)

	(1)	(2)	(3)	(4)	(5)
△ IPW	0.00128*** (7.25)	-0.000346 (-1.65)	-0.000336 (-1.55)	-0.000384 (-1.69)	-0.000384 (-1.84)
Manufacture			-0.298 (-1.07)	-0.460 (-1.74)	-0.380 (-1.49)
Female				-0.137 (-0.89)	-0.0175 (-0.12)
Youth				-0.205 (-1.31)	-0.135 (-0.84)
Rural				-0.559*** (-5.58)	-0.439*** (-4.67)
Activeness					0.336** (3.06)
Educated					0.819*** (7.20)
Hindu					0.164 (1.56)
Backward					-0.107 (-1.93)
<i>N</i>	5651	5651	5183	5183	5183
<i>r</i> ²	0.0333	0.187	0.177	0.195	0.219

t statistics in parentheses

p* < 0.05; *p* < 0.01; ****p* < 0.001

Table 10 Chinese imports and district residual wage variance (OLS)

	(1)	(2)	(3)	(4)	(5)
△ IPW	-0.0000958 (-1.68)	-0.000130* (-2.20)	-0.000137* (-2.31)	-0.000132* (-2.31)	-0.000133* (-2.22)
Manufacture			0.174* (2.05)	0.146 (1.67)	0.169 (1.90)
Female				0.120* (2.10)	0.156* (2.65)
Youth				0.208*** (5.80)	0.223*** (6.23)
Rural				-0.132*** (-4.12)	-0.0936** (-3.04)
Activeness					0.106** (3.54)

Table 10 continued

	(1)	(2)	(3)	(4)	(5)
Educated					0.278*** (5.39)
Hindu					0.0300 (0.95)
Backward					-0.00760 (-0.24)
<i>N</i>	5651	5651	5183	5183	5183
<i>r</i> ²	0.00137	0.00434	0.00643	0.0226	0.0394

t statistics in parentheses

p* < 0.05; *p* < 0.01; ****p* < 0.001

Table 11 Chinese imports and district employment rate (OLS)

	(1)	(2)	(3)	(4)	(5)
Δ IPW	-0.0000303 (-0.65)	0.000109* (2.11)	0.0000981* (2.04)	0.0000811 (1.83)	0.0000720 (1.69)
Manufacture			0.326*** (8.30)	0.313*** (8.81)	0.302*** (9.26)
Female				-0.252*** (-5.14)	-0.288*** (-6.15)
Youth				-0.219*** (-4.57)	-0.231*** (-4.94)
Rural				0.00108 (0.06)	-0.00831 (-0.61)
Activeness					-0.185*** (-4.97)
Educated					-0.0651 (-1.93)
Hindu					-0.0127 (-0.93)
Backward					0.0285 (1.51)
<i>N</i>	5676	5676	5203	5203	5203
<i>r</i> ²	0.000425	0.0153	0.0365	0.0901	0.114

t statistics in parentheses

p* < 0.05; *p* < 0.01; ****p* < 0.001

Table 12 Chinese imports and district unemployment rate (OLS)

	(1)	(2)	(3)	(4)	(5)
△ IPW	-0.0000258 (-1.91)	-0.0000402 (-1.86)	-0.0000397 (-1.83)	-0.0000398 (-1.88)	-0.0000404 (-1.89)
Manufacture			-0.0148 (-1.11)	-0.0179 (-1.45)	-0.0160 (-1.21)
Female				-0.0121 (-1.50)	-0.00969 (-1.09)
Youth				0.0229* (2.21)	0.0243* (2.17)
Rural				-0.0118* (-2.57)	-0.00815 (-1.65)
Activeness					0.000710 (0.07)
Educated					0.0287* (2.18)
Hindu					0.00593 (1.12)
Backward					0.00189 (0.39)
<i>N</i>	5676	5676	5203	5203	5203
<i>r</i> ²	0.00388	0.0165	0.0171	0.0245	0.0308

t statistics in parentheses

p* < 0.05; *p* < 0.01; ****p* < 0.001

Table 13 Chinese imports and district underemployment rate (OLS)

