The Gendered Impact of Uneven Spatial Growth in India

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Abstract

This paper studies the gendered labor market impact of tradable sector growth in India. The tradable sectors (manufacturing and exportable services) drive local employment as they are not constrained by local market demand and create additional jobs through increased demand for local goods and services. The local labor demand is particularly crucial for Indian women who seldom migrate for work. Using a shift-share instrument for local tradable employment growth, I show that an increase in the tradable sector employment at the district level positively affected the female LFPR between 1987-88 and 2011-12. The results are driven by the fact that tradable growth leads to an increase in overall local labor demand through a multiplier effect. In response to positive tradable employment shocks, women's employment increases in agriculture and female-intensive consumer services due to rising local consumer demand. I find that men migrate to districts with high tradable employment growth in response to the negative local labor demand shock, while women primarily drop out of the labor force. The analysis suggests that spatially uneven and sluggish growth in the tradable sectors significantly contributed to declining female LFPR in India.

JEL Classification: J23, R11, R23

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1 Introduction

A large and growing body of literature focuses on low and declining female labor force participation rate (LFPR) in India. This is because it coincided with a period of high economic growth, decreasing fertility rate, and increasing educational attainment. Much of the existing literature has explored the role of various factors such as social norms (Jayachandran, 2021), sexual violence (Chakraborty et al., 2018; Siddique, 2022), rising household incomes and education levels (Afridi et al., 2018) on female labor supply. However, how the evolution of local labor market conditions can specifically influence women's employment opportunities has remained largely understudied in the existing literature. Local employment opportunities are crucial for Indian women, with low mobility and work-related migration (Tumbe, 2015; Goel, 2023). In Deshpande and Singh (2023), we show that structural change negatively affected local labor demand in Indian districts with a relatively higher initial share of agriculture employment. The decline in labour demand subsequently caused a decline in female LFPR. Having established the role of structural change, particularly of declining agriculture, in this paper, I focus on non-agriculture sectors and examine the impact of changing tradable sector employment on the evolution of female LFPR.

The tradable sectors broadly include both traditional manufacturing and modern exportable services such as IT, software, consulting, etc.[1] The tradable sectors importantly distinguish themselves from agriculture and conventional non-tradable service sectors (such as education and retail trade) in terms of driving local labor demand for the following reasons. First, the production of tradable industries is often concentrated in a few locations to benefit from economies of scale. Second, they do not face the demand constraints of a local consumer market; tradable goods and services can be produced at one location and can be exported to places with higher demand (Rodrik, 2016). In this way, local labor demand can persist even when local product demand is low. Third, tradable sectors exhibit a multiplier effect (Moretti, 2010), creating additional demand for employment in non-tradable services due to forward and backward linkages of these industries with tradable industries as well as demand for consumer services due to rising household income (Dehejia and Panagariya, 2016; Avdiu et al., 2022). Since female labor supply could be particularly responsive to local

[1]It is not trivial to classify industries into tradable and non-tradable. This paper uses the geographical concentration method introduced by Jensen and Kletzer (2006) to classify industries.

labor demand conditions, I study the causal impact of changing local labor demand driven through the tradable sector on female LFPR in India between 1987-88 and 2011-12.

The period of decline in female LFPR in India coincided with a phase of relative stagnation in tradable employment growth. The female LFPR declined from 43 percent in 1987-88 to 31 percent in 2011-12. The decline was driven by the withdrawal of rural women from the labor force; while it remained stagnant in urban areas. During the same period, the overall employment share of the tradable sectors remained below 15 percent. Further, the tradable sector employment growth was concentrated in a limited number of districts, while it declined in more than 80 percent of districts between 1987-88 and 2011-12. This paper explores the relationship between low and uneven tradable employment growth and the evolution of female LFPR during this period.

In this analysis, I consider administrative districts as local labor markets and exploit the district-level variation in tradable employment growth between 1987-88 and 2011-12 to examine its impact on female LFPR. The descriptive statistics show a significant positive relationship between tradable sector employment growth and female LFPR. There was no decline in female LFPR in the top 10 percent of districts in terms of tradable employment growth, while the decline in female LFPR was more than 15 percentage points in the bottom 10 percent of districts. Further, the urban female LFPR remained stagnant in the country for two decades and appears in a steady state. The spatial trends across districts present a different picture. I find that the top 10 districts witnessed an increase in urban female LFPR, while it declined by more than 10 percentage points in districts with the highest decline in tradable employment. Similarly, the decline in rural female LFPR was less than five percentage points in the top 10 percent of districts, while the decline was above 20 percentage points in the bottom 10 percent of districts.

However, it is econometrically challenging to estimate the causal impact of tradable sector employment growth on LFPR using OLS due to plausible omitted variables and simultaneity biases. To address these issues, I include state fixed effects for state-specific growth in tradable employment and female LFPR. I control for gender-specific demographic changes that could affect women's labor supply. However, there still could be district-level unobservable characteristics driving both tradable sector employment and female LFPR. For example, an improvement in transport connectivity in a district over time could lead to a rise in both manufacturing activities and women's labor supply. Therefore, I resort to the instrumental variable approach.

I use a shift-share or Bartik-type instrument as a source of exogenous change in local demand for tradable employment. The shift-share instrument uses the idea that in a given time period, different industries grow at different rates at the national level and districts differ in the initial shares of employment in the different industries. Now, the national growth in any specific industry would affect the district-level employment demand based on the initial share of employment of the industry in the district (Bartik, 1991; Bound and Holzer, 2000a). For example, if Bangalore specializes in the IT sector; then nationwide growth in the IT sector would disproportionately increase the labor demand in Bangalore compared to other districts. The exogeneity of the instrument requires that the labor demand shocks driven by nationwide change in the industry are unrelated to the local labor supply changes or the district-specific omitted variables. Recent literature shows that the shift-share instrument is valid if either the initial share of industries in districts or the national shocks (industry employment growth) are exogenous (Goldsmith-Pinkham et al., 2020; Borusyak et al., 2022). In my setting, the instrument's validity follows from share exogeneity – there should not be any other factor that is correlated with the initial share of industry in the district and affects change in female LFPR by responding to national shocks. I provide suggestive evidence on the instrument's validity as recommended by Goldsmith-Pinkham et al. (2020).

A brief summary of the results is as follows. First, I find that growth in tradable employment in a district positively affects women's labor force participation rate. A one standard deviation increase in tradable employment is associated with an 11 percentage points increase in female LFPR. In absolute terms, adding 21 tradable jobs per 100 workers in a district leads to approximately 11 additional per 100 working-age women in labor force in the district. In other words, the decline in female LFPR is the lowest in the districts with the highest growth of the tradable. The heterogeneity analysis shows that the impact was noticeable both in urban and rural areas, explaining the decline in female LFPR in rural areas and its stagnation in urban areas. The stagnation in urban female LFPR results from the fact that female LFPR increased in the districts with high growth in tradable sector employment and declined in the remaining. For men, the impact is limited and concentrated among those below 30 years of age. This is possibly on account of most men joining the labor force after a certain age even if jobs are low-paying or their ability to migrate for work in situations of low labor demand.

I also examine the plausible mechanisms influencing my findings. Particularly, why does local tradable employment growth affect women disproportionately? As noted earlier, the overall local labor demand is particularly important for women due to the lack of work-related migration, I check the effect of the tradable growth on total local employment in the district. I find that tradable sector employment growth leads to an increase in the labor demand in non-tradable sector and agriculture. A one standard deviation increase in tradable sector employment (21 jobs per 100 workers) leads to an additional 39 jobs in non-tradable sectors. This is driven by the fact that the tradable sector growth leads to higher household income and population (due to in-migration for work) and urbanization in districts. Consequently, this causes an additional demand for non-tradable services and agricultural products for consumption in the local market. Within non-tradable, the tradable growth is associated with increasing employment in consumer service. This is consistent with the results of Dehejia and Panagariya (2016) and Avdiu et al. (2022).

Second, I examine the migration pattern by gender and find that men migrate to overcome the problem of low local labor demand. However, I do not find this mechanism important in the case of women. I find that both men and women migrate from districts with low tradable growth to districts with high tradable growth. However, the level of migration for work is very low among women. A one standard deviation increase in tradable sector employment (or adding 21 tradable jobs per 100 workers) in a district leads to nine additional male migrants and only 1.4 female migrants in the district. Similarly, I examine the out-migration pattern and find that the share of out-migration is 14 times larger for men compared to women in situations of negative tradable sector employment shocks.[2] Therefore, a decline in local labor demand disproportionately affects women as men migrate to districts with high tradable employment growth in response to the negative local labor demand shock, while women primarily drop out of the labor force.

[2] The difference in out-migration and in-migration numbers is due to the different data sources and how migration is measured.

Next, I examine sectoral reallocation vis-à-vis tradable growth. I find that men's employment increases significantly in both tradable and non-tradable sectors in response to tradable employment growth with no impact on agricultural employment. In contrast, women's employment rises in non-tradable sectors and agriculture. Within non-tradable sectors, the growth in women's employment is driven by female-intensive consumer service industries – education, health, personal services and retail trade. Further, the demand for agricultural products in response to the tradable sector growth increases women's employment in agriculture.

