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Import Shock and Local Labour Market Outcomes: A Sino-Indian Case Study

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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 comparing with prior studies. The range of labour market outcome variables examined is also much wider, including wage, residual wage fluctuation, and employment and underemployment as shares of working-age population. By exploiting spatial variations in industrial activities and labour participation in the industries, the paper finds that, unlike in some other cases, the import competition from China did not have a significant impact on the Indian district average wages. However, it did result in an increase in employment share. In further contribution, the paper also 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 certain socio-economic characteristics.

JEL classification: F14; F16; J16

Keywords: International Trade, Wages, Income Inequality, Import shock, Underemployment

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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 Heckscher Ohlin model suggests that trade can have 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 affect employment and wage of the respective industries in a developed economy and aggravate 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, Dorn, and Hanson (2013, 2016) find that rising import competition had a detrimental impact on employment in the US, whereas Choi and Xu (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. However, 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 examining 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 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 valuing 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 constitutes a quasi-experiment setting, makes it an interesting South-South case to investigate the labour market impacts of 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 in industrial activities and labour compositions. As these differences can translate to different levels of exposure to trade shock, they are used here to create the weighted import per worker index to examine the impact of import competition on local labour markets. The four variables used to represent the different aspects of change in the Indian local labour markets include district-level average log wage, residual wage variance, and employment and underemployment as shares of the working-age population. To study such relationships, this paper uses detailed trade and Indian labour data and focuses on the Sino-Indian trade dynamics in the late 1990s to early 2010s. Using the variations following China's accession into the WTO, it investigates the impacts of the drastic increase in import exposure on the local labour markets.

To access 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 shares of manufacturing workers, female, youth, rural, educated, Hindu population and share of population defined as from "backward" social groups[2]. However, endogeneity problem stemming from confounding variables is suspected for the OLS estimations. The instrumental variables estimation (IV) is therefore adopted 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 Indonesia, Malaysia and the Philippines. 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.

By focusing on South-South trade, this paper contributes to the literature in this understudied but growing area of international trade and development. It uses local labour market data on the district-level and detailed individual-level socio-economic information[3] to provide a micro-foundation in the examination of trade and competition's labour market impacts. Comparing with existing studies, the novelty of the pa-

[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 is 511.

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

[3] Such as age, gender, level of education, religion, social group, wage, employment, industrial class of activity and so on. Detailed information is available below in the data section and in the appendix at the end.

per concentrates on the significant improvement of 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 records of the districts, this study increases the data coverage from 366 districts (ibid.) 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 on 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, section 2 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 the economic shocks. Section 3 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 on the international trade activities today, such as South-South trade. Moving to a different approach, this section then briefly summarises some empirical examinations on the effects of import competition. Explanations on the methodology and data used for this paper's investigation are provided in section 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 section 6, and then section 7 concludes the paper.

2 Historical Background

2.1 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 side line (Topalova and Khandelwal 2011, p.996).

It was not until the mid-80s did the sluggish growth motivate 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 is positive, it remained slow and close to linear. Going from the 80s to the 90s, however, the growth rate went from 3.5% to around 5%, reflecting the acceleration during this period (Kotwal, Ramaswami, and Wadhwa 2011). Overall, the GDP increased from around 220 billion USD to 1.2 trillion USD[4] for the period of 1970 to 2005 (World Bank n.d.).

When looking at the drivers of growth, the Indian case shows 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 (T. Roy 2012). The richer supply of talent coupling with rupee depreciation thus makes Indian products

[4]The GDP values are in terms of constant 2010 USD value.

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 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 (S. 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 (T. Roy 2012). This is also reflected by growth of India's export to the world. Banik (2001) records that the years 1995-96 saw a 63% rise in Indian export of electronic goods and 13.9% in machinery and instruments.

2.2 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, labour 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 manufacture, for example, experienced a significant increase in employment growth. The growth rate going from 1977(-78)-1983 to 1987(-88)-1993(-94)[5] more than five-folded. Moreover, there also was an increase in self-employment in the 90s (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 (T. Roy 2012).

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

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 (ibid., p.165). Without 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 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 et al. (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 going 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 Rodgers 2017). Beside 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 opportunity and wages for those that 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.

3 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. While newer theories have been developed to examine possible micro-level drivers, the empirical investigation is limited by the availability of firm-level data, therefore it is not discussed here. On the empirical side, this section also reviews some existing studies that use classic trade theories as foundations, and examine the impacts of import shocks and their re-distributive powers.

3.1 International trade theories

Classic trade theories widely cited in empirical researches largely focus on comparative advantage in motivating trade. To highlight the distinctions in comparative advantages, the modelling of these theories are mostly on North-South trade. The assumption is that the developed countries (North) have better access to capitals, whereas developing countries, such as India, are assumed to 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, Fischer, and Samuelson 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 in exchange of the other good that has a higher opportunity cost. India, as a country from the global "South", is expected to have different technologies comparing with advanced economies. As it 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 chemicals[6] 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. Comparing against empirical observations, the key sectors of exports are largely as expected. However, as the theory does not provide clear indication on the specific variables beyond predicting specialisation, further investigation is still required identify the effect of trade shock on labour market outcomes.

Looking more towards the 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. In the case of India, therefore, it is 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 (Alburo and Abella 2002; Birdsall and Sabot 1991; Esteve-Volart 2004).

In addition to the difficulty in meeting the conditions set in the models, the international trade relations are also more complex in the real world than the models. For example, migration can change the endowments of countries, and labour markets also have frictions that can hinder mobility. Moreover, focusing on the pairing of 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,

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

despite the demand for the 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 can be more challenging to fit South-South trade into the settings of these classic international trade models. Newer trade theories, such as the Krugman (1979) model and the Melitz (2003) model, on the other hand, step beyond the concept of comparative advantage, and of using nation as the unit of analysis. However, it is difficult to identify the exact macro-level labour market dynamics, and to procure detailed firm-level data, particularly in the context of developing countries. Due to these limitations, it is imprudent to solely examine through the theoretical approach the direction and magnitude of the effects, if any, of China's accession into the WTO on the Indian local labour markets. This paper thus looks to the empirical side for identification.

3.2 Effect of import competition

China's accession to the WTO, with its significant impact on world trade, provides a quasi-experiment setting. Arguably, the higher availability of cheap labour may crowd out labour from partner countries base on the cost-effectiveness. Thus, welfare and developmental implications are to be expected. The classic Autor, Dorn, and Hanson (2013) paper investigates the effect of China's imports on the US's local labour market. In order to identify the causality, they construct an import competition exposure index for each commuting zone in the US. To resolve the endogeneity problem, they instrument China's import to the US with that to other key partner countries, which, during the same period, experienced drastic growth in import coming from China and similarly modest from other regions. 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, 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 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 Xu (2020) study trade between South Korea and China between 1993 and 2003. South Korea is seen as a highly developed economy, thus the relationship still classifies as North-South trade. 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[7], they find that, while tariff-form of trade restrictions have a significant negative effect on wage, that of imports is positive and significant. Moreover, they also identify that more trade activities are linked with lower wage differentials within the same industry's same professional occupation across countries.

As seen above, the North-South combination is widely used to test standard theory predictions. With increased globalisation, there is a need to focus on South-South trade relationships, but this is more theoretically ambiguous in terms of predictions. India, for example, is a typical large-size developing economy sharing some similarities in factor endowment as China. Some papers thus focus on this trade relationship, which is more theoretically ambiguous in its prediction. Owing to a growing import surge from China, Deb and Hauk (2020) try to identify any 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 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. The more recent studies such as Saha et al. (2021) corroborate these findings using district-level data.

4 Method and Data

As theories have a limited application in this setting and the evidence from other studies have 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.

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

4.1 Method

Four key labour market variables are the centre for this investigation, namely the change in district average log wage[8], average log residual wage variance[9], the share of employed workers[10] against the working-age population and the share of underemployed workers against the working-age population[11]. 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, 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 trade shock, it also represents the districts' levels of susceptibility to the shock. The IPW index's constructions here broadly follows that in the classic study of Autor, Dorn, and Hanson (2013):

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

where d denotes district, t denotes the year, and i denotes the industry. Different from the Autor, Dorn, and Hanson (ibid.) paper[12], 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. $\triangle Import$ 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,

[8]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 of 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 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.