	(1)	(2)	(3)	(4)	(5)
△ IPW	0.0000466 (1.79)	-0.0000547 (-1.75)	-0.0000545 (-1.72)	-0.0000530 (-1.69)	-0.0000609 (-1.92)
Manufacture			-0.0121 (-0.49)	-0.0139 (-0.55)	-0.0184 (-0.63)
Female				0.0644** (3.35)	0.0432* (2.43)
Youth				0.0176 (0.59)	0.0159 (0.57)
Rural				-0.0174 (-1.86)	-0.0150 (-1.65)
Activeness					-0.138***

Table 13 continued

	(1)	(2)	(3)	(4)	(5)
					(-5.77)
Educated					0.00487 (0.25)
Hindu					0.00857 (0.81)
Backward					-0.000797 (-0.06)
<i>N</i>	5676	5676	5203	5203	5203
<i>r</i> ²	0.00215	0.0571	0.0602	0.0652	0.0848

t statistics in parentheses

p* < 0.05; *p* < 0.01; ****p* < 0.001

8.3 Full output tables from the analyses by group

This subsection presents the full result tables from the analyses by group (Tables 14, 15, 16, 17, 18).³³

³³ This notes that the group counts are different and certain groups may be absent in a district; the number of observations is not necessarily constant throughout the analyses.

Table 14 Consumption group-level labour market outcomes (IV-full)

	(1) Wage	(2) Residual Wage	(3) Employment	(4) Underemployment
Δ IPW	-0.00181*** (-6.90)	-0.0000278 (-0.43)	0.000142 (1.92)	-0.0000250 (-1.15)
sss2	0.00142*** (6.80)	-0.0000527 (-0.86)	-0.000133 (-1.74)	-0.0000645* (-2.19)
sss3	0.00292*** (7.59)	0.000141 (1.59)	-0.000267** (-3.02)	0.0000251 (0.69)
group2	-0.105*** (-20.84)	0.000224 (0.21)	0.0104*** (7.30)	0.00179*** (4.83)
group3	-0.211*** (-23.26)	-0.0133*** (-6.38)	0.00825*** (3.31)	0.00395*** (4.04)
Activeness	0.227 (1.54)	0.0284 (1.37)	-0.0854** (-2.60)	-0.119*** (-6.41)
Manufacture	-0.510 (-1.96)	0.106 (1.71)	0.197*** (5.07)	-0.0173 (-0.83)
Female	-0.115 (-0.85)	0.00384 (0.13)	-0.272*** (-7.54)	0.0280* (2.29)
Youth	-0.199 (-1.50)	0.0638*** (3.53)	-0.178*** (-5.43)	0.0207 (0.94)
Rural	-0.358*** (-5.09)	-0.0677*** (-3.49)	-0.0376* (-2.39)	-0.0147 (-1.52)
Educated	0.491*** (5.89)	0.100*** (3.37)	-0.0440 (-1.51)	0.0256 (1.29)
Hindu	0.122 (1.34)	0.0110 (0.72)	-0.0178 (-1.35)	-0.00163 (-0.19)
<i>N</i>	15,314	15,314	15,314	15,314
<i>r</i> ²	0.214	0.0370	0.0685	0.0594

t statistics in parentheses

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

Table 15 Age group-level labour market outcomes (IV)