In summary, the tradable sectors are crucial for driving local labor demand and increasing women's employment. I find that low and uneven spatial growth in tradable sector employment in India significantly contributed to the decline in female LFPR. My findings suggest that both the magnitude and location of the overall local employment are important for women due to low mobility. Therefore, we need to focus on industry policy and place-based policies to increase employment opportunities across districts to boost the female LFPR.

1.1 Contribution to the literature

This paper contributes broadly to three strands of literature. First, the paper contributes to the large and growing literature on declining female LFPR in India. The issue of declining female LFPR is distinct from low levels of LFPR and the latter is related to gender norms, restriction on mobility, harassment, underestimation in the measurement of women's work, the responsibility of household chores, etc (Jayachandran, 2021; Deshpande and Kabeer, 2024). The early literature focuses on the supply-side factors and argues that female LFPR is declining due to rising education enrolment and household income (Kannan and Raveendran, 2012; Afridi et al., 2018). However, the supply-side factors explain only a part of the decline in female LFPR (Chatterjee et al., 2018; Deshpande and Singh, 2023). Contrary to this, other studies suggest that a decline in women's demand in agriculture due to mechanization (Afridi et al., 2022), without a commensurate increase in non-farm employment, explains the decline in rural areas (Chatterjee et al., 2015). This paper along with Deshpande and Singh (2023), contributes to the literature on declining female LFPR by examining the effect of local labor demand. In Deshpande and Singh (2023), we study how the process of structural change affects the evolution of female LFPR between 2004-05 and 2017-18. As the share of agriculture declined in the Indian economy, districts that initially specialized in agriculture witnessed a relatively lower labor demand growth than districts with higher non-agriculture sectors. Hence, the structural change led to heterogeneous growth in local labor demand across Indian districts and affected the female LFPR. Having established the role of structural change, particularly of declining agriculture, on female LFPR, in this paper, I focus on how the composition of the non-agricultural sector might affect the evolution of female LFPR. Within the non-agriculture sector, I examine the effect of tradable sectors, which are important in driving local labor demand.

Second, the paper adds to the literature on group-specific labor supply response to local labor demand shocks. The existing literature examines the differential impact of local labor demand for the relatively low mobility groups such as the old, women, less educated, and low-skilled workers (Bound and Holzer, 2000b; Maestas et al., 2013; Notowidigdo, 2020; Fallah et al., 2021; Bhalotra and Fernández, 2023). The literature shows that some demographic groups have low mobility compared to others, and therefore, local labor demand could have a differential impact. This paper contributes to the literature by examining the gendered impact of uneven tradable growth in India because of the differential migration rates for males and females. I show how supply-side factors such as mobility constraints for women interact with low labor demand and create adverse outcomes for women in the labor market.

Third, the paper is related to the literature on jobless growth and premature deindustrialization in India. This paper links the three most discussed features of India's growth story – premature deindustrialization, jobless growth, and declining female LFPR. The economic growth during the period of study witnessed stagnation in manufacturing sectors at below 15 percent (Amirapu and Subramanian, 2015). I combine manufacturing with modern tradable services that have similar features in terms of economies of scale and access to international markets. I show that the job-creating tradable sectors declined in more than 70 percent of districts in India causing lower employment growth overall, i.e. "jobless growth". Further, I show that the decline in women's LFPR was also more pronounced in districts with a decline in tradable sector employment.

The paper also related to the literature on how tradable sectors have a local multiplier effect on non-tradable sectors (Moretti, 2010; Moretti and Thulin, 2013; Frocrain et al., 2018).

Dehejia and Panagariya (2016) and Avdiu et al. (2022) show that growth in manufacturing and tradable services, respectively, create demand for non-tradable services in India. Both show that tradable growth increases household income in districts and creates demand for non-tradable consumer services. I combine both manufacturing and tradable services and confirm their results. Further, Avdiu et al. (2022) examines the impact of tradable service growth and finds a relatively large impact for women, particularly in female-headed firms, in consumer service sectors due to the comparative advantage of women in pink-collar jobs. However, employment in tradable services is still small (below 3 percent of total employment in 2011-12) and concentrated in a limited number of urbanized districts to drive female LFPR across districts. In contrast, I study the impact of overall tradable sector (including both manufacturing and tradable services) employment growth on female LFPR in districts. I find the positive impact of tradable growth on female LFPR is majorly driven by the increase in local agriculture employment. Further, I show the disproportionate impact of low local demand is due to the low migration by women for work.

The paper briefly touches upon the literature on urbanization and structural change. Gollin et al. (2016) discuss the trend of growing urbanization without industrialization in developing countries – leading to an increasing number of consumption cities. Jedwab et al. (2022) compare cities across countries and find that labor market outcomes are worse in consumption cities. I also find that districts with a relatively large increase in tradable employment led to higher wages, household consumption, and labor force participation. While the districts with a relatively higher share of non-tradable employment had worse labor market outcomes.

The rest of the paper is organized as follows. In Section 2, I present the data sources and classify the industries into tradable and non-tradable sectors. Section 3 discusses the empirical strategy, followed by results in Section 4. The paper ends with a summary of the results and concluding remarks in Section 5.

2 Data

This section presents various data sources used for the analysis.

NSS Employment and Unemployment Survey (EUS): The primary data source for the labor force estimation and industry-wise employment comes from various rounds of the NSS Employment and Unemployment Survey (EUS). EUS is a nationally representative household survey for the measurement of labor force indicators in India. The survey records detailed information on employment status, wages, and demographic characteristics. I primarily use the 43rd round (1987-88) and 68th round (2011-12) for labor force participation rate and industry-wise employment. I use the "Usual Principal and Subsidiary Status" (UPSS) definition to estimate the female LFPR. In the robustness check, I provide details on different definitions and consistency of results irrespective of the definitions.

NSS Employment, Unemployment and Migration Survey, 2007-08, 64th: The 64th round collects information on the migration particulars of household members. I use the survey schedule on out-migrant members of households. The schedule includes age and gender of migrant members, the reason for migration, years since migration, and the location of migration (within the district, outside the district, outside of the state, or out of the country). I use this information along with survey weights to estimate the number of men and women who out-migrated for employment out of the respected districts.

Population Census, 2011: I use district-level migration tables from Population Census, 2011 to estimate in-migration in each district. The migration tables report the total migrants in each district by gender, reasons for migration, years since migration, and location of migration (within district, outside the district, outside of the state, or out of the country). I estimate the total number of migrants by gender in each district who immigrated from other districts for employment.

Economic Census (EC): I use two rounds (1990 and 2013) of the Economic Census to estimate the industry-wise employment in each district. The EC surveys all non-farm enterprises in India and reports industry code and employees by gender. The sample size in NSS surveys is small to calculate the aggregate employment in a district for each industry group. So, I use this while creating the shift-share instrument where I need employment in each industry at finer levels. I use EC-1090 and EC-2013 corresponding to NSS EUS 1987-88 and NSS EUS 2011-12, respectively. The main drawback of the EC is that it does not include household-based work and construction activities for housework which constitute a significant proportion of India's workforce.

Creating district-level data: I create district-level variables for labor force participation, employment level by industries and supply-side demographic measures using survey weights. The geographical boundaries of districts change over time in India due to the delimitation of district boundaries. Usually, new districts get created out of single or multiple districts. The number of districts changed from 473 to 625 between EUS 1987-88 to 2012-12. I harmonized them to create 434 consistent district regions. I restrict the analysis to 358 districts in large states and exclude smaller northeastern states, Jammu & Kashmir, union territories, and districts not surveyed in the main analysis. Both NSS and EC surveys report the industry code of employment and establishment respectively. The surveys over the years use different industry classifications based on the National Industrial Classification (NIC) codes. I use the concordance table created by Fan et al. (2023) which divides the industry codes into 60 industry groups.

Next, I create district-level variables using survey weights for the two rounds. I estimate the district-level labor force participation rate for age between 15 and 59 years, absolute employment in each industry, and share of industry in district employment. I also create district-level demographic characteristics – share of different age groups, share of education levels, mean per capita household consumption (as a proxy for household income), share of married individuals, share of religious and caste groups. Similarly, I create district-level immigration and outmigration per 100 working-age population.

Table 1 presents the district-level female LFPR and other demographic variables. The district average of female LFPR declined by 14 percentage points from 49.3 percent in 1987-88 to 35 percent in 2011-12. The education level, which is an important determinant of female labor supply, increased sharply during the period of study. The share of illiterate women declined to almost half, and the share of women with education above secondary tripled. The share of different age groups, married women, caste and religions did not change significantly. The portion of rural households in districts declined by 4.4 percentage points. The mean value of real monthly per capita expenditure (in 1987-88 prices) in districts increased from Rs. 189 to Rs. 235. I describe the change in female LFPR and tradable employment in detail after classifying the industries into tradable and non-tradable sectors in the next subsection.

2.1 Classifying industries into tradable and non-tradable

Traditionally, manufacturing activities are considered tradable and services were non-tradable. The non-tradable service sectors include education, health, retail trade, etc. are non-tradable. There is a recent surge in business services such as consulting, IT, software production, etc. They have features similar to manufacturing as they can produced at one location and exported to another, and production is often concentrated in a few locations to benefit from economies of scale. Therefore, service industries require systematically classifying them into tradable and non-tradable. The following are popular approaches proposed in the literature to measure tradability of industries- 1) geographical concentration (Jensen and Kletzer, 2006; Gervais and Jensen, 2019) and 2) implied bilateral trade cost (Head and Ries, 2001; Chen and Novy, 2011).