[9]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) are then used in the analysis.

[10]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.)).

[11]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).

[12]The results with long-differenced data as in this paper are also presented in the additional result section. Since the last round of labour-side survey was conducted with a much shorter interval, some interpolation was done to create panel with three-year interval. While the level of significance for some findings changed, the estimated direction and magnitude of impacts are roughly inline with the year-on-year results.

$Employment_{dt}$ is the number of people employed in a district d in year t, and $Employment_{dit}$ the number of people employed in industry i in district d in year t. With these four components, the $\triangle IPW_{dt}$ is generated for each district for each according year, namely, for each industry, the per worker import trade values for the district is adjusted by its 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 followed:

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

where $\triangle L_{dt}$ 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 C'_{it}, and year dummies. The control matrix includes the lagged district share[13] 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 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, 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 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

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

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:

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

where, in addition to the OLS specification, $\triangle\widehat{IPW}_{dt(g)}$ is instrumented by $\triangle IPW_{IV_{d_t}}$ 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 included[14] 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.

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 employment[15] by industry, and the ratio of female employment for each district. For the analysis, the data

[14] Details on the group divisions are available in the 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.

[15] 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. Statistics on other categories are less relevant, thus excluded, but are available in the survey.

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 provides relatively more rounds of data in the period of interest. As it is a 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, is a primary source of labour data that include micro-level records on labours' characteristics, such as weekly wage[16], 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 wages variance is also calculated by first identifying the leftover wage after accounting for the level of education successfully completed, work time, and then calculating the weighted district-level variance.

As China's accession took place on December the 11$^{\text{th}}$ 2001, the most appropriate rounds of the NSS data for the investigation are the 55$^{\text{th}}$ (1999-2000), the 61$^{\text{st}}$ (2004-2005), the 66$^{\text{th}}$ (2009-2010), and the 68$^{\text{th}}$ (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 a linear interpolation.

On the control side, the district-level characteristics include the share of highly educated population, the share of 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 worker, and the share of underemployment are investigated. Youth worker here is defined as those that normally engage in paid

[16]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 are 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.

work as categorised by their usual principle working status[17], 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 (NSSO 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 with 366 districts out of over 500 districts based on the division at the time of the earliest round of Survey. While some studies, like 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 in 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[18]. 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 468 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, thus were beyond the coverage of the NSS Survey. Secondly, the geographical change of some districts are complex, in that one district can be formed by taking various blocks or tehsil 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 coding standard most similar to that of the NSS

[17] The categories considered here are consistent with that for district employment.

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

data, the trade data were then procured from the World Integrated Trade Solution (WITS) software with ISIC revision 3 system of product coding[19]. In order to have a meaningful number of observations for each industry, the final grouping of NIC and trade product 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. In a previous study, import data from Bangladesh and South Korea were included in the analysis as instruments. However, there exists a gap in the detailed data with the same coding system for the years required for Bangladesh, and data from South Korea was found to have weak correlation with those from India. Therefore, this paper uses the trade values from Indonesia, Malaysia and the Philippines as instrument for India' 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 the left-hand-side figure below[20]. Pre-2001, the import and export were close in value and showed 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 is visibly accelerating, while export trade rather 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 the right-hand-side figure below[21]. For each district, the share of the worker employed in the manufacturing industry is calculated for the rounds of surveys available. Then it is plotted against the average estimated import per worker[22] for the according years. It is visible that,

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

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

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

[22] The import per worker is calculated with $\triangle$import value and thus should be considered when interpreting.

despite both districts' average share of manufacturing employment and average import per worker were trending up going 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[23]. 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 is observed to bounce back with higher growth than that of manufacturing employment share.

Figure 1: Sino-Indian Trade Values

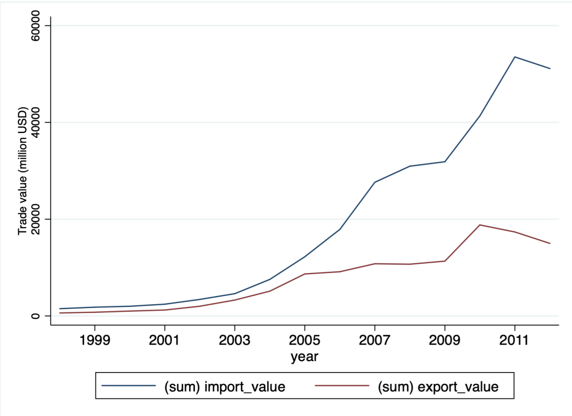
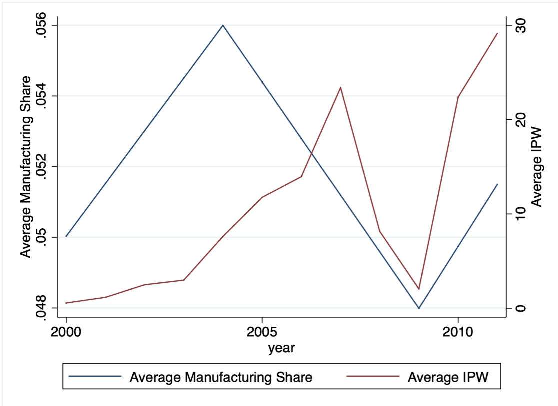


Figure 2: Average District Manufacturing Employment Share and IPW



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 (OECD 2021). For the variables of interest, the district-level weighted mean log wage and residual are calculated for the according years, also the share of employed and underemployed workers as shares of working-age residences in the according year and districts. From the table below, 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 10$^{\text{th}}$ percentile and that at the 90$^{\text{th}}$ percentile has also become smaller. The 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 going 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, it is possible to also investigate

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

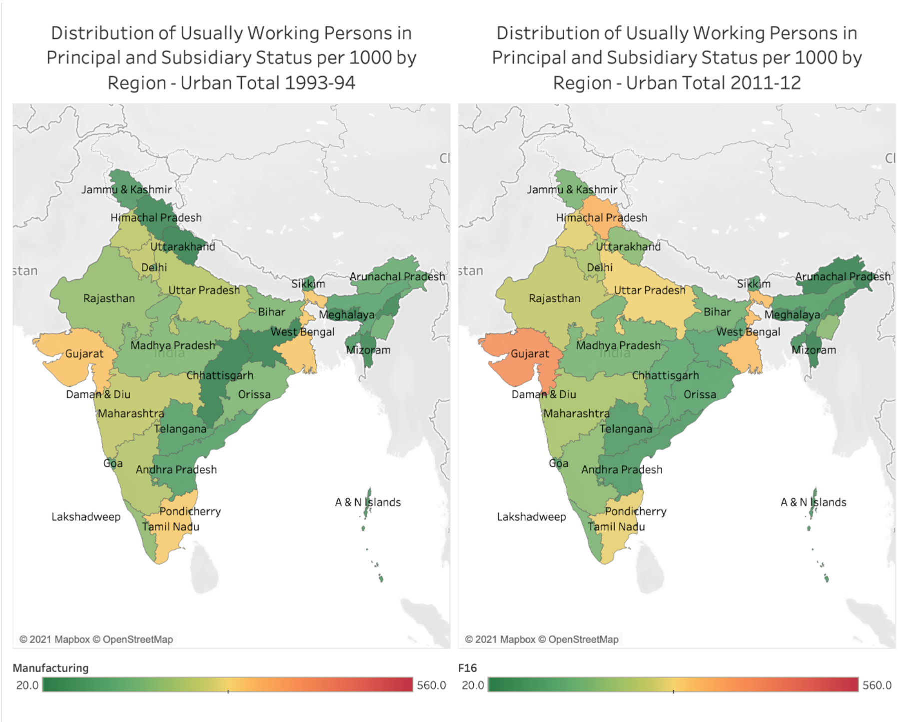
the changes in districts' share of workers that were underemployed in a normally invisible way. From 1999 to 2011, it is seen that the average district share of underemployment has decreased. This could mean that the labours are being more effectively hired and allocated in the market, and the training they received is becoming better matched with the sectors' ability to employ workers. The gap between the 10^{th} and 90^{th} 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, that differently trained workers could be employed in their usual field, other districts became more specialised in a few industries, and 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 going 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 10^{th} to the 90^{th} percentile, there is a significant difference in the levels of exposure, which can be used to identify the impacts of the import shock.