	(1) Wage	(2) Residual Wage	(3) Employment	(4) Underemployment
Δ IPW	-0.000380 (-1.23)	0.000102* (2.29)	0.000160* (2.49)	-0.000110** (-2.67)
Δ IPW * age2	-0.0000320 (-0.21)	-0.0000366 (-0.65)	-0.0000313 (-0.38)	0.0000765* (2.49)
Δ IPW * age3	0.0000457 (0.18)	-0.000116* (-2.12)	-0.0000298 (-0.51)	0.0000618** (2.91)
Δ IPW * age4	-0.000411 (-1.45)	-0.000139 (-1.51)	-0.000129* (-2.19)	0.0000681 (1.58)
group2	-0.0104*** (-5.05)	0.00378*** (4.54)	0.00263* (2.09)	0.000153 (0.46)
group3	-0.0126*** (-5.26)	0.00495*** (5.49)	0.00488*** (4.52)	0.000209 (0.62)
group4	-0.00309 (-0.76)	0.00669*** (5.05)	0.00769*** (7.89)	0.00150** (2.97)
Activeness	0.231* (2.23)	0.00344 (0.12)	-0.166*** (-4.14)	-0.137*** (-5.99)
Manufacture	-0.0355 (-0.16)	0.146* (2.19)	0.256*** (6.33)	-0.0206 (-0.90)
Female	0.0815 (0.54)	-0.0207 (-0.62)	-0.364*** (-8.83)	0.0440** (2.72)
Youth	-0.00400 (-0.02)	0.100*** (5.77)	0.0176 (0.45)	0.0376 (1.33)
Rural	-0.412*** (-5.20)	-0.0398* (-1.97)	0.00305 (0.22)	-0.0175 (-1.90)
Educated	0.831*** (6.24)	0.119*** (3.34)	-0.0450 (-1.08)	0.00730 (0.37)
Hindu	0.195 (1.51)	0.0114 (0.60)	-0.00952 (-0.95)	0.0105 (0.93)
Backward	-0.107 (-1.73)	0.00863 (0.45)	0.0343* (2.34)	-0.00136 (-0.10)
<i>N</i>	20,543	20,543	20,543	20,543
<i>r</i> ²	0.0882	0.0198	0.0450	0.0584

t statistics in parentheses

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

Table 16 Gender group-level labour market outcomes (IV-full)

	(1) Wage	(2) Residual Wage	(3) Employment	(4) Underemployment
Δ IPW	-0.000402 (-1.25)	-0.000120 (-1.81)	0.000115 (1.29)	-0.00000179 (-0.03)
Δ IPW * Female	0.0000348 (0.14)	0.0000837 (1.96)	-0.0000311 (-0.44)	-0.0000337 (-1.02)
Female	0.00780 (1.63)	-0.000876 (-1.20)	-0.00269* (-2.38)	0.0000728 (0.12)
Activeness	0.335* (2.03)	0.000453 (0.02)	-0.174*** (-4.65)	-0.135*** (-5.60)
Manufacture	-0.118 (-0.35)	0.143* (2.13)	0.285*** (9.59)	-0.0138 (-0.56)
Youth	-0.135 (-0.68)	0.0603** (2.65)	-0.212*** (-5.44)	0.0232 (0.96)
Rural	-0.381*** (-5.48)	-0.0644*** (-3.36)	-0.0114 (-0.73)	-0.0158 (-1.65)
Educated	1.008*** (8.68)	0.144*** (3.48)	-0.0798* (-2.18)	0.0151 (0.73)
Hindu	0.247 (1.40)	0.0116 (0.73)	-0.0102 (-0.91)	0.00571 (0.53)
Backward	-0.0461 (-0.65)	0.0107 (0.55)	0.0228 (1.38)	0.00117 (0.10)
<i>N</i>	10,278	10,278	10,278	10,278
<i>r</i> ²	0.108	0.0306	0.0639	0.0723

t statistics in parentheses

p* < 0.05; *p* < 0.01; ****p* < 0.001

Table 17 Occupation group-level labour market outcomes (IV-full)

	(1) Wage	(2) Residual Wage	(3) Employment	(4) Underemployment
Δ IPW	0.000639*** (4.12)	0.0000602 (0.74)	-0.000122** (-2.62)	-0.0000682 (-0.11)
Δ IPW * Production	-0.00204*** (-7.88)	-0.0000232 (-0.30)	0.000364*** (7.16)	-0.0000686 (-1.48)
Production	0.120*** (12.09)	0.00251 (1.13)	-0.0205*** (-11.63)	0.00194 (1.01)
Activeness	0.0840 (1.07)	0.0503 (1.01)	-0.0566* (-2.15)	-0.112*** (-3.81)
Manufacture	-0.378 (-1.79)	0.0737 (1.15)	0.0970 (1.63)	-0.0276 (-1.01)
Female	-0.0505 (-0.36)	0.0718 (1.20)	-0.147*** (-3.76)	0.0326 (1.63)
Youth	-0.151 (-0.90)	0.131* (2.49)	-0.0716** (-3.09)	0.0604* (2.18)
Rural	-0.325*** (-3.54)	-0.0436 (-1.26)	-0.00294 (-0.22)	-0.0105 (-0.86)
Educated	0.638*** (7.93)	0.189*** (3.33)	-0.0462 (-1.69)	0.0424 (1.70)
Hindu	0.0877 (0.88)	0.0208 (0.40)	-0.00330 (-0.17)	0.0186 (1.33)
Backward	-0.0818 (-1.70)	0.0181 (0.68)	0.00413 (0.21)	-0.00353 (-0.30)
<i>N</i>	10,274	10,274	10,274	10,274
<i>r</i> ²	0.179	0.0537	0.186	0.0481