I use the geographical concentration (GC) approach proposed by Jensen and Kletzer (2006). The GC approach uses the idea that tradable goods and services benefit from an increasing return to scale, access to natural resources, and/or agglomeration; therefore, they are geographically concentrated and produced at a few locations. On the other hand, non-tradable services are locally produced and consumed; therefore, they are found everywhere. For example, restaurants and retail shops are present everywhere as they primarily serve the local population. Contrary to that, software-related services are tradable and produced at very few locations depending on the comparative advantage or other reasons stated above. Gervais and Jensen (2019) improves over Jensen and Kletzer (2006) by considering the difference between local demand and production into account. However, the existing data in India do not allow us to use this improved measurement method. So, I use the traditional measure of geographical concentration.

Avdiu et al. (2022) use the implied trade cost approach proposed by Head and Ries (2001) to measure readability in the Indian context. The implied trade cost method is based on the idea that if international trade is higher for a particular industry than domestic trade, then that industry is likely to have less relative trade costs and more tradability. In the robustness checks, I use the classification created by Avdiu et al. (2022) and find consistent results. Fan et al. (2023) use a different method to classify the services into tradable and non-tradable. They use the idea that smaller firms are more likely to sell to consumers and large firms to other firms. They use the firm size distribution and downstream buyer information (consumer or other firms) to create the probability of non-tradable for each industry group by firm size.

I define the geographical concentration (GC) index as

$$\mathrm{GC}_i = \textstyle\sum_d (s_{i,d} - x_d)^2$$

where i is industry and d is district; $s_{i,d}$ is district's share in industry i's employment; x_d: district's share in aggregate employment. A higher value of the GC index for an industry shows higher concentration. I estimate GC for each of the 54 non-agricultural industry groups using the Economic Census 1990.[3]

Table 2 shows values of the GC index for each industry group in descending order from top-left to bottom right. The retail trade has the lowest GC index, while the metal ore mining group has the highest index. Since each industry gets a positive value of the GC index, we need to decide a cut-off above which an industry would be considered as tradable and the rest non-tradable. One way could be to classify all manufacturing sectors as tradable and services with a GC index larger than any manufacturing industry. However, some manufacturing industries could have a very high GI index due to low tradability if the transport cost is higher. For example, the furniture group has a very low GC index and lower than many non-tradable services. So, I take the index value of food products industry group as the threshold and consider all the industry groups with GI index larger than that as tradable

[3]This paper considers agriculture as a third sector. I exclude industry groups "Goods-producing activities for own use", "Service-producing activities for own use" and "Extraterritorial organizations" out of 60 industry groups in Fan et al. (2023) for the GI estimation. These industry groups are introduced in recent versions of the NIC code and do not exist in earlier rounds of the economic census. I classify them as non-tradable sectors.

sectors.[4] Therefore, I consider industries in the left columns of Table 2 as tradable and the right column as non-tradable for the analysis.

As expected, traditional consumer service industries like education, health, personal services, retail trade, land and water transport, etc. have low concentration indices and are classified as non-tradable in this approach. Business and management consultancy, other business services, accounting, and computer-related activities groups have relatively high GC indices and get classified as tradable, irrespective of cut-off. Financial services, legal activities, research and development, and real estate activities also have high concentration compared to many manufacturing and are classified as tradable services. Next, I present the descriptive trends of tradable growth and district-level spatial patterns.

First, I check the trends of sectoral shares in total employment over the years. Figure 2 shows the share of agriculture, manufacturing, tradable services, and non-tradable sectors in total employment. The share of agriculture in employment declined from 66 percent to below 50 percent during the period of study. The decline in agriculture was broadly replaced with an increase in non-tradable sectors. The manufacturing sector stagnated at 11-12 percent during the 20 years. There was a significant rise in the IT sector in India. However, the share of tradable services, including IT, remained below three percent. Overall, the share of tradable (manufacturing and tradable services combined) increased only slightly from 12 percent to 15 percent due to increased tradable services.

Figure 3 shows the geographical distribution of the share of tradable sector in total employment for each district. In most districts, the share of tradables remained below 10 percent. The tradable employment is relatively large in southern states, coastal regions, and national capital region. Tradable sectors are concentrated in a small number of districts, with the top 10 percent districts accounting for 50 percent of tradable employment, while the bottom 50 percent accounts for only 11 percent of total tradable employment. Regarding employment growth, the districts with a relatively high share of tradable employment remained similar between 1987-88 and 2011-12. Further, the growth in tradable sector em-

[4] This cut-off process assumes that most manufacturing industries are tradable. For example, the wood products and non-metallic mineral groups have a low GC index because the trade costs are high due to the low value-per-weight ratio. In the robustness checks, I increase the cut-off to include manufacturing industries into non-tradable. The results remain robust to the cut-off change.

ployment was highly concentrated in 10 percent of districts (Figure A.1). Over 70 percent of districts observed an absolute decline in tradable sector employment. In summary, the tradable employment is concentrated in a few districts and further declined in most districts.

Figure 4 shows the district-level change in female LFPR between 1987-88 and 2011-12. The districts in the central region (lighter color) show a decline in LFPR by more than 10 percentage points. The dark red color districts have some increase in female LFPR. There is a visible overlap between districts with a relatively high share of tradable in total district employment and the change in female LFPR. To observe a systematic correlation, I created 10 deciles of districts (approximately 36 districts in each decile) in the order of tradable employment growth per working-age population. Figure 5 draws the change in female LFPR for each decile of tradable growth. The figure shows a sharp linear pattern of positive relationship between tradable and female LFPR growth. The districts with the lowest growth in tradable employment observed an average 20 percentage points decline in female LFPR between 1987-2011. On the other hand, the districts with the highest increase in tradable employment witnessed almost no decline in female LFPR. The next section discusses the empirical strategy to formalize this association in a regression framework.

3 Empirical strategy

I estimate the impact of tradable employment growth on female labor force participation rate using the following regression equation –

$$\Delta\text{Female LFPR}_{d,s} = \beta_0 + \beta_1 \Delta\text{tradable emp}_{d,s} + \beta_2 \text{X}_{d,s} + \mu_s + \epsilon_{d,s} \tag{1}$$

where d is district and s is state. $\Delta\text{Female LFPR}_{d,s}$ is the change in female LFPR in percentage points between 1987-88 and 2011-12 in district d. $\Delta\text{tradable emp}_{d,s}$ is defined as the absolute change in tradable employment between 1987-88 and 2011-12 in district d, divided by the initial total employment of the district in 1987[5]. I standardized the variable

[5]In the numerator, I use initial total employment instead of initial tradable employment (to create percentage growth interpretation) because percentage growth would not be a correct measure in this setting for

Δtradable emp$_{d,s}$ for easier interpretation. X$_{d,s}$ are district-level supply-side variables mentioned in Column (3) of Table 1 to control for district level demographic changes that could affect female LFPR. μ_s are state fixed effects to control for state-specific trends.

Estimation Equation (1) using OLS will likely be inconsistent due to plausible omitted variables and simultaneity biases. There could be district-level time-varying unobservable characteristics affecting both the tradable sector employment and female LFPR. For example, improving transport connectivity in a district over time could increase both manufacturing activities and women's labor supply. In that case, the OLS estimates will be biased upward. On the other hand, if the administration responds to the decline in female LFPR (and/or overall employment opportunities) in the district by promoting tradable industries, then OLS estimates would be biased downward. Therefore, I use an instrumental variable approach.

I use a shift-share or Bartik-type instrument as a source of exogenous variation in local demand for tradable employment. The shift-share instrument uses the idea that in a given time period, different industries grow at different rates at the national level and districts differ in the initial shares of employment in these different industries. Now, the national growth in any specific industry would affect the district-level employment demand based on the initial share of employment of that industry in the district (Bartik, 1991; Bound and Holzer, 2000a). For example, if the Ludhiana district specializes in textile manufacturing, then nationwide growth in the textile sector would disproportionately increase the labor demand in Ludhiana compared to other districts. Essentially, the instrument isolates local variations in tradable employment growth stemming from national-level industry growth from shifts in the supply side factors. The instrument is constructed as follows –

$$\text{shift-share instrument}_d = \left(\sum_{k \epsilon K} \left(\frac{EMP_{k,d,t_0}}{EMP_{K,d,t_0}} \right) \times \Delta L_{k,-d,t_1} \right) \times \left(\frac{EMP_{K,d,t_0}}{EMP_{d,t_0}} \right) \qquad (2)$$

districts with a very small share of tradable employment to begin with. For a district with a small value of initial tradable employment, even a small absolute increase in employment would assign a large value to the explanatory variable. Also, I winsorize the top two percent observation of tradable growth variable due to non-linearity. For example, if a district witnessed tradable growth of 500 percent. The district might not see the rise in female LFPR at the same level because the latter depends on factors other than labor demand.

where, $k \epsilon K$ are tradable industries mentioned in the left column of Table 2; d is district, t_0 is 1987-88 and t_1 is 2011-12. The left side of the expression is the conventional shift-share type instrument. $\frac{EMP_{k,d,t_0}}{EMP_{K,d,t_0}}$ is "initial share" of industry k in district d's total tradable employment. $\Delta L_{k,-d,t_1}$ is employment growth in the industry k in the rest of the country between 1987-88 and 2011-12. Since I define the main explanatory variable, growth in tradable employment, in Equation (1) as the change in absolute tradable sector employment with respect to the initial *total employment*, I multiply the conventional instrument (left side term) by the right side term, which is the ratio of tradable employment and total employment of districts in 1987-88.[6] I use the initial share of different tradable industries from the Economic Census 1990 instead of NSS because NSS has a very small sample size to precisely estimate the district-level share of each industry.