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

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 principle and (or) subsidiary activity across the 28 states[24], 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 finding in the table above.

Figure 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.

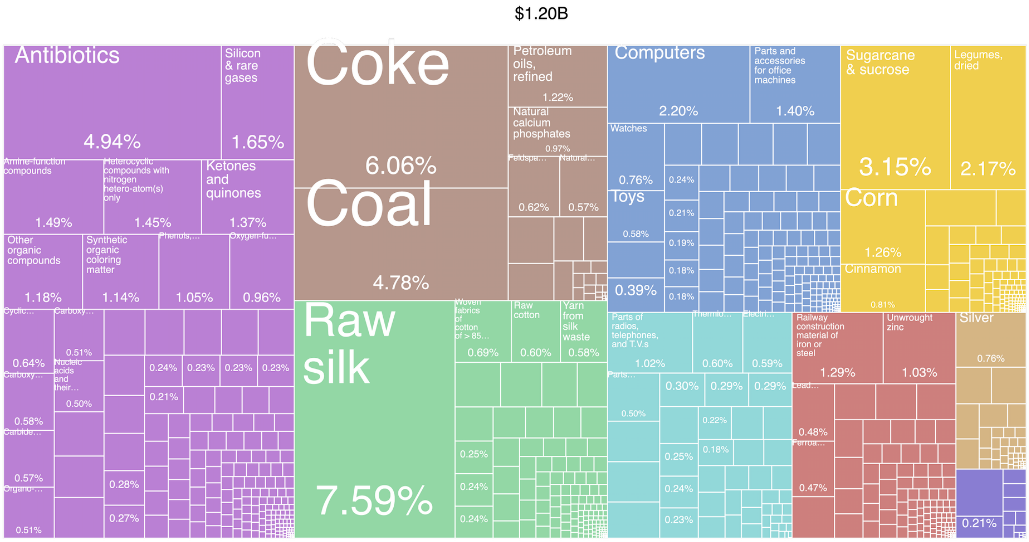
On the trade side, the origins and content of India's imports have also evolved in the period of interest. Following China's accession into the WTO, the share of imports from China has increased significantly (Harvard Growth Lab n.d.) for India. In recent years, China also became one of the largest trading 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" (ibid.). 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 are more

[24] The density is measured per 1000. 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 the Andhra Pradesh prior to the separation, 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.

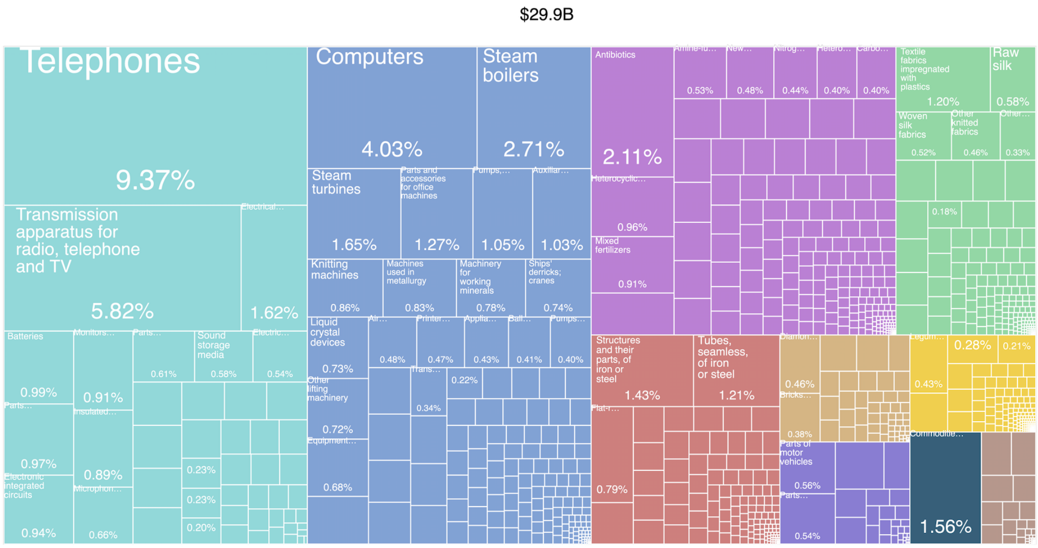
heavily concentrated in the chemical, agriculture and minerals sectors. The top goods imported were raw silk (7.59%) and coke (6.06%). In 2009, on the other hand, the sectors of concentration shifted significantly to electronics and machinery. The most imported goods include telephones (9.37%), transmission 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.

Figure 4: Change in the Content of India's Imports from China

(a) 1999



(b) 2009



Source: The Atlas of Economic Complexity, (Harvard Growth Lab n.d.).

5.2 Baseline regression results

Following the general econometric model, this subsection presents the results of baseline OLS estimations. The order of the variables for investigation is firstly district average log wage, then average residual log wage, followed by the share of employment and share of underemployment[25]. The variables generated for the analysis on group levels are weighted by the multipliers provided along with individual entries. For each specification, the standard errors are clustered at the state level, and year dummies are added as specified.

5.2.1 District average wage

Table 2: Chinese imports and district average wage (OLS)

	(1)	(2)	(3)	(4)	(5)
△ IPW	0.00128***	-0.000346	-0.000435	-0.000353	-0.000263
	(7.25)	(-1.65)	(-1.61)	(-1.50)	(-1.11)
Manufacture			0.0359	0.0885	0.0845
			(0.86)	(2.02)	(1.81)
Female				0.0000955	-0.00510
				(0.00)	(-0.14)
Youth				-0.139***	-0.129***
				(-4.01)	(-3.89)
Rural				0.0405***	0.0261
				(4.10)	(1.73)
Educated					-0.0454
					(-1.23)
Hindu					-0.00572
					(-0.60)
Backward					0.0246**
					(2.87)
N	5651	5651	5651	5651	5651
year dummy	no	yes	yes	yes	yes

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Firstly, the import exposure indices are regressed on the districts' change in average log wage. The results show that generally there is not a statistically significant relationship between import per worker and

[25]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

districts' average log wage. When the average daily log wage is regressed solely on the import per worker index, the coefficient is positive and significant at 0.1% level. This means that, as the district's import exposure increases, the district's log average wage is also expected to increase, that a rise of 1000 USD in district's per worker exposure to import is correlated to 1.28 higher log points in the average district log daily wage. However, as the model does not include further controls for potentially changing district-level characteristics, the estimate is most likely to be biased. When the year dummy is introduced to account for the year-specific variation, the estimate dropped from positive to negative. This indicates that the year-specific variations in district change in average wage could have contributed to the positive effect estimated in column (1), while the correlation with import per worker is not statistically different from zero. The estimates for this index also remains insignificant across specifications from column (3) to (5) where more detailed district-level controls are added. 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.

On other observations, column (4) includes the demographic controls for the lagged share of female, youth and rural populations. The results show that districts with a higher share of youth are estimated to have decreasing log wages, and the estimate remains negative and significant at 0.1% level when the full set of controls are added. From speculation, a possible explanation for this observation could be about the type of work youth workers usually engage in. As younger workers tend to have a limited time frame for education and training, it is possible that jobs that have relatively low requirements in education and training became more available for the younger workers, but at the same time lock them in lower wages. District share of the population from "backward" social groups, however, has a positive significant estimate in column (5) when all the control variables are included, reflecting a possible improvement in earnings for this sub-population.