t statistics in parentheses

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

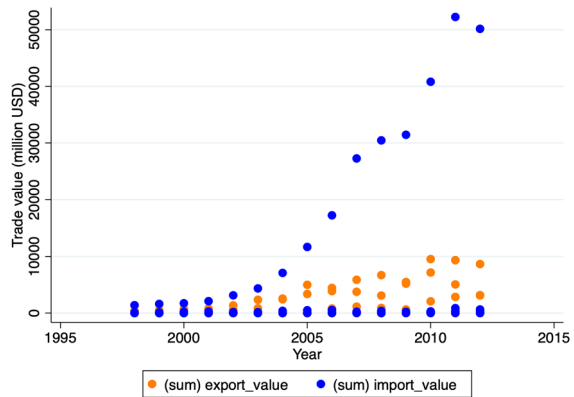
Table 18 Industrial group-level labour market outcomes (IV-full)

	(1) Wage	(2) Residual Wage	(3) Employment	(4) Underemployment
Δ IPW	-0.000139 (-0.82)	-0.0000674 (-1.09)	0.0000221 (1.06)	-0.0000549 (-1.95)
Δ IPW * Sales	-0.000891** (-2.77)	0.000165 (1.06)	0.000144** (2.59)	-0.0000722 (-1.29)
Δ IPW * Others	-0.000703 (-1.39)	0.000203 (1.34)	-0.0000350 (-0.92)	0.0000611 (0.95)
Δ IPW * Blue	-0.000609 (-1.79)	0.00000744 (0.00)	-0.000254** (-2.85)	0.000494*** (3.40)
Sales	0.0116 (1.83)	-0.00547** (-2.76)	-0.00351*** (-5.44)	0.00149 (1.66)
Others	-0.00318 (-0.72)	-0.00668*** (-4.40)	0.000131 (0.20)	0.000310 (0.41)
Blue	0.0257*** (3.98)	-0.00613** (-2.83)	0.00392** (3.08)	-0.000213 (-0.18)
Activeness	-0.0173 (-0.13)	0.0929 (1.79)	0.0151 (0.92)	-0.123*** (-4.46)
Manufacture	-0.262 (-1.27)	0.218*** (3.54)	0.0675*** (3.72)	-0.0440 (-1.54)
Female	0.0202 (0.16)	0.157** (2.76)	-0.0898*** (-4.35)	0.0625** (2.64)
Youth	-0.150 (-1.41)	0.116* (2.08)	-0.0184 (-0.92)	0.0521 (1.78)
Rural	-0.154** (-2.67)	-0.00677 (-0.24)	-0.0237* (-1.97)	-0.00843 (-0.78)
Educated	0.731*** (8.06)	0.130 (1.96)	0.000660 (0.04)	0.0790** (2.90)
Hindu	0.196** (2.80)	0.0393 (1.15)	0.0102 (1.22)	0.00208 (0.14)
Backward	-0.174* (-2.13)	-0.0275 (-1.42)	-0.00367 (-0.58)	0.0198 (1.71)
<i>N</i>	19,457	19,457	19,457	19,457
<i>r</i> ²	0.0901	0.00998	0.0145	0.0214

t statistics in parentheses

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

Fig. 5 Sino-Indian trade data



8.4 Impact of export on the district labour markets

Another aspect of concern is the impact of exports. While the district labour market outcomes could be under the influence of import competition changes, if there were changes in export activities, then the change in labour market outcomes could also be affected by this source. To examine this aspect, the study then takes two approaches—a simple visual examination of trends and a quick quantitative test, to capture the export side dynamics (Fig. 5).