The exogeneity of the instrument requires that the labor demand shock driven by the nationwide change in the industry is unrelated to the local labor supply changes or district-specific omitted variables. The recent literature shows that the identification in the case of shift-share type instruments is either based on exogeneity of the initial share or exogeneity of the national shock conditional on the controls (Goldsmith-Pinkham et al., 2020; Borusyak et al., 2022). Goldsmith-Pinkham et al. (2020) argues that in settings similar to this paper, the identification comes from the endogeneity of the initial share. It means that there should not be any other factor that is correlated with the initial share of an industry in a district and affects female LFPR by responding to the national shock. Goldsmith-Pinkham et al. (2020) suggest tests to examine the instrument's validity. First, they suggest checking the pre-trends of the initial share. However, it is not possible to check that in this case due to data limitations for the period before 1987-88. Next, Goldsmith-Pinkham et al. (2020) show that the shift-share instrument has multiple underlying instruments and suggests checking the individual contribution of each of them. They also suggest controlling for initial level variables, which could affect growth in tradable and/or female LFPR. Further, the instrument performs better (in terms of exogeneity and relevance) if we consider only tradable industries in the instrument, as in this paper. The non-tradable industries are more likely endogenous due to low variation across geographical regions and driven by local consumer

[6] The expression is equivalent to $\left(\sum_{k \epsilon K} \left(\frac{EMP_{k,d,t_0}}{EMP_{d,t_0}}\right) \times \Delta L_{k,-d,t_1}\right)$.

demand.[7]

First, I check the validity of the instrument variable. Figure 6 shows the binned scatterplot between tradable growth residuals and instrument residuals after controlling for changes in demographic variables (Column (3) of Table 1) and state fixed effects. As expected, the correlation between predicted tradable demand (the instrument) and tradable growth is positive and statistically significant. In the results section, I check this relationship with different sets of controls and found F-statistics above 10 for all the specifications. Next, I provide suggestive evidence on the exclusion restrictions suggested by Goldsmith-Pinkham et al. (2020). As the shift-share instrument is a combination of multiple instruments for each industry, I examine the important industries in driving the variation. Table 3 shows the top five industry groups with the highest share of weight in the instrument. The top five industry groups contribute 78 percent of positive weights with the "textile and wearing apparel" having 26 percent of positive weights. Next, I examine whether the initial share (1987-88) of these industry groups in a district is correlated with the initial share of other demographic and supply-side factors. Table 4 shows the estimates from regressing the initial share of each of the top five industries in the district's employment on various factors such as district's mean household MPCE (monthly per capita expenditure), share of urban population, share of age groups, caste groups and religion groups. First, I do not find any systematic relationship between the share of the "textile and wearing apparel" industry group with the district-level characteristics. Second, the share of "other business services" and "other manufacturing" industries is positively associated with urban population share in districts. This is expected as business services require educated and skilled workers and the tradable sectors themselves drive urbanization as I show in my results. In summary, we do not find a systematic relationship between the initial share of the important industries (in the instrument) and population characteristics at the district level except with the urbanization level. Next, I check the relationship between the instrument variable and dependent variable by regressing the residuals of change in female LFPR on instrument residuals. Figure 7 shows the positive and significant relationship between the instrument (predicted local tradable employment demand) and female LFPR.

[7] In the robustness checks, I remove industries with low geographical concentration indices from tradable employment classification and find similar results.

4 Results

First, I discuss the results from the OLS estimation of the Equation (1) reported in Table 5. All the specifications include state fixed effects. Different control variables are progressively added from Specification (1) to Specification (4). Specification (2) is the preferred specification with potentially exogenous variables such as change in age groups, caste groups, and religious groups, and married women share. Specification (3) includes changes in education share, per capita household consumption expenditure (a proxy for household income), and share of urban population, which could be intermediate outcomes. A rise in tradable employment may increase average household income, education levels, and urbanization and the latter could affect female LFPR. I also add growth in non-tradable sector employment as a control in the Specification (4). The explanatory variable is in standardized values. The results show that a one standard deviation increase in tradable employment is associated with approximately nine percentage points increase in female LFPR. The coefficients across specifications remain stable at around 0.09. Interestingly, non-tradable employment growth has no additional impact on female LFPR after controlling for tradable employment growth (Specification (4)).

Table 6 shows the 2SLS regression estimates using the shift-share instrument. I find that one standard deviation increase in tradable growth is associated with an increase in female LFPR of around 11 percentage points. In terms of absolute numbers, adding 21 tradable jobs per 100 workers in a district increases the female LFPR by 11. The IV estimates are larger than the OLS estimates, suggesting that the OLS underestimates the true effect. Similar to OLS estimation, non-tradable sectors do not have any additional impact on female LFPR after accounting for tradable sector employment growth. Further, the results remain unchanged if I include the change in the share of agricultural employment instead of rural share as a control in the regressions. This shows tradable sectors have a positive impact on female LFPR in addition to the impact of a decline in agricultural employment, as we find in Deshpande and Singh (2023). Next, I use initial level controls as suggested by Goldsmith-Pinkham et al. (2020) because initial (1987-88) district-level characteristics could be associated with the instrument (through the initial share of industry in district employment) and could be related to the trend in female LFPR. The results are robust if I include 1987-88 district-level demographic-related control variables (Table 7).

Table 8 shows the impact of tradable growth for rural and urban areas. I find that the relationship holds both for rural and urban areas, with the impact being relatively large in rural areas. If I interpret the results in terms of change in female LFPR in the period of study, the decline in rural female LFPR would have been lower if the tradable employment growth had been large. Similarly, the female LFPR would have been increased in urban areas instead of remaining stagnant. Appendix Figure A.2 shows the change in female LFPR between 1987-88 and 2011-12 by deciles of tradable employment growth for rural and urban. The decline in rural female LFPR was less than five percentage points in the top 10 percent of districts, while the decline was above 20 percentage points in the bottom 10 percent of districts. Similarly, the urban female LFPR remained stagnant in the country for two decades and appears to be in a steady state. However, it looks different if we see the spatial trends across districts. I find that the top 10 districts witnessed an increase in urban female LFPR, while it declined by more than 10 percentage points in districts with the highest decline in tradable employment.

Next, we analyze the impact of tradable employment growth on labor market outcomes of men. Table 9 shows the IV estimates with outcome variables: change in male LFPR, workforce participation rate (WPR), and unemployment rate.[8] First, the effect on male LFPR is significant, but the magnitude is very small compared to women. One standard deviation increase in tradable employment is associated with a 3.7 percentage points increase in male LFPR. The impact is much larger on WPR as a large share of the male population enters the labor force but remains unemployed in districts with lower growth in tradable employment. I check the labor market outcomes separately for the younger age group (15-30 years) and those above 30 years. As expected, the results are driven by the younger age group with no impact on male employment indicators at extensive margins. This is possibly on account of most men joining the labor force after a certain age even if jobs are low-paying or their ability to migrate for work in situations of low labor demand. In the next section, I provide suggestive mechanisms on why tradable employment affects labor force participation and why it is particularly high for women.

[8] I report the results for WPR and unemployment for women in the robustness checks. Women are hardly reported as unemployed in India. Therefore, we do not see a significant impact on unemployment, and the magnitude of impact is similar for LFPR and WPR for women. Further, I discuss more on this by comparing WPR with LFPR with different measurements of women's work.

4.1 Mechanism

First, I examine how districts evolve in response to tradable sector employment growth. Table 11 shows the impact of tradable sector employment growth on changes in the working-age (15-59 years) population, urbanization, and consumption expenditure. The increase in the working-age population is 82% higher in districts if tradable sector employment increases by one standard deviation. One possible explanation for this could be the high in-migration and low out-migration in districts with high tradable growth, as I show later. Second, tradable sector growth leads to urbanization as the share of the district population living in urban increases by 12 percentage points. Next, the household income (proxied by monthly per capita household expenditure) increases by 30 percent. Overall, the tradable sector employment growth leads to an increase in the district's population, urbanization and an increase in the average income. I use these facts to substantiate my findings later. Therefore, tradable sector growth increases the labor demand both in non-tradable and agriculture sectors, which could affect the women's labor force participation rate.