5.2.2 District residual wage variance

Table 3: Chinese imports and district residual wage variance (OLS)

	(1)	(2)	(3)	(4)	(5)
△ IPW	-0.0000958	-0.000130*	-0.0000756	-0.0000612	-0.0000597
	(-1.68)	(-2.20)	(-0.89)	(-0.73)	(-0.74)
Manufacture			-0.0218	-0.0131	-0.00715
			(-1.06)	(-0.58)	(-0.31)
Female				-0.0204	-0.0163
				(-1.53)	(-1.37)

Youth				-0.00418	-0.00680
				(-0.31)	(-0.49)
Rural				0.00661*	0.00697
				(2.04)	(1.55)
Educated					-0.00139
					(-0.10)
Hindu					-0.00767*
					(-2.25)
Backward					-0.00265
					(-0.68)
N	5651	5651	5651	5651	5651
year dummy	no	yes	yes	yes	yes

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

For the analysis of the district residual wage variances, if the coefficient on 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 the first row of the table below, the coefficient estimates for the import per worker index are negative across the specification. This means that the higher the import exposure of a district, the lower the fluctuations in residual wage in the district after controlling for education, work status and occupation division. This finding is consistent with the neoclassical argument that, as trade intensifies, competition makes the cost of discrimination amongst workers of different socio-economic groups more costly, thus improves the level of inequality (Becker 1985). However, for the findings here, the import per worker index estimate is significant at 5% level when only year and lagged manufacturing worker share are controlled, but it became not statistically different from zero once further demographic and socio-economic controls are added. Therefore, there is no strong evidence for a correlation between import competition exposure and residual wage fluctuations. For the control variables, in the specification with the full set of controls, the estimate for lagged share of Hindu population remains negative and statistically significant at 5%. This signifies that when increasing lagged share of the Hindu population in a district is correlated with decreasing residual wage fluctuations, which could be a reflection of clustering in religious groups and differentiated outcome dynamics across them.

5.2.3 District employment share

Table 4: Chinese imports and district employment rate (OLS)

	(1)	(2)	(3)	(4)	(5)
$\triangle IPW$	-0.0000303	0.000109*	0.000186**	0.000180**	0.000168*
	(-0.65)	(2.11)	(3.15)	(2.88)	(2.61)
Manufacture			-0.0308**	-0.0335**	-0.0322**
			(-2.89)	(-3.21)	(-2.96)
Female				0.0180*	0.0202*
				(2.31)	(2.72)
Youth				0.0336***	0.0312***
				(4.03)	(4.18)
Rural				-0.00364	-0.00296
				(-1.91)	(-1.36)
Educated					-0.00320
					(-0.35)
Hindu					-0.000527
					(-0.22)
Backward					-0.00736**
					(-3.61)
N	5676	5676	5676	5676	5676
year dummy	no	yes	yes	yes	yes

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

For the argument of 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. In column (1), the estimation is indeed negative. However, it does not control for any other district characteristics and also is not statistically different from zero. As soon as the year control is added, the result became positive and significant. In column (3), the lagged share of manufacturing workers is added, the result indicates that a 1000 USD rise in district's import per worker is correlated to a 0.186 percentage points increase in employment share. While this estimate decreases as more controls are added in the specifications, the change is relatively modest and the estimates remain statistically significant. When all controls are added, column (5) shows that a rise of 1000 USD in the district's import per worker is correlated to 0.168 percentage points higher district employment share. This result is also statistically significant at the 5% level. 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 positive significant relationship between districts' import exposure and share of employment.

Besides the variable of interest, the results also show a negative relationship between districts' share of manufacturing workers and district employment share. Lagged youth share, on the other hand, has a positive estimate in column (5) with a 0.1% level significance. It entails that, for a 1 percentage point increase in lagged youth population share, the district level of employment is expected to rise by 0.0312 percentage points. Seeing together with the estimate from district change in average log wage, it is possible that the youth gained more employment opportunities, but perhaps mostly for low-paying work. For the lagged share of the population belonging to the "backward" social groups, the results from wage and employment seem to suggest the opposite of those for youth. It is found that, while there is a positive relationship with district average log wage, a 1 percentage point increase in the share of this sub-population translates to 0.00736 percentage points drop in employment share, which could be a sign of the difficulties they face in seeking recognised employment in the local labour markets.

5.2.4 District underemployment share

Table 5: Chinese imports and district underemployment rate (OLS)

	(1)	(2)	(3)	(4)	(5)
$\triangle IPW$	0.0000466	-0.0000547	-0.0000644	-0.0000640	-0.0000639
	(1.79)	(-1.75)	(-1.65)	(-1.60)	(-1.71)
Manufacture			0.00392	0.00430	0.00196
			(0.58)	(0.64)	(0.31)
Female				0.00318	0.00181
				(0.34)	(0.20)
Youth				0.00709	0.00784
				(0.98)	(1.17)
Rural				-0.000116	-0.000833
				(-0.09)	(-0.33)
Educated					-0.00326
					(-0.39)
Hindu					0.00273
					(1.79)

Backward					-0.000160
					(-0.14)
N	5676	5676	5676	5676	5676
year dummy	no	yes	yes	yes	yes

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

When looking at the share of people working in fields other than their usual principle 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 results, it is estimated that the import per worker index generally is negatively correlated with the district share of underemployment. This, when significant, can be a reflection of the potential positive effects of import trade competition on the efficiency of production factor allocation. The p-value of the estimates, however, are greater than the critical values, thus the analysis fails to reject the null hypothesis of the coefficient being zero, in that import per worker and underemployment share are not correlated. The magnitude of the estimates are also quite small, which could be because the shares of the underemployed population, in general, are quite low. On other variables, lagged share of female, youth and Hindu population all have positive estimates. This could be an indication of a higher chance of being inefficiently employed for these sub-populations. However, the estimates are still not significant, there is not a clear correlation identified using this sample.

5.3 Instrumental variable results

Using the trade data from Indonesia, Malaysia and the Philippines, 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 $IPW_{IV_{d_t}}$ is a strong instrument for $\triangle IPW_{dt}$ for the two-stage least squares analyses. The results of the second stage with the full set of controls are shown in the table below:

Table 6: District-level labour market outcomes (IV)

	(1)	(2)	(3)	(4)
	Wage	Residual Wage	Employment	Underemployment
$\triangle IPW$	-0.000464	0.0000959	0.000246***	-0.0000694
	(-1.69)	(0.75)	(3.97)	(-1.66)
Manufacture	0.102*	-0.0281	-0.0478***	0.00899
	(2.26)	(-1.03)	(-4.60)	(1.27)

Female	-0.0349	-0.00895	0.0240**	0.00655
	(-0.75)	(-0.65)	(2.62)	(0.75)
Youth	-0.0931	-0.0298*	0.0362***	-0.00413
	(-1.73)	(-2.10)	(4.46)	(-0.59)
Rural	0.0363*	0.00116	-0.00415	-0.000916
	(2.09)	(0.24)	(-1.64)	(-0.33)
Educated	-0.0269	-0.0303*	-0.0116	-0.00384
	(-0.59)	(-2.02)	(-1.16)	(-0.38)
Hindu	-0.0148	-0.000253	-0.000705	0.00369
	(-0.80)	(-0.06)	(-0.34)	(1.63)
Backward	0.0114	0.000325	-0.00748*	-0.000861
	(1.05)	(0.08)	(-2.56)	(-0.52)
N	5651	5651	5676	5676

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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 suggests that an increase of 1000 USD in import per worker is estimated to reduce the district average log wage by 0.464 log points. However, the estimate is not statistically different from zero. Therefore, from this sample, it is seen that import per worker has no meaningful impact on district average log wage. This is also for the district-level variance of residual wage in column (2) and underemployment share in column (4). For employment share, however, the estimate remains positive and became more statistically significant. As shown in column (3), a 1000 USD higher import per worker is found to increase the district share of employment by 0.246 percentage points. This is in line with the finding in Choi and Xu (2020). Therefore, the district-level analyses reflect that, while for the wage-related variables and for underemployment, the import exposure measure by the import per worker index is not estimated to have statistically significant effects, the impact estimated on district share of employment is positive and significant. From speculation, this result may be due to a rise in intermediate goods' trade between India and China, which could also raise the demand for domestic workers in certain sectors (WTO 2017).

For the control variables, it is interesting to note that, for lagged manufacturing share, a one percentage point increase translates to a 0.0478 percentage point decrease in district share of employment. This could mean that the manufacturing sector is shrinking in terms of human capital. The direction of effect is the same for the lagged share of the population of "backward" social groups, which also mirrors its OLS estimation. This finding could be a reflection of caste-based labour market discrimination. On the lagged share of youth, it is found that a higher share of the youth population is estimated to have lower residual wage variance and higher employment rate. The estimate for wage is negative, but it is no longer significantly different from zero. These findings are still largely consistent with the speculation from the OLS estimations, that the youth in the Indian labour market could be locked in growing but low-paying jobs. However, key components of the analyses are evaluated on the district level, it is difficult to discuss more detailed associations between import shock and socio-economic groups.