Firstly, the figure shows import and export trends in Sino-Indian trade. The data points represent industry-cluster level data that were aggregated at a level that is able to be kept consistent through the period and align with labour side data for the purpose of this study. It is visible that while India's exports grew steadily, the increase in imports from China is much more visible and significant. This showcases that while there is a steady increase in export trade, it is of consistently lower magnitude and yet can still cause multicollinearity issues as argued in similar investigations. As the study uses China's accession into the WTO as a sudden shock to the Indian economy, the primary variation that drives the analysis is the sudden change; therefore, the export side is not included in the main part of the discussion.

Secondly, the study also runs a quick test on potential treatment effects using additional data. The hypothesis is that industries faced with higher competition from China would face downward pressure on their exports after China's accession into the WTO. By industry, a treatment variable is constructed, where the industries that were faced with higher than mean import trade value are seen as treated and periods after 2005 (accounting for a possible lag in effect) as treated. The estimated coefficient on the interaction term from this short analysis using additional data on India's exports to the world is not statistically significant. While the simple test is not designed to claim a stringent causal impact, it provides reasons, to some extent, for the exclusion of the export-related elaborations from this study as in most of the existing literature on this topic.

Table 19 District-level labour market outcomes (share instrument)

	(1) Wage	(2) Residual Wage	(3) Employment	(4) Unemployment	(5) Underemployment
Δ IPW	-0.00137** (-3.17)	-0.000178 (-1.62)	0.000150* (2.29)	-0.0000699* (-2.52)	-0.0000546 (-0.77)
Activeness	0.226* (1.96)	0.108*** (3.51)	-0.165*** (-4.42)	0.000336 (0.03)	-0.134*** (-5.46)
Manufacture	-0.305 (-1.15)	0.145 (1.66)	0.291*** (8.60)	-0.0143 (-1.14)	-0.0150 (-0.60)
Female	0.0109 (0.08)	0.148* (2.51)	-0.295*** (-6.86)	-0.0169 (-1.44)	0.0484*** (3.45)
Youth	-0.154 (-0.97)	0.219*** (6.49)	-0.214*** (-5.33)	0.0214* (1.98)	0.0256 (1.08)
Rural	-0.452*** (-4.86)	-0.0962** (-3.26)	-0.0112 (-0.73)	-0.00589 (-0.97)	-0.0175* (-1.99)
Educated	0.946*** (8.09)	0.268*** (4.82)	-0.0765* (-2.20)	0.0286* (2.46)	0.0161 (0.84)
Hindu	0.155 (1.52)	0.0302 (0.97)	-0.0123 (-0.95)	0.00651 (1.28)	0.00829 (0.79)
Backward	-0.0752 (-1.32)	-0.00578 (-0.18)	0.0248 (1.42)	0.00180 (0.38)	0.000507 (0.04)
<i>N</i>	5183	5183	5183	5183	5183
<i>r</i> ²	0.229	0.0551	0.125	0.0785	0.105 Year FE
Yes	Yes	Yes	Yes	Yes	
State FE	Yes	Yes	Yes	Yes	Yes

t statistics in parentheses
 p* < 0.05; *p* < 0.01; ****p* < 0.001
 Using data from 1999–2011

8.5 Bartik instrument

As discussed in Sect. 4.1 of the paper, the methodology of the classic Autor et al. (2013) paper is also being re-examined by more recent studies. As this study exploits the drastic exposure change in trade relations between China and India, the mechanism that drives the instrumental variable approach is provided by the national-level shock brought by China’s accession to the WTO. The district industry shares are used in the construction of the index, but not based on the assumption that they and the level of the labour market outcome variables are not correlated. Given that the outcomes of interests are differentials in changes in the variables, the methodology remains valid (Goldsmith-Pinkham et al. 2020). As the Bartik district-level shift-share instrument approach pertaining to industry-specific shock, it is not used for the analysis. The regression analysis using shares as instruments, however, is done, and the estimates are shown in Table 19. The estimate from column (1) suggests that a 1,000 USD higher