As discussed in the Introduction section, the tradable sector has a multiplier impact on non-tradable employment, leading to an overall increase in local non-farm labor demand (Moretti, 2010). And, the local labor demand is particularly important for women due to low mobility. Therefore, I check the effect of tradable employment growth on non-tradable employment growth. Table 10 shows the impact of tradable employment growth on non-tradable, non-agricultural (tradable and non-tradable combined), and agricultural employment. All the dependent variables are defined as the change in absolute employment in the non-tradable /non-agriculture/ariculture divided by the total district employment in 1987-88. I find that a one standard deviation increase (21 tradable sector jobs) in tradable employment is associated with an increase of 37 jobs in non-tradable employment. The results are comparable with Moretti (2010), who finds a multiplier of 1.6. If I combine the tradable and non-tradable sectors, the growth in tradable sector employment by one standard deviation leads to overall growth in non-farm employment by 72 jobs (columns (3) and (4)). Next, I also check the impact of tradable employment growth on agriculture employment in districts (Columns (5) and (6)) and find a positive effect. One possible explanation for this could be the rising demand for agricultural products due to increasing incomes, and population due to migration. Particularly, there could be a possible rise in local demand for perishable products such as fruits and vegetables.

Next, I check how the growing tradable sector employment affects sectoral change and structural transformation. I find that a one standard deviation increase in tradable sector employment leads to a decline in the share of agriculture in district employment by eight percentage points and an increase in the share of tradable sector employment by seven percentage points in districts' overall employment. The share of non-tradable sectors in employment remains unchanged despite an increase in absolute level. Overall, the tradable sector leads to structural transformation with higher urbanization and non-agriculture employment.

Next, I check sector-wise employment growth separately for men and women. Table 12 shows the employment growth for men in agriculture, tradable, and non-tradable sectors in response to the growth in tradable employment. I find no significant effects of tradable sector employment growth on men's agri employment.

Table 13 shows the impact of tradable sector employment growth on female employment in different sectors. I define each of the variables as the change in sector employment between 1987-88 and 2011-12 per working-age females. Contrary to the impact on men, I find a significant rise in agriculture employment for women in districts with higher tradable employment growth. There could be Two possible explanations for the same are as follows. First, the rise in tradable employment increases consumer demand for agricultural products, as discussed above. Second, men join non-agriculture sectors in response to rising tradable (and, therefore, overall non-farm) employment and women work in agriculture.

Next, I find a positive effect of tradable sector employment growth on women's employment in both tradable and non-tradable sectors. However, the impact is weak, since I only find significant results in the OLS specification, and the IV estimates are insignificant. Within non-tradable sectors, I focus on female-intensive industries where women are relatively better represented. I combine employment in education, health, and personal services industry groups since, all of these industries have at least a 30% share of women employees, both in 1987-88 and 2011-12. I find that tradable employment growth increases women's employment in the female-intensive sectors due to the multiplier effect. A one standard deviation increase in tradable employment growth leads to approximately four additional jobs for women in these sectors. Overall, women's employment increases in women-intensive consumer services and in agriculture (also women-intensive). The next subsection analyzes the migration pattern in response to rising tradable employment.

4.2 Tradable growth and work migration pattern

I find that the employment impact of tradable growth is larger for women than men. One possible channel for this could be that men migrate in case of low local labor demand in their own districts. With the publicly available dataset, we do not know both the origin and destination districts of a migrant. However, we can observe the number of in-migrants in each district as well as the number of out-migrated members for each district. For in-migration, I use the Population Census 2011 to estimate the number of migrants in a district who moved from other districts for work in the past 20 years. Similarly, for out-migration, I use the NSS survey 2007-08 to estimate the number of household members migrating to other districts for work in the past 20 years. Therefore, I create two measures for in-migration and out-migration, for work in each district. I define migration as the total number of migrants per 100 working-age (15-59 years) population of the district in 1987-88 as follows:

$$\text{in-migration} = \frac{\text{total in-migrants for work}}{\text{district working-age population}} \times 100$$

$$\text{out-migration} = \frac{\text{total out-migrants for work}}{\text{district working-age population}} \times 100$$

Table 14 reports the results from estimating Equation (1) with dependent variable in-migration for work in each district. The positive coefficient shows that in-migration is relatively large in districts with higher tradable employment growth both for men and women. A One standard deviation increase in tradable sector employment is associated with an additional approximately nine male migrants per 100 working-age population and only 1.4 female migrants. The difference in magnitude is around 6.5 times; i.e., for every 6.5 male migrants, there is only one female work-related migrant in districts. In summary, the districts with tradable growth are positively associated with a rise in migrants from low tradable growth districts, primarily dominated by men.

Table 15 reports the results from estimating Equation (1) with dependent variable out-migration for work from each district. In line with the results on in-migration, the negative coefficients show that districts with high tradable employment growth have relatively low out-migration. In other words, districts with relatively low tradable employment growth have high out-migration, and vice-versa. A one standard deviation decline in the tradable sector employment leads to around two male out-migrants and 0.3 female out-migrants. Again, the magnitude for women is very low and the rate of migration for men is 14 times larger compared to women in IV estimates.[9]

Overall, the migration pattern could be interpreted as men migrating from districts with low local employment opportunities to districts with high tradable employment growth with higher local labor demand. However, only a small number of women migrate due to lower mobility and drop out of the labor force when facing low labor demand – contributing to a decline in female LFPR.

4.3 Robustness checks

In this section, I conduct robustness checks to see the consistency of the results. First, one issue with the main estimation could be that it is not possible to control for individual and household-level variables in the current framework which are significant predictors of female LFPR in India. For example, education and household income have a inverted U-shape relationship with female LFPR. Therefore, I estimate the following regression equation with individual-level observations:

$$\text{Female LF status}_{i,d,s,2011-12} = \beta_0 + \beta_1 \Delta\text{tradable emp}_{d,s} + \beta_2 \text{X}_{i,d,s} + \mu_s + \epsilon_{i,d,s} \qquad (3)$$

[9]The difference in magnitude of out-migration and in-migration is possibly due to the measurement differences in data. For out-migration, I am using the NSS data, which asks for the details of household members who have migrated out for work. Therefore, the out-migration from NSS primarily measures the temporary out-migration which is dominated by men. Contrary to this, I use the population census for in-migration which asks the residents of a district about their origins. Therefore, the in-migration from the census primarily measures permanent migration.

Here, i is individual, d is district and s is state. The dependent variable is female labor force status, a dummy variable which takes value 1 if women i is in the labor force and 0 otherwise in 2011-12. tradable $\text{emp}_{d,s}$ is tradable sector employment growth similar to Equation (1). $X_{i,d,s}$ are individual and household level control variables for education, age group, caste, religion, monthly household consumption expenditure, and rural location indicator. I also include state fixed effects and control for the district's female LFPR in 1987-88.

Table A.2 shows the results from estimating Equation (3). Column (1) shows a negative relationship between tradable growth and female LFPR in 2011-12. However, it does not account for the districts' female LFPR to begin with. As I control for the district's female LFPR in 1987-88, and other individual and district level controls, the sign changes (Columns (2) and (3)). Therefore, the probability of participation in the labor force is higher in districts with relatively large growth in tradable sector employment, after controlling for initial district-level female LFPR and demographic characters. Columns (3)-(6) show the results from estimating Equation (3) using the shift-share instrument. I find that a one standard deviation increase in tradable sector employment in the district leads to a 4.5 percentage point higher probability of women being in the labor force in that district. Therefore, I find qualitatively similar results to the main analysis using the district-level analysis.

Second, I check for different measurements of female LFPR. We can estimate labor force participation and employment in multiple ways with different reference periods using NSS EUS. First, the "Usual Principal Activity status" (UPA) is based on an annual reference period and considers an individual in the labor force if he/she has spent a relatively longer period of the past 365 days, either working or looking for work. Further, individuals are asked whether they were working for at least one month in the preceding year, then they are considered employed in the "Usual Principal Subsidiary status" (USA) status. Combining these two, the "Usual Principal and Subsidiary status" (UPSS) considers an individual in the labor force if he/she satisfies any of the UPS or USA criteria. In the main analysis, I used the UPSS definition which has relaxed criteria to consider someone in the labor force compared to the UPS definition. Similar to the LFPR, we can estimate the WPR (workforce participation rate) using both definitions.

Table A.3 reports the regression estimates for LFPR and WPR with different definitions.

We find the results consistent for both OLS and IV. The impact is larger with the UPSS definition compared to the UPS definition. A possible explanation could be that women's employment is higher in agriculture in response to the growth in tradable employment. And, if women work in agriculture for a short period only (less than six months in the previous year), then it does not get measured in the UPS definition, which has stricter criteria for work. Further, the similar magnitude between WPR and LFPR is consistent with the fact women hardly report as unemployed.

Next, the results are robust to the change of GC index cut-off for the classification of industries into tradable and non-tradable. I increase the cut-off of the GI index above which an industry gets classified as tradable. In the main analysis, I considered GC index of the food products industry group as cut-off, and the industries with the cut-off above were classified as tradable. However, industries like food products, wood products, etc. have low tradability because they have high trade costs and may not have an increasing return to scale. Therefore, these industries might not create a multiplier effect similar to other tradable industries. I change the cut-off and consider all the industries in Table 2 with the GI index above than that of the textile and wearing apparel industry, and find results similar to the main specification (Table A.4).

5 Summary and Concluding Remarks

Since the early 1990s India's economy started to grow significantly after the reforms and remained one of the fastest-growing countries in the world. The average annual GDP growth was above 4% between 1987 and 2011. The GDP growth rate has been above 7 % since the early 2000s until the recent slowdown. However, the employment indicators worsened during the same period with poor job creation. Particularly, the female LFPR declined sharply since 2004-05. This paper provides an explanation of why female LFPR declined in the period of high economic growth by focusing on growth in tradable sector employment.