5.4 Results by socio-economic groups

By looking at district-level outcomes, it is seen that, aside from employment, there is little evidence that the trade shock affected the Indian labour markets. One potential explanation for this finding 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, while 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[26].

5.4.1 Consumption group

First, the impact of trade shock is allowed to vary across different consumption groups. The results are shown in the table below:

Table 7: Consumption group-level labour market outcomes (IV)

	(1)	(2)	(3)	(4)
	Wage	Residual Wage Variance	Employment	Underemployment
$\triangle IPW$	-0.00271***	0.0000987	0.000328***	-0.0000160
	(-6.90)	(1.09)	(3.49)	(-0.55)
sss2	0.00219***	-0.0000852	-0.000208*	-0.000105**

[26]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. It should also be noted that, when the analysis is with regards to one dimension of the socio-economic groups, attenuation in estimations is still possible from the other dimension of the individuals' characteristics.

	(7.56)	(-1.15)	(-2.07)	(-2.70)
sss3	0.00465***	0.000169	-0.000373**	0.00000675
	(7.76)	(1.46)	(-3.13)	(0.15)
group2	-0.125***	0.00110	0.0126***	0.00275***
	(-21.91)	(0.91)	(7.05)	(6.54)
group3	-0.257***	-0.0130***	0.0108***	0.00476***
	(-22.54)	(-5.20)	(3.55)	(4.41)
N	16682	16682	16973	16973

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Focusing on the first row, the import per worker index here estimates the effect on the individuals that belong to the 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. On employment share, the import per worker has a significant positive effect for the top spending groups, but the effect is much lower for the individuals coming from the middle bracket [27] and negative for the bottom group [28]. Regarding underemployment, the import per worker is estimated to have a negative effect for the people from the middle bracket, which means that they are less likely to be working in a field that is not their usual principle field. This effect for the other two groups, however, are not statistically different from zero. In another word, 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 for the top and bottom groups.

5.4.2 Age group

Table 8: Age group-level labour market outcomes (IV)

	(1)	(2)	(3)	(4)
	Wage	Residual Wage	Employment	Underemployment
$\triangle IPW$	-0.000845	-0.0000632	0.0000389	0.000143
	(-1.27)	(-0.33)	(0.30)	(1.61)
$\triangle IPW * age2$	0.0000505	0.0000182	0.0000369	-0.000101*

[27]This includes rural households, which have non-agricultural activity as their principal source of earning, and urban households with an MPCE in the middle 60%.

[28]This includes all the other rural households not yet listed and the urban households with MPCE in the bottom 30% bracket.

	(0.27)	(0.25)	(0.38)	(-2.57)
$\triangle IPW * age3$	-0.0000230	0.000114	0.0000427	-0.0000802**
	(-0.08)	(1.70)	(0.59)	(-2.63)
$\triangle IPW * age4$	0.000550	0.000152	0.000222**	-0.0000961
	(1.56)	(1.39)	(2.80)	(-1.72)
group2	0.00978***	-0.00287**	-0.00256*	0.000150
	(4.42)	(-3.04)	(-2.05)	(0.37)
group3	0.0113***	-0.00401***	-0.00478***	0.0000662
	(3.95)	(-4.08)	(-4.15)	(0.13)
group4	0.0000839	-0.00610***	-0.00952***	-0.000989
	(0.02)	(-4.67)	(-9.65)	(-1.92)
N	22377	22377	22704	22704

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

As the share of youth population shows interesting findings in the district-level investigation, this section aims to see if the effects of import shock can also differ across different age groups. From the table above, it is seen that, for the two wage-related specifications, there is no significant distinction in the estimates of import per worker's impacts on the variables for the according groups. However, from the group dummies, it is seen that there is a concave relationship between district-group-wise average log wage and age. For employment share, it is seen that the impact of import exposure is significantly positive for the oldest group. This could be because import increases the demand for experienced labour, which disproportionately benefits the higher age groups. Regarding the age group dummies, the older labour groups still have relatively lower growth in employment comparing with the younger groups. For underemployment, it is seen that import per worker tends to decrease the share of underemployment among the younger groups, but the effect is insignificant for the highest age group. This means that import exposure is estimated to have a positive impact on employment efficiency for younger age groups.

5.4.3 Gender

When the effects are allowed to vary by gender groups, it is seen that the estimate for males is negative regarding group average log wage, but that for the female is positive. This could mean that import competition actually improves the average earnings for females. However, as the results are not statistically significant, 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, but it is observed that the import per work continues to show a positive significant effect on group employment share, and female groups tend to have a lower employment share than their male counterparts.

Table 9: Gender group-level labour market outcomes (IV)

	(1)	(2)	(3)	(4)
	Wage	Residual Wage	Employment	Underemployment
$\triangle IPW$	-0.000515	0.0000177	0.000241*	0.0000155
	(-1.30)	(0.17)	(2.19)	(0.22)
$\triangle IPW * Female$	0.0000672	0.0000857	-0.0000359	-0.0000528
	(0.22)	(1.69)	(-0.42)	(-1.31)
Female Group	0.00655	-0.000611	-0.00264*	0.000355
	(1.30)	(-0.83)	(-2.16)	(0.56)
N	11202	11193	11352	11352

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

5.4.4 Occupation groups

Table 10: Occupation Group-level labour market outcomes (IV)

	(1)	(2)	(3)	(4)
	Wage	Residual Wage	Employment	Underemployment
$\triangle IPW$	0.000549*	0.0000922	-0.0000708	-0.0000234
	(2.05)	(0.68)	(-1.04)	(-0.29)
$\triangle IPW * Production$	-0.00215***	-0.000000365	0.000422***	-0.000134**
	(-7.19)	(-0.00)	(6.23)	(-2.58)
Production	0.111***	0.00179	-0.0202***	0.00379*
	(11.22)	(0.76)	(-10.11)	(2.12)
N	11262	11262	11262	11262

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Another dimension through which the impact of import shock may produce heterogeneous effects is by occupation groups. This investigation implemented a bifurcation 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 import goods. For the group not directly related to production, the impact of import per worker is positive, but only at 5% significance level. This positive result may be because of the increase in importance and return for trained labour. For employment, however, the import per worker has a highly significant positive effect on the employment share of production- and sales-related workers, but no significant effect for the other group. A 1000 USD rise in import per worker is estimated to increase the production- and sales-related group's employment share by 0.422 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, higher import per worker translates to a lower share of underemployment for the production- and sales-related workers, which is consistent with the speculation of rising employment in the sector and improved employment efficiency.

5.4.5 Industrial groups

Table 11: Industrial group-level labour market outcomes (IV)

	(1)	(2)	(3)	(4)
	Wage	Residual Wage	Employment	Underemployment
$\triangle IPW$	-0.000320	0.0000537	0.0000520	-0.0000782
	(-1.16)	(0.60)	(1.68)	(-1.81)
$\triangle IPW * Sales$	-0.000442	0.0000860	0.0000784*	-0.0000520
	(-1.68)	(0.75)	(2.07)	(-1.21)
$\triangle IPW * Others$	-0.000522	0.000130	-0.0000229	0.0000563
	(-1.31)	(0.88)	(-0.75)	(1.17)
$\triangle IPW * Blue$	-0.000554*	0.0000265	-0.0000782	0.000353**
	(-2.09)	(0.17)	(-1.08)	(2.96)
Sales	0.00501	-0.00440*	-0.00264***	0.00113
	(0.78)	(-2.33)	(-5.68)	(1.32)
Others	-0.00542	-0.00573**	-0.0000757	0.000384
	(-1.14)	(-3.17)	(-0.10)	(0.50)
Blue	0.0247***	-0.00650**	0.00153	0.00159
	(3.79)	(-2.96)	(1.12)	(1.21)
N	16682	16682	16682	16682

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Four groups were identified to see if the impact of import competition varies. These include people working in hospitality and sales (Sales), manufacture, agriculture and mining (Blue), storage, communication and financial services (Services) and others (Others)[29]. While the estimates for the "Service" industrial group are not significant, import per worker has a positive impact on employment for people working in the "Sales" industrial group. A 1000 USD increase in import per worker is estimated to increase employment by 0.0784 percentage points. Here it is speculated that, as a result of the import growth, activities in the "Sales" industries became more active, thus attracted the most employment growth. Significant results are also observed for the "Blue" industrial group. For them, the group average log wage seems to be negatively affected by the import per worker - a 1000 USD increase in import per worker lowers the average wage by 0.554 log points, significant at the 5% level. The effect on employment is insignificant. As this group includes workers in manufacturing, it can be an indication of a previously attenuated effect, that is increased import competition depressed average wages without visibly affecting employment. For underemployment, it is estimated that a 1000 USD increase in import per worker raises the share of underemployment for the "Blue" industrial group by 0.353 percentage points, significant at 1% level. This suggests that people tend to find other subsidiary work to complement their work and earnings in the "Blue" industries.