Table 20 Weighted Bartik instrument approach

	(1) Wage	(2) Residual Wage	(3) Employment	(4) Underemployment
Δ IPW	0.00225 (1.40)	-0.000753 (-1.57)	0.0000249 (0.15)	0.000407 (1.46)
Activeness	-0.0277 (-0.47)	0.0694** (2.72)	0.0197* (2.00)	-0.0356 (-1.65)
Female	-0.267*** (-5.21)	0.120*** (6.22)	-0.0764*** (-7.40)	0.0409*** (4.31)
Youth	-0.470*** (-7.48)	0.0714*** (3.47)	-0.0413*** (-3.46)	0.0411** (2.64)
Rural	-0.104*** (-4.42)	0.00113 (0.10)	0.0101* (2.26)	0.000443 (0.05)
Educated	0.416*** (9.14)	0.0361* (2.09)	0.0155* (1.99)	-0.0277*** (-3.58)
Hindu	0.0728 (1.87)	0.0434* (2.06)	0.00627 (0.53)	-0.0124 (-1.22)
Backward	-0.0340 (-1.15)	-0.0191 (-1.09)	-0.00747 (-1.81)	-0.00163 (-0.20)
<i>N</i>	19,712	18,660	21,412	21,412
r^2	0.106	0.00796	0.0238	0.00436
Year FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes

t statistics in parentheses

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

Using data from 1999–2011

import per worker lowers the district average wage by 1.37 percentage points. For the employment effect, as shown in column (3), a 1,000 USD higher import per worker increases the average share of employment by 0.151 percentage points.

Developing further on the industry-level change that could potentially be more nuanced, the study also constructed Rotemberg weight for the industries for the Bartik shift-share instrument approach. The results (with the industry weights applied accordingly to all the trading industry clusters covered in the main part of the analysis) appear more statistically muted, but the directions of change indicated by the estimates are still consistent with the main conclusions of the paper (Table 20).

8.6 Manufacturing industry

As the manufacturing industry accounts for a significant share of China's participation in international export trade, it is also expected that the partner country's manufacturing industry may experience a more significant negative impact. This section thus narrows the attention to this industry. From the results, it is seen that there still is a negative

Table 21 District-level manufacturing labour market outcomes (IV)

	(1) Wage	(2) Residual Wage	(3) Employment	(4) Underemployment
Δ IPW	−0.000227 (−0.90)	−0.000159 (−1.32)	−0.0000822 (−0.75)	0.000138* (2.41)
Female	0.103 (0.52)	−0.0631 (−0.53)	−0.0509 (−0.88)	0.0480 (0.94)
Youth	−0.425 (−1.26)	0.00296 (0.03)	−0.174* (−2.16)	0.133* (2.01)
Rural	−0.138 (−0.67)	−0.00763 (−0.16)	0.0833 (1.80)	−0.0138 (−0.45)
Educated	0.535 (1.85)	0.0873 (0.94)	0.0911 (1.10)	0.0197 (0.27)
Hindu	0.190 (0.92)	−0.0357 (−0.65)	0.000262 (0.01)	0.0542 (1.91)
Backward	−0.0212 (−0.29)	−0.0337 (−0.52)	−0.00433 (−0.15)	0.0223 (0.90)
<i>N</i>	4413	4377	5015	5015
r^2	0.0902	0.0101	0.0128	0.0232
Year FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes

t statistics in parentheses

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

Using data from 1999–2011

estimate of the wage effect, but statistically insignificant. On employment, the estimate is now negative, but still not statistically different from zero. The significant effect that has been identified is the positive effect on underemployment. The estimate is positive and significant at 5% level, indicating that a 1,000 USD increase in import per worker increases the average underemployment share by 0.138 percentage points. This may reflect evidence of labour reallocation due to trade competition. This channel may also hint at the labour market self-readjustment, which could explain the muted impact on wages and employment (Table 21).

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Data availability The key sources of data used in this paper include the National Sample Survey (NSS)-Employment and Unemployment Surveys (EUS) (NSSO n.d.), which is available online via the Indian Ministry of Statistics and Programme Implementation, and the Census of India (Government of India n.d.[d]), which can be retrieved from the website of the Office of the Registrar General & Census Commissioner, India. Relevant sampling methods and information are also available from the respective websites. A working paper version of this study has been published: Shi, F., 2022. *Import Shock and Local Labour Market Outcomes: A Sino-Indian Case Study* (No. 04-2022). Economics Section, The Graduate Institute of International Studies. The data treatment for analysis has been modified since then, and the results have also been updated.

Declarations

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