The stagnation in tradable sectors (mainly manufacturing) is not specific to India. The decline of the manufacturing sector across countries in the last few decades has become a concern; particularly in the low-income countries. It was expected that underdeveloped countries would go through the industrialization phase to converge with developed countries. However, many underdeveloped and developing countries witnessed deindustrialization at a much lower per capita income level compared to today's developed countries – called premature deindustrialization (Rodrik, 2016). My findings suggest that deindustrialization could be particularly worrying for women in countries where women's labor supply is highly responsive to the local labor demand. In terms of policy implication, it is important to revisit the industrial policy for overall employment growth. This is not unique to India as many countries are showing interest in the industrial policy against the backdrop of competition from China and facing challenges in creating good jobs (Juhász et al., 2023; Juhász and Steinwender, 2023). Additionally, we need to emphasize place-based policy to target regional disparities in industrial growth because of labor mobility is low in India.

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Table 1: Summary Statistics

	(1) 1987-88		(2) 2011-12		(3) change	
	mean	sd	mean	sd	mean	sd
LFPR	0.493	(0.212)	0.351	(0.176)	-0.141	(0.176)
Education level						
Illiterate	0.679	(0.185)	0.367	(0.164)	-0.312	(0.105)
Primary	0.175	(0.093)	0.208	(0.077)	0.033	(0.104)
Secondary	0.130	(0.097)	0.358	(0.122)	0.228	(0.084)
College	0.016	(0.019)	0.068	(0.053)	0.052	(0.043)
Age group (in years)						
15-20	0.222	(0.030)	0.186	(0.046)	-0.036	(0.056)
21-30	0.322	(0.035)	0.287	(0.051)	-0.035	(0.056)
31-40	0.218	(0.026)	0.260	(0.049)	0.042	(0.054)
41-50	0.161	(0.023)	0.175	(0.040)	0.014	(0.048)
50-59	0.077	(0.020)	0.092	(0.032)	0.016	(0.035)
Caste category						
ST	0.088	(0.146)	0.085	(0.146)	-0.003	(0.064)
SC	0.177	(0.082)	0.190	(0.099)	0.013	(0.089)
Other	0.735	(0.141)	0.725	(0.146)	-0.010	(0.100)
Religion						
Hindu	0.843	(0.140)	0.833	(0.145)	-0.010	(0.079)
Muslim	0.102	(0.100)	0.119	(0.112)	0.017	(0.068)
Sikh	0.021	(0.104)	0.019	(0.099)	-0.002	(0.027)
Other	0.034	(0.058)	0.029	(0.061)	-0.005	(0.038)
Married	0.786	(0.078)	0.752	(0.057)	-0.034	(0.078)
Rural	0.783	(0.169)	0.739	(0.190)	-0.044	(0.078)
Monthly capita expenditure	188.515	(74.607)	253.716	(93.535)	65.201	(78.116)
Observations	358		358		358	

Notes: The table reports the weighted mean and standard deviations of variables at the district level using the sample of women between age of 15 to 59 years. The change variable in Column (3) is estimated as absolute change between 1987-88 and 2011-12.

Table 2: Classifying industries into tradable and non-tradable

Tradable		Non-tradable	
Industry	Index	Industry	Index
Metal ores	.3373	Post and telecommunications	.0042
Air transport	.3102	Water supply	.0035
Crude petroleum and natural gas	.137	Land transport	.0035
Advertising	.1062	Wholesale	.0033
Coal, lignite, and peat	.0883	Membership organizations	.0028
Other business activities	.0868	Hotels	.0028
Business and management consultancy	.0795	Recreational cultural and sporting activities	.0022
Accounting	.0747	Furniture	.002
Refined petroleum	.0704	Construction	.0016
Architecture and engineering	.0615	Education	.0014
Water transport	.049	Public administration and defense	.0013
Transport equipment	.0392	Repair services	.0012
Computer and related activities	.0368	Restaurants	.0008
Tobacco products	.0342	Personal service	.0005
Medical, precision, and optical instruments	.0308	Health and social work	.0005
Real estate activities	.0288	Retail	.0002
Basic metals	.0271		
Chemicals	.027		
Other manufacturing	.0267		
Rubber and plastics products	.0225		
Leather products	.0193		
Other mining and quarrying	.0174		
Sewerage and waste treatment	.0154		
Insurance and pension	.013		
Research and development	.0126		
Paper products, printing, and publishing	.0101		
Machinery and equipment	.0099		
Renting	.0079		
Supporting and auxiliary transport activities	.0071		
Gambling	.0064		
Electricity, gas, steam supply	.0062		
Fabricated metal	.0061		
Financial service	.0057		
Textiles and wearing apparel	.0057		
Legal activities	.0056		
Wood products	.0053		
Other non-metallic mineral products	.005		
Food products	.0045		

The table reports the geographical concentration index for each industry group. This does not include the following industry groups – agriculture sectors, extra-territorial organizations, Goods-producing activities for own use, and service-producing activities for own use industry groups. I classify agriculture as a separate sector and remaining as non-tradable.

Table 3: Top five industries with the highest weight in the instrument

	Industry	weight
1	Textiles and wearing apparel	0.26
2	Other business activities	0.17
3	Computer and related activities	0.15
4	Other manufacturing	0.10
5	Real estate activities	0.08
	Total	0.78

Note: Other manufacturing includes the manufacture of jewellery and related articles, musical instruments, sports goods, games and toys, medical and dental instruments and supplier, Other manufacturing n.e.c. Other business activities include specialized design activities, Photographic activities, scientific and technical activities; Employment activities, Security and investigation activities; Services to buildings and landscape activities; Office administrative, office support and other business support activities.

Table 4: Relationship between initial industry share and district level characteristics

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Textiles and wearing apparel	Other business activities	Computer and related activities	Other manufacturing	Real estate activities
Urban pop	0.105	0.026***	0.004	0.069**	-0.001
	(0.068)	(0.009)	(0.003)	(0.031)	(0.002)
Mean MPCE	0.045	-0.004	-0.000	0.005	-0.000
	(0.034)	(0.003)	(0.001)	(0.008)	(0.001)
Illiterate	0.225	0.063	-0.016	-0.345*	0.010
	(0.410)	(0.064)	(0.024)	(0.182)	(0.012)
Primary	0.484	-0.240	-0.005	0.125	-0.021
	(0.526)	(0.170)	(0.018)	(0.223)	(0.014)
Secondary	0.530	-0.230	-0.008	0.342*	-0.018
	(0.528)	(0.167)	(0.017)	(0.203)	(0.014)
ST	0.472	-0.234	0.007	-0.061	-0.021
	(0.578)	(0.180)	(0.026)	(0.311)	(0.014)
SC	0.036	0.015	0.000	-0.017	-0.002
	(0.054)	(0.010)	(0.001)	(0.040)	(0.002)
Hindu	0.170*	0.023	0.002	-0.119	-0.001
	(0.103)	(0.018)	(0.006)	(0.074)	(0.003)
Muslim	0.058	-0.007	0.004	0.042	-0.013
	(0.070)	(0.011)	(0.004)	(0.027)	(0.012)
Sikh	0.092	0.019	-0.001	-0.017	-0.012
	(0.086)	(0.017)	(0.002)	(0.039)	(0.013)
21-30	0.008	-0.016	-0.001	0.057*	-0.010
	(0.084)	(0.014)	(0.002)	(0.031)	(0.011)
31-40	0.008	0.021	0.007	-0.251**	0.023
	(0.308)	(0.037)	(0.005)	(0.123)	(0.016)
41-50	0.363	-0.029	-0.009	-0.233*	0.025
	(0.315)	(0.057)	(0.015)	(0.136)	(0.019)
Constant	-0.788	0.243	0.003	0.038	0.020
	(0.666)	(0.168)	(0.019)	(0.267)	(0.016)
Observations	358	358	358	358	358
R-squared	0.031	0.194	0.072	0.116	0.144

Notes: Each column reports the results of a single regression of a 1987-88 industry share on 1987-88 characteristics.