5.5 Additional long-difference examination

In comparison with prior works, this study uses year-on-year changes in variables to conduct the analysis. There are two reasons for this change in methodology. Firstly, the trade-side data is available on an annual basis. By conducting year-on-year investigation, the more detailed trade-side variations can be accounted for, particularly assuming long and relatively smooth adjustments on the labour side. Secondly, labour-side survey data were collected at relatively short and inconsistent intervals. With year-on-year analysis, more rounds of the NSSO surveys can be included in the analysis, and the difference in intervals can also be accounted for. However, to further verify the findings more in line with the Autor, Dorn, and Hanson (2013) paper, long-difference analysis [30] is also completed to verify the consistency of the results. As the OLS estimations suffer from endogeneity issues, only the IV estimations are presented here. It is seen that the results are robust against data changes and are still largely consistent with those obtained from the year-on-year analysis in terms of significance and direction. For wage, residual wage, and rate of underemployment, the estimated coefficients on the import per work index remain statistically insignificant. Regarding the rate of employment, the result from long-difference data shows larger magnitude of impact, that 1000 USD higher import per worker is found to increase the district share of employment by 0.988 percentage points.

[29] Details are provided in the appendix.

[30] Here the long-difference is considered with three-year interval, giving four periods of differenced data in total.

Table 12: District-level labour market outcomes (IV - Additional)

	(1)	(2)	(3)	(4)
	Wage	Residual Wage	Employment	Underemployment
$\triangle IPW$	-0.000716	0.000329	0.000988***	-0.0000871
	(-0.68)	(0.97)	(5.80)	(-0.62)
Manufacture	-0.163	0.0386	-0.537***	-0.00522
	(-0.35)	(0.19)	(-5.37)	(-0.06)
Female	0.0884	-0.328*	0.236**	-0.0440
	(0.36)	(-2.31)	(2.71)	(-0.49)
Youth	0.408	-0.263**	0.246***	-0.0690
	(1.12)	(-2.96)	(4.44)	(-1.45)
Rural	-0.0328	-0.00334	-0.0253	-0.00461
	(-0.25)	(-0.06)	(-0.88)	(-0.16)
Education	-1.021**	-0.250**	0.0786	-0.117
	(-2.85)	(-2.73)	(1.22)	(-1.22)
Hindu	0.0170	-0.0345	-0.000642	0.0168
	(0.17)	(-1.11)	(-0.04)	(1.06)
Backward	-0.123	0.0397	-0.0323	-0.0164
	(-1.60)	(1.03)	(-1.48)	(-1.34)
N	473	473	473	473

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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 of 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 positive impact on the share of employment in the Indian districts and 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 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 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 weekly basis and has 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 into 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 regards 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 does not fully account for the differences in levels of work intensity, 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 have been discontinued after the 68^{th} round, it may not be possible to include more recent data into 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 on this type of trade relations can also allow more understanding in 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 import 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 on trade shock on district average log wage, residual wage variance, employment share, unemployment share, and the effects by groups.

From the district-level analysis, the paper finds no significant impact of import trade shock on the change in average log wage, 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 1000 USD rise in import per worker increases employment by 0.246 percentage points. Overall, the results of the investigation reflect that there is no 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. The positive impact of trade shock on employment, for example, is mostly driven by the positive effect from the top spending groups, whereas for the lowest consumption group the impact is negative. Or that, while the estimate for older age group is insignificant, import trade shock is found to increase the employment efficiency for the younger age groups. As the estimated impacts do 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.

References

Aigbokhan, Ben E (2000). *Poverty, growth and inequality in Nigeria: A case study.* AERC.

Akhtar, Gulshan (2013). "Indian pharmaceutical industry: an overview". In: *IOSR journal of Humanities and Social Science* 13.3, pp. 51–66.

Alburo, Florian A and Danilo I Abella (2002). *Skilled labour migration from developing countries: Study on the Philippines.* ILO Geneva.

Autor, David, David Dorn, and Gordon H Hanson (2013). "The China syndrome: Local labor market effects of import competition in the United States". In: *American Economic Review* 103.6, pp. 2121–68.

– (2016). "The China shock: Learning from labor-market adjustment to large changes in trade". In: *Annual Review of Economics* 8, pp. 205–240.

Banik, Nilanjan (2001). "An Analysis of India's Exports during the 1990s". In: *Economic and Political Weekly*, pp. 4222–4230.

Barnes, Thomas (2013). "The IT industry and economic development in India: A critical study". In: *Journal of South Asian Development* 8.1, pp. 61–83.

Becker, Gary S (1985). "Human capital, effort, and the sexual division of labor". In: *Journal of labor economics* 3.1, Part 2, S33–S58.

Birdsall, Nancy and Richard Sabot (1991). *Unfair advantage: Labor market discrimination in developing countries.* The World Bank.

Chakravarty, Deepita (1999). "Labour Market under Trade Liberalisation in India: Some Issues concerning Reallocation". In: *Economic and Political Weekly*, pp. M163–M168.

Chan, Anita (2003). "Racing to the bottom: international trade without a social clause". In: *Third world quarterly* 24.6, pp. 1011–1028.

Choi, Jaerim and Mingzhi Xu (2020). "The labor market effects of the China Syndrome: Evidence from South Korean manufacturing". In: *The World Economy* 43.11, pp. 3039–3087.

Das, Sandwip Kumar and Alokesh Barua (1996). "Regional inequalities, economic growth and liberalisation: A study of the Indian economy". In: *The Journal of Development Studies* 32.3, pp. 364–390.

Deb, Kaveri and William R Hauk (2020). "The Impact of Chinese Imports on Indian Wage Inequality". In: *The Indian Journal of Labour Economics* 63.2, pp. 267–290.

Dornbusch, Rudiger, Stanley Fischer, and Paul Anthony Samuelson (1977). "Comparative advantage, trade, and payments in a Ricardian model with a continuum of goods". In: *The American Economic Review* 67.5, pp. 823–839.

Esteve-Volart, Berta (2004). "Gender discrimination and growth: Theory and evidence from India". In.

Federal Reserve Economic Data (n.d.). *Real Broad Effective Exchange Rate for India (RBINBIS)*. URL: https://fred.stlouisfed.org/series/RBINBIS. (accessed: 18.04.2021).

Feenstra, Robert C and Gordon H Hanson (1999). "The impact of outsourcing and high-technology capital on wages: estimates for the United States, 1979–1990". In: *The quarterly journal of economics* 114.3, pp. 907–940.

Ganguly, Sumit and Rahul Mukherji (2011). *India since 1980*. Cambridge University Press.

Goldberg, Pinelopi Koujianou and Nina Pavcnik (2007). "Distributional effects of globalization in developing countries". In: *Journal of economic Literature* 45.1, pp. 39–82.

Government of India (n.d.[a]). *Know India: Districts*. URL: https://knowindia.gov.in/districts/. (accessed: 07.04.2021).

– (n.d.[b]). *NATIONAL CLASSIFICATION OF OCCUPATIONS (NCO 1968)*. URL: http://lsi.gov.in:8081/jspui/bitstream/123456789/130/1/53065_1991_NCO.pdf. (accessed: 10.06.2021).

– (n.d.[c]). *NATIONAL CLASSIFICATION OF OCCUPATIONS (NCO 2004)*. URL: https://labour.gov.in/sites/default/files/Preface.pdf. (accessed: 10.06.2021).

Growth Lab - Harvard University (n.d.). *Atlas of Economic Complexity*. URL: https://atlas.cid.harvard.edu/. (accessed: 12.04.2021).

Holmström, Mark and Holmstrom Mark (1984). *Industry and inequality: The social anthropology of Indian labour*. Cambridge University Press.

Jensen, Leif and Tim Slack (2003). "Underemployment in America: Measurement and evidence". In: *American journal of community psychology* 32.1-2, pp. 21–31.

Kotwal, Ashok, Bharat Ramaswami, and Wilima Wadhwa (2011). "Economic liberalization and Indian economic growth: What's the evidence?" In: *Journal of Economic Literature* 49.4, pp. 1152–99.

Krugman, Paul R (1979). "Increasing returns, monopolistic competition, and international trade". In: *Journal of international Economics* 9.4, pp. 469–479.

Lawrence, Robert Z (2008). *Blue-collar blues: is trade to blame for rising US income inequality?* Vol. 85. Peterson Institute.

Leamer, Edward E et al. (1995). *The Heckscher-Ohlin model in theory and practice*.

Lundberg, Mattias and Lyn Squire (2003). "The simultaneous evolution of growth and inequality". In: *The economic journal* 113.487, pp. 326–344.

Madheswaran, Subramaniam and Paul Attewell (2007). "Caste discrimination in the Indian urban labour market: Evidence from the National Sample Survey". In: *Economic and political Weekly*, pp. 4146–4153.

Malgouyres, Clement (2017). "The impact of Chinese import competition on the local structure of employment and wages: evidence from France". In: *Journal of Regional Science* 57.3, pp. 411–441.

Mazumdar, Indrani et al. (2011). “Gender dimensions: employment trends in India, 1993-94 to 2009-10”. In: *eSocialSciences*.

Melitz, Marc J (2003). “The impact of trade on intra-industry reallocations and aggregate industry productivity”. In: *econometrica* 71.6, pp. 1695–1725.

Menon, Nidhiya and Yana Van Der Meulen Rodgers (2017). “The impact of the minimum wage on male and female employment and earnings in India”. In: *Asian Development Review* 34.1, pp. 28–64.

Mitra, Arup (2008). *The Indian labour market: An overview.* International Labour Organization, Subregional Office for South Asia.

National Sample Survey Office (2014). “Employment and Unemployment Situation in India”. In: *National Sample Survey Report* NSS 68th Round.

– (n.d.). *Employment and Unemployment.* URL: http://microdata.gov.in/nada43/index.php/catalog/EUE. (accessed: 07.01.2021).

Organisation for Economic Co-operation and Development (2021). *Working age population (indicator).* URL: https://doi.org/10.1787/d339918b-en. (accessed: 22.04.2021).

Organization, World Trade (2017). *World Trade Report 2017: Impact of trade on labour market outcomes.* World Trade Organization.

Panagariya, Arvind (2005). “India in the 1980s and the 1990s: A Triumph of Reforms”. In: *India’s and China’s recent experience with reform and growth.* Springer, pp. 170–200.

Registrar General and Census Commissioner of India, Ministry of Home Affairs, Government of India (n.d.[d]). *Census of India.* URL: https://censusindia.gov.in/digitallibrary/TablesSeries2001.aspx. (accessed: 15.03.2021).

Rodrik, Dani (2014). “Good and bad inequality”. In: *Project Syndicate* 11.

Roy, Sumit (2009). “Investigations into the Process of Innovation in the Indian Automotive Component Manufacturers with Reference to Pune as a Dynamic City-Region”. In: *Retrieved 18th November* 2009.

Roy, Tirthankar (2012). *India in the world economy: from antiquity to the present.* 10. Cambridge University Press.

SAARC (2006). “Country Paper on Economic Activity Classification in India”. In: *SAARCSTAT Workshop on Classification and System of National Accounts* DOC.NO.SAARCSTAT/CSNA/WKSH/(8)-Annex IV.

Saha, Kajari et al. (2021). *The China trade shock and the gender wage gap in India: A District-level analysis.* Tech. rep.

Shahbaz, Muhammad et al. (2015). “Financial development and income inequality: Is there any financial Kuznets curve in Iran?” In: *Social Indicators Research* 124.2, pp. 357–382.

Sharma, Alakh N (2006). "Flexibility, employment and labour market reforms in India". In: *Economic and Political Weekly*, pp. 2078–2085.

Statista (n.d.). *India: Youth unemployment rate from 1999 to 2020*. URL: https://www.statista.com/statistics/812106/youth-unemployment-rate-in-india/. (accessed: 10.05.2021).

Stone, Susan and Ricardo Cavazos Cepeda (2011). *Wage implications of trade liberalisation: Evidence for effective policy formation*. Tech. rep. OECD Publishing.

The World Bank (n.d.). *GDP (constant 2010 US$) - India*. URL: https://data.worldbank.org/indicator/NY.GDP.MKTP.KD?end=2006&locations=IN&start=1970. (accessed: 21.04.2021).

Topalova, Petia (2007). "Trade liberalization, poverty and inequality: Evidence from Indian districts". In: *Globalization and poverty*. University of Chicago Press, pp. 291–336.

Topalova, Petia and Amit Khandelwal (2011). "Trade liberalization and firm productivity: The case of India". In: *Review of economics and statistics* 93.3, pp. 995–1009.

Village Dynamics in South Asia (VDSA) (2015). "District Level Database Documentation - 19 States of India". In: *ICRISAT-ICAR-IRRI Collaborative Research Project* Module I (ICRISAT Component). URL: http://vdsa.icrisat.ac.in/Include/document/all-apportioned-web-document.pdf.

World Integrated Trade Solution (n.d.[a]). *China trade balance, exports and imports by country and region 2011*. URL: https://wits.worldbank.org/CountryProfile/en/Country/CHN/Year/2011/TradeFlow/EXPIMP. (accessed: 18.02.2021).

– (n.d.[b]). *India Trade Summary 2008 - India exports, imports, tariff by year*. URL: https://wits.worldbank.org/CountryProfile/en/Country/IND/Year/2008/Summarytext. (accessed: 21.04.2021).

8 Appendix

8.1 Group divisions in the further analyses

1. For the analysis by consumption groups, the groups are divided according the 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, heath, 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 analyses by group

This subsection present the full result tables from the analyses by group [31].

Table 13: Consumption group-level labour market outcomes (IV-full)

	(1)	(2)	(3)	(4)
	Wage	Residual Wage Variance	Employment	Underemployment
$\triangle IPW$	-0.00271***	0.0000987	0.000328***	-0.0000160
	(-6.90)	(1.09)	(3.49)	(-0.55)

[31]This notes that the group counts are different and certain groups may be absent in a district, the number of observations are not necessarily constant throughout the analyses.