Table 5: Impact of tradable sector employment growth on female LFPR: OLS estimates

	(1)	(2)	(3)	(4)
Change in tradable	0.0928***	0.0901***	0.0935***	0.0982***
	(0.0186)	(0.0186)	(0.0218)	(0.0241)
Change in non-tradable				-0.00872
				(0.0116)
Δ age-group shares		Yes	Yes	Yes
Δ caste shares		Yes	Yes	Yes
Δ religion shares		Yes	Yes	Yes
Δ married share		Yes	Yes	Yes
Δ education levels			Yes	Yes
Δ household consumption			Yes	Yes
Δ urban share			Yes	Yes
State FE	Yes	Yes	Yes	Yes
Observations	358	358	358	358
R-squared	0.171	0.222	0.292	0.293

Note: This table corresponds to the regression results of Equation (1). The dependent variable is the change in LFPR in percentage points. The main explanatory variable "change in tradable" is the standardized value of absolute change in tradable employment in the district divided by total employment in the district in 1987-88. The "change in non-tradable" variable is also defined in a similar way. All regressions include state fixed effects. All controls are in percentage point change values between 1987-88 and 2011-12. Age groups, caste groups, religious groups and education level controls have multiple sub-categories as mentioned in Table 1. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 6: Impact of tradable sector employment growth on female LFPR: 2SLS estimates

	(1)	(2)	(3)	(4)
Change in tradable emp	0.131***	0.114***	0.105***	0.112***
	(0.0270)	(0.0264)	(0.0335)	(0.0388)
Change in non-tradable emp				-0.0115
				(0.0132)
Δ age-group shares		Yes	Yes	Yes
Δ caste shares		Yes	Yes	Yes
Δ religion shares		Yes	Yes	Yes
Δ married share		Yes	Yes	Yes
Δ education levels			Yes	Yes
Δ household consumption			Yes	Yes
Δ urban share			Yes	Yes
State FE	Yes	Yes	Yes	Yes
Observations	358	358	358	358
R-squared	0.009	0.014	0.017	0.011
1st stage F-stat	70.18	74.05	50.00	43.07

Note: This table corresponds to the regression results of Equation (1) using IV. The dependent variable is the change in LFPR in percentage points. The main explanatory variable "change in tradable" is the standardized value of absolute change in tradable employment in the district divided by total employment in the district in 1987-88. The "change in non-tradable" variable is also defined in a similar way. All regressions include state fixed effects. All controls are in percentage point change values between 1987-88 and 2011-12. Age groups, caste-groups, religious groups and education level controls have multiple sub-categories as mentioned in Table 1. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 7: Impact of tradable sector employment growth on female LFPR

	(1)	(2)	(3)	(4)
	2SLS estimates			
change in tradable	0.131***	0.113***	0.0778***	0.107***
	(0.0270)	(0.0263)	(0.0279)	(0.0394)
change in non-tradable				-0.0259
				(0.0159)
Initial level controls				
caste shares		Yes	Yes	Yes
religion shares		Yes	Yes	Yes
married share		Yes	Yes	Yes
education levels			Yes	Yes
household consumption			Yes	Yes
urban share			Yes	Yes
State FE	Yes	Yes	Yes	Yes
Observations	358	358	358	358
R-squared	0.009	0.014	0.017	0.011

Note: This table corresponds to the regression results of Equation (1) with IV. The main explanatory variable "change in tradable" is the standardized value of absolute change in tradable employment in the district divided by total employment in the district in 1987-88. The "change in non-tradable" variable is also defined in a similar way. All regressions include state fixed effects. All controls are defined for the initial level (1987-88) of the working-age population as in Column (1) of 1. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 8: Impact of tradable sector employment growth on female LFPR

	(1)	(2)	(3)	(4)
	Rural		Urban	
	OLS	IV	OLS	IV
Change in tradable	0.0675***	0.116***	0.0655***	0.0766***
	(0.0253)	(0.0394)	(0.0146)	(0.0256)
Controls	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Observations	355	355	344	344
R-squared	0.285	0.038	0.297	0.080

Note: This table corresponds to the regression results of Equation (1). The dependent variable is the change in rural LFPR in percentage points for Columns (1) and (2) and it is the change in urban LFPR in percentage points for Columns (3) and (4). The main explanatory variable "change in tradable" is the standardized value of absolute change in tradable employment in the district divided by total employment in the district in 1987-88. All regressions include state fixed effects controls similar to Column (3) of Table 5. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 9: Impact of tradable employment growth on male employment: 2SLS estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	All age			Age (15-30)			Age (31-59)		
	LFPR	WPR	Unemp rate	LFPR	WPR	Unemp rate	LFPR	WPR	Unemp rate
Change in tradable	0.0376***	0.0753***	-0.0435***	0.131***	0.187***	-0.0838***	-0.00341	-0.000167	-0.00340
	(0.0141)	(0.0167)	(0.0105)	(0.0412)	(0.0460)	(0.0143)	(0.00529)	(0.00655)	(0.00309)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	358	358	358	358	358	358	358	358	358
R-squared	0.125	0.048	-0.029	0.081	-0.003	0.009	0.101	0.066	0.074

Note: This table corresponds to the regression results of Equation (1) using IV for the male sample. The dependent variables are the change in male LFPR (percentage points) in Columns (1), (4), and (7); the change in male WPR (percentage points) in Columns (2), (5), and (8); the change in the male unemployment rate(percentage points) in Columns (3), (6), and (9). The dependent variables are estimated using the working-age male sample for Columns (1) to (3); while the same is estimated for sub-groups for Columns (4) to (6) as mentioned in the cluster column headings. The main explanatory variable "change in tradable" is the standardized value of absolute change in tradable employment in the district divided by total employment in the district in 1987-88. All regressions include state fixed effects controls similar to Column (3) of Table 7. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 10: Impact of tradable employment growth on local employment

	(1)	(2)	(3)	(4)	(5)	(6)
	Δ non-tradable employment		Δ non-farm employment		Δ agri employment	
	OLS	IV	OLS	IV	OLS	IV
Change in tradable	0.278***	0.372***	0.637***	0.727***	0.0271	0.112*
	(0.0318)	(0.0545)	(0.0558)	(0.0845)	(0.0340)	(0.0635)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	358	358	358	358	358	358
R-squared	0.676	0.632	0.453	0.351	0.195	-0.019

Note: This table corresponds to the regression results of Equation (1) with the following dependent variables. The dependent variables are the change in absolute employment in the "sector" divided by the total district employment in 1987-88; where the sector is non-tradable employment in Columns (1) and (2), all non-farm employment in Columns (3) and (4), and agriculture employment in Columns (5) and (6). The main explanatory variable "change in tradable" is the standardized value of absolute change in tradable employment in the district divided by total employment in the district in 1987-88. All regressions include state fixed effects controls similar to Column (3) of Table 7. Robust standard errors are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 11: Impact of tradable employment growth on the evolution of districts

	(1)	(2)	(3)	(4)	(5)	(6)
	Δ Population growth		Δ Urbanization		Δ Consumption expenditure	
	OLS	IV	OLS	IV	OLS	IV
Change in tradable	0.656***	0.820***	0.0794***	0.118***	0.179***	0.306***
	(0.0884)	(0.151)	(0.0103)	(0.0180)	(0.0374)	(0.0764)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	358	358	358	358	358	358
R-squared	0.486	0.406	0.363	0.223	0.605	0.430

Note: This table corresponds to the regression results of Equation (1) with the following dependent variables. The dependent variables are percentage growth in population in districts for Columns (1) and (2), the change in share of the urban population in districts for Columns (3) and (4), the percentage growth in real monthly per capita consumption expenditure in districts for Columns (5) and (6). The main explanatory variable "change in tradable" is the standardized value of absolute change in tradable employment in the district divided by total employment in the district in 1987-88. All regressions include state fixed effects controls similar to Column (3) of Table 7. Robust standard errors are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 12: Impact of tradable employment growth on sector-wise employment growth for men

	(1)	(2)	(3)	(4)	(5)	(6)
		OLS			IV	
	Δ Agri	Δ Tradable	Δ Non-tradable	Δ Agri	Δ Tradable	Δ Non-tradable
Change in tradable growth in tradable	-0.0136	0.381***	0.336***	0.0352	0.435***	0.424***
	(0.0349)	(0.0386)	(0.0512)	(0.0589)	(0.0704)	(0.0738)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	358	358	358	358	358	358
R-squared	0.228	0.727	0.398	0.041	0.677	0.324

Note: This table corresponds to the regression results of Equation (1) with the following dependent variables. The dependent variables are change in absolute employment in the "sector" divided by the total male employment of the district in 1987-88; where the sector is agriculture employment in Columns (1) and (4), tradable employment in Columns (2) and (5), and non-tradable employment in Columns (3) and (6). The main explanatory variable "change in tradable" is the standardized value of absolute change in tradable employment in the district divided by total employment in the district in 1987-88. All regressions include state fixed effects controls similar to Column (3) of Table 7. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 13: Impact of tradable employment growth on sectoral employment growth for women

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS				IV			
	Δ Agri	Δ Tradable	Δ Non-tradable	Δ Women-intensive	Δ Agri	Δ Tradable	Δ Non-tradable	Δ Women-intensive
Change in tradable	0.0823**	0.136**	0.135*	0.0232***	0.174**	0.150	0.200*	0.0379***
	(0.0404)	(0.0584)	(0.0690)	(0.00815)	(0.0713)	(0.0973)	(0.113)	(0.0111)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	358	358	358	358	358	358	358	358
R-squared	0.339	0.337	0.259	0.414	0.080	0.283	0.196	0.201

Note: This table corresponds to the regression results of Equation (1) with the following dependent variables. The dependent variables are the standardized value of change in absolute employment in the "sector" divided by the total female working-age population of the district in 1987-88; where the sector is agriculture employment in Columns (1) and (4), tradable employment in Columns (2) and (5), non-tradable employment in Columns (3) and (6), and employment in female intensive sectors (education, health and personal services) in Columns (4) and (8). The main explanatory variable "change in tradable" is the standardized value of absolute change in tradable employment in the district divided by total employment in the district in 1987-88. All regressions include state fixed effects controls similar to Column (3) of Table 7. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 14: Impact of tradable growth on district level in-migration