sss2	0.00219***	-0.0000852	-0.000208*	-0.000105**
	(7.56)	(-1.15)	(-2.07)	(-2.70)
sss3	0.00465***	0.000169	-0.000373**	0.00000675
	(7.76)	(1.46)	(-3.13)	(0.15)
group2	-0.125***	0.00110	0.0126***	0.00275***
	(-21.91)	(0.91)	(7.05)	(6.54)
group3	-0.257***	-0.0130***	0.0108***	0.00476***
	(-22.54)	(-5.20)	(3.55)	(4.41)
Manufacture	0.0798	-0.0176	-0.0453**	0.00656
	(1.16)	(-0.83)	(-2.96)	(1.03)
Female	-0.0646	-0.00289	0.0265***	0.00546
	(-1.88)	(-0.44)	(3.63)	(0.86)
Youth	-0.0940	-0.0101	0.0328***	-0.00310
	(-1.91)	(-1.04)	(3.94)	(-0.51)
Rural	0.0482*	0.00961*	-0.00885**	-0.000572
	(1.98)	(2.38)	(-3.21)	(-0.24)
Educated	0.0722	-0.0144	-0.0239*	-0.00139
	(1.15)	(-1.36)	(-2.49)	(-0.19)
Hindu	-0.0273	-0.00308	-0.00195	0.00331
	(-1.55)	(-0.80)	(-0.96)	(1.54)
Backward	0.00907	-0.00295	-0.00616*	-0.00148
	(1.01)	(-1.19)	(-2.19)	(-0.81)
N	16682	16682	16973	16973

t statistics in parentheses

* ($p < 0.05$), ** ($p < 0.01$) ,

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

	(1)	(2)	(3)	(4)
	Wage	Residual Wage	Employment	Underemployment
$\triangle IPW$	-0.000845	-0.0000632	0.0000389	0.000143
	(-1.27)	(-0.33)	(0.30)	(1.61)
$\triangle IPW * age2$	0.0000505	0.0000182	0.0000369	-0.000101*
	(0.27)	(0.25)	(0.38)	(-2.57)
$\triangle IPW * age3$	-0.0000230	0.000114	0.0000427	-0.0000802**
	(-0.08)	(1.70)	(0.59)	(-2.63)
$\triangle IPW * age4$	0.000550	0.000152	0.000222**	-0.0000961
	(1.56)	(1.39)	(2.80)	(-1.72)
group2	0.00978***	-0.00287**	-0.00256*	0.000150

	(4.42)	(-3.04)	(-2.05)	(0.37)
group3	0.0113***	-0.00401***	-0.00478***	0.0000662
	(3.95)	(-4.08)	(-4.15)	(0.13)
group4	0.0000839	-0.00610***	-0.00952***	-0.000989
	(0.02)	(-4.67)	(-9.65)	(-1.92)
Manufacture	0.104	-0.0239	-0.0468***	0.00733
	(1.78)	(-1.17)	(-5.18)	(0.88)
Female	-0.0340	0.000266	0.0259*	0.00744
	(-0.75)	(0.02)	(2.39)	(0.85)
Youth	-0.104*	-0.00242	0.0135	-0.00396
	(-2.23)	(-0.24)	(1.67)	(-0.59)
Rural	0.0331*	0.00461	-0.00324	-0.000726
	(2.08)	(1.20)	(-1.31)	(-0.27)
Educated	-0.0501	-0.0104	-0.0127	-0.00446
	(-1.38)	(-0.97)	(-1.27)	(-0.43)
Hindu	-0.0114	-0.00101	-0.00382	0.00240
	(-0.67)	(-0.25)	(-1.33)	(1.14)
Backward	0.00775	-0.00387	-0.00563*	-0.000729
	(0.76)	(-1.48)	(-1.99)	(-0.41)
N	22377	22377	22704	22704

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 15: Gender group-level labour market outcomes (IV-full)

	(1)	(2)	(3)	(4)
	Wage	Residual Wage	Employment	Underemployment
$\triangle IPW$	-0.000515	0.0000177	0.000241*	0.0000155
	(-1.30)	(0.17)	(2.19)	(0.22)
$\triangle IPW * Female$	0.0000672	0.0000857	-0.0000359	-0.0000528
	(0.22)	(1.69)	(-0.42)	(-1.31)
Female Group	0.00655	-0.000611	-0.00264*	0.000355
	(1.30)	(-0.83)	(-2.16)	(0.56)
Manufacture	0.151*	-0.0334	-0.0412***	0.00823
	(2.43)	(-1.75)	(-5.02)	(1.20)
Female share	-0.0571	-0.0128	-0.0147*	0.00419
	(-1.11)	(-1.62)	(-2.08)	(0.57)
Youth	-0.137***	-0.000465	0.0358***	-0.00476

	(-3.34)	(-0.04)	(5.17)	(-0.76)
Rural	0.0346	0.00156	-0.00389	-0.000772
	(1.85)	(0.46)	(-1.56)	(-0.28)
Educated	-0.00798	-0.0169*	-0.0105	-0.00336
	(-0.15)	(-2.11)	(-1.10)	(-0.34)
Hindu	-0.0216	-0.000545	0.00123	0.00360
	(-0.94)	(-0.19)	(0.66)	(1.66)
Backward	0.0349*	-0.00272	-0.00731*	-0.000640
	(2.27)	(-1.01)	(-2.20)	(-0.43)
N	11202	11193	11352	11352

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 16: Occupation Group-level labour market outcomes (IV-full)

	(1)	(2)	(3)	(4)
	Wage	Residual Wage	Employment	Underemployment
$\triangle IPW$	0.000549*	0.0000922	-0.0000708	-0.0000234
	(2.05)	(0.68)	(-1.04)	(-0.29)
$\triangle IPW * Production$	-0.00215***	-0.000000365	0.000422***	-0.000134**
	(-7.19)	(-0.00)	(6.23)	(-2.58)
Production	0.111***	0.00179	-0.0202***	0.00379*
	(11.22)	(0.76)	(-10.11)	(2.12)
Manufacture	0.112	-0.00739	-0.0206	0.0184
	(1.84)	(-0.25)	(-1.95)	(1.66)
Female	-0.0346	-0.00338	0.0212*	0.00869
	(-0.81)	(-0.19)	(2.27)	(0.87)
Youth	-0.0707	-0.0385*	0.00690	0.00317
	(-1.74)	(-2.38)	(0.97)	(0.33)
Rural	0.0263*	0.00485	0.00422	-0.00504
	(2.28)	(0.85)	(1.48)	(-1.49)
Educated	0.0105	0.00841	0.00458	-0.00546
	(0.31)	(0.57)	(0.46)	(-0.52)
Hindu	-0.0163	-0.00329	-0.000314	0.00364
	(-1.24)	(-0.77)	(-0.16)	(1.22)
Backward	0.00605	-0.00130	-0.00527*	-0.000989
	(0.74)	(-0.32)	(-2.42)	(-0.46)
N	11262	11262	11262	11262

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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

	(1)	(2)	(3)	(4)
	Wage	Residual Wage	Employment	Underemployment
$\triangle IPW$	-0.000320	0.0000537	0.0000520	-0.0000782
	(-1.16)	(0.60)	(1.68)	(-1.81)
$\triangle IPW * Sales$	-0.000442	0.0000860	0.0000784*	-0.0000520
	(-1.68)	(0.75)	(2.07)	(-1.21)
$\triangle IPW * Others$	-0.000522	0.000130	-0.0000229	0.0000563
	(-1.31)	(0.88)	(-0.75)	(1.17)
$\triangle IPW * Blue$	-0.000554*	0.0000265	-0.0000782	0.000353**
	(-2.09)	(0.17)	(-1.08)	(2.96)
Sales	0.00501	-0.00440*	-0.00264***	0.00113
	(0.78)	(-2.33)	(-5.68)	(1.32)
Others	-0.00542	-0.00573**	-0.0000757	0.000384
	(-1.14)	(-3.17)	(-0.10)	(0.50)
Blue	0.0247***	-0.00650**	0.00153	0.00159
	(3.79)	(-2.96)	(1.12)	(1.21)
Manufacture	0.0902*	-0.0460*	-0.0123*	0.0156*
	(2.36)	(-2.09)	(-2.43)	(2.18)
Female	-0.00408	-0.0236	0.00740	0.00662
	(-0.11)	(-1.86)	(1.74)	(0.79)
Youth	-0.00116	-0.0295	0.00445	0.000348
	(-0.03)	(-1.89)	(1.04)	(0.07)
Rural	0.00853	-0.00318	0.00189	-0.00178
	(0.78)	(-0.83)	(1.26)	(-0.82)
Educated	0.000327	-0.0187	0.00504	-0.00809
	(0.01)	(-1.68)	(1.07)	(-1.02)
Hindu	-0.00934	-0.00173	-0.00193	0.00186
	(-0.73)	(-0.43)	(-1.03)	(0.88)
Backward	-0.0131	-0.000304	-0.000375	-0.00251
	(-1.39)	(-0.08)	(-0.23)	(-1.44)
N	16682	16682	16682	16682

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

9 Declarations

1. 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 method and information are also available from the respective websites.

2. There is no known conflict of interest.

3. The author received no financial support for this research of this article.