	(1)	(2)	(3)	(4)
	OLS		2SLS	
	M	F	M	F
Change in tradable	5.375***	0.864***	9.128***	1.404***
	(1.047)	(0.223)	(1.474)	(0.340)
Constant	-18.41	-5.203	-18.72	-5.083
	(23.16)	(4.198)	(25.51)	(4.351)
Controls	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Observations	358	358	358	358
R-squared	0.569	0.406	0.407	0.306
Mean	2.543	0.409	2.543	0.409

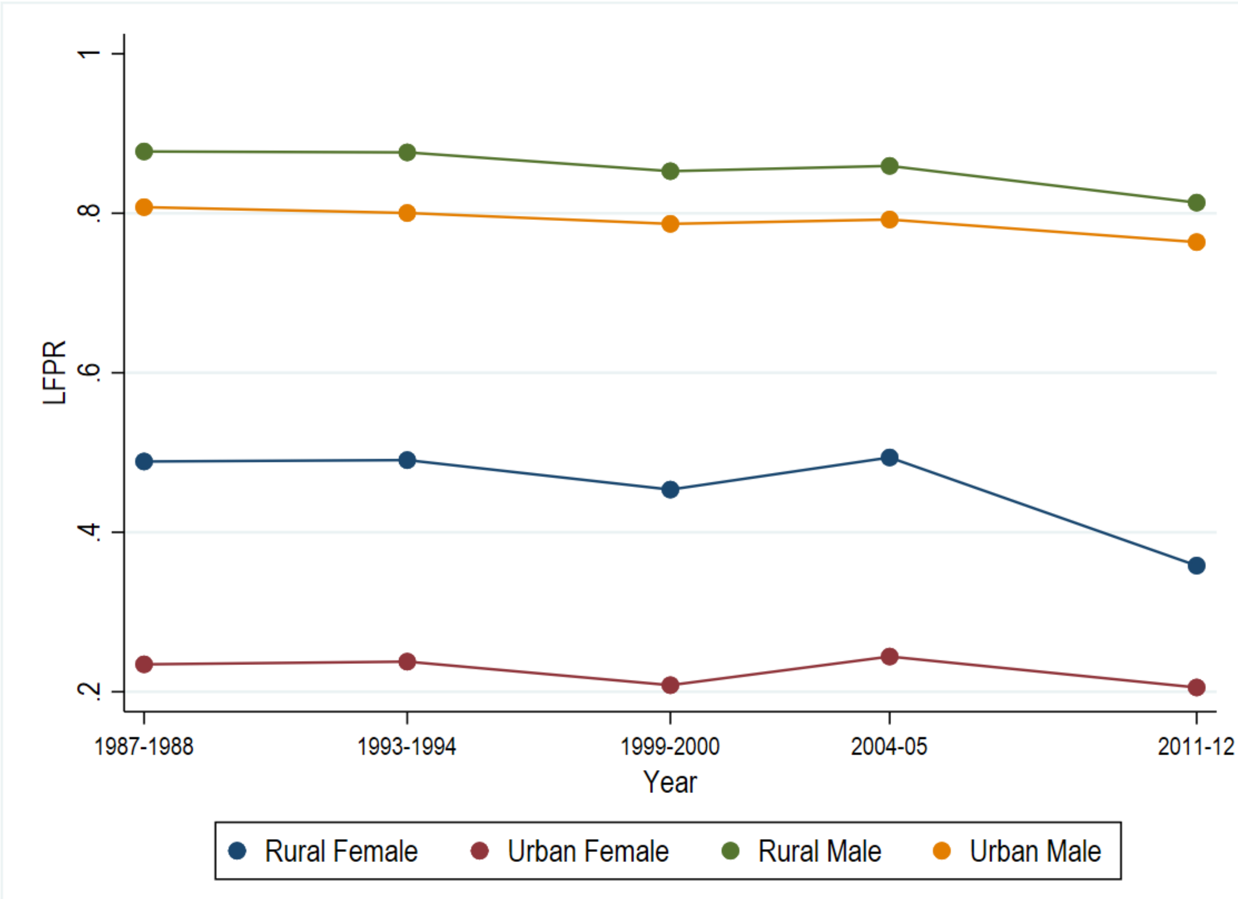
Note: This table corresponds to the regression results of Equation (1) with the dependent variables as migration in the district. The migration variable is defined as the total number of male migrants per 100 working-age population in the district in Columns (1) and (3); and similarly for females in Columns (2) and (4). The main explanatory variable "change in tradable" is the standardized value of absolute change in tradable employment in the district divided by total employment in the district in 1987-88. All regressions include state fixed effects controls similar to Column (3) of Table 7. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 15: Impact of tradable growth on district level out-migration

	(1)	(2)	(3)	(4)
	OLS		2SLS	
	M	F	M	F
Change in tradable	-1.134***	-0.0487**	-1.900***	-0.133**
	(0.239)	(0.0227)	(0.393)	(0.0543)
Constant	3.667***	0.178***	2.167***	0.198***
	(0.156)	(0.0154)	(0.366)	(0.0582)
Controls	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Observations	358	358	358	358
R-squared	0.303	0.119	0.290	0.101
Mean	3.753	0.182	3.753	0.182

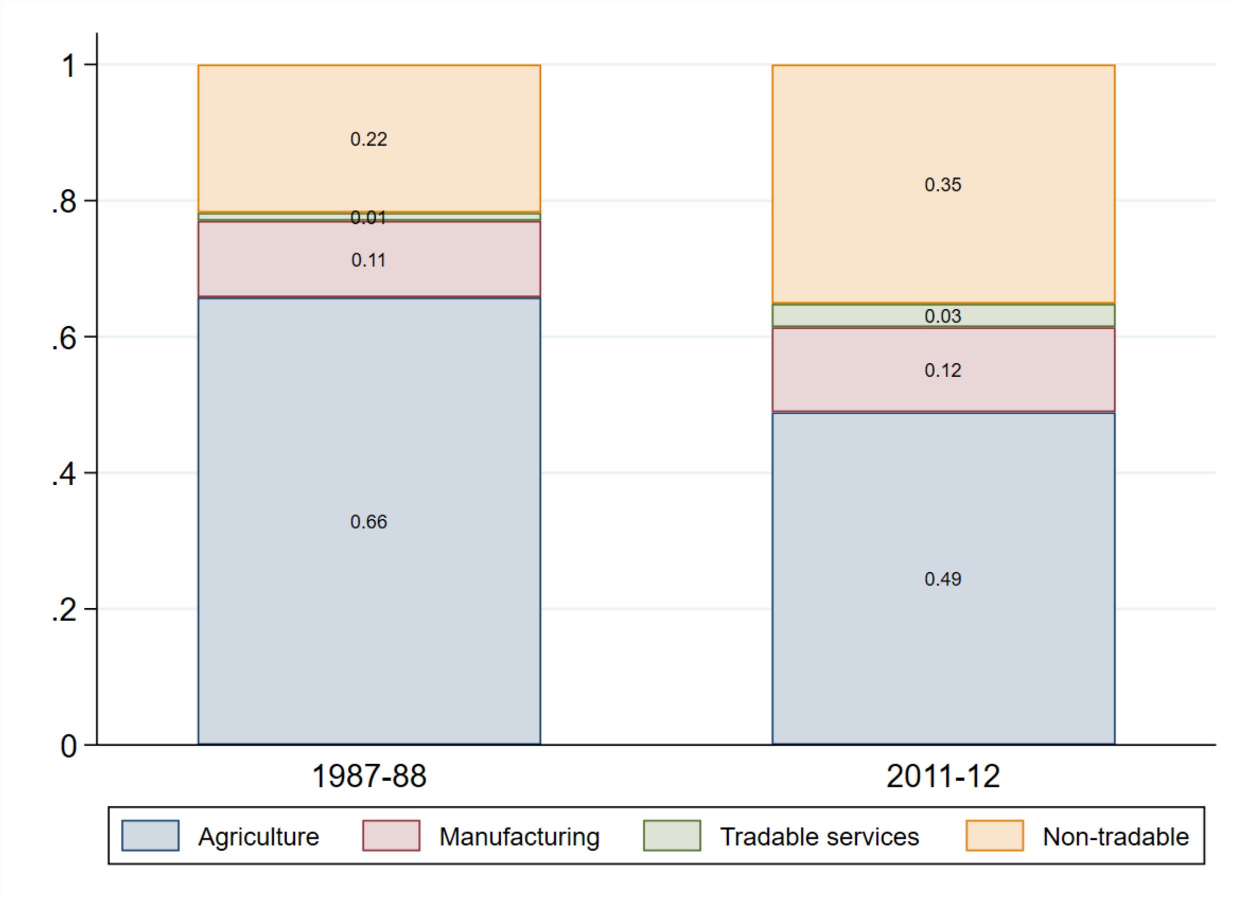
Note: This table corresponds to the regression results of Equation (1) with the dependent variables as migration in the district. The migration variable is defined as the total number of male outmigrants per 100 working-age population from the district in Columns (1) and (3); and similarly for females in Columns (2) and (4). The main explanatory variable "change in tradable" is the standardized value of absolute change in tradable employment in the district divided by total employment in the district in 1987-88. All regressions include state fixed effects controls similar to Column (3) of Table 7. Robust standard errors are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Figure 1: Labor force participation rate (1987-88 to 2011-12)



Notes: The figure shows the labor force participation rate (UPSS) by gender and urban-rural using various rounds of NSS EUS surveys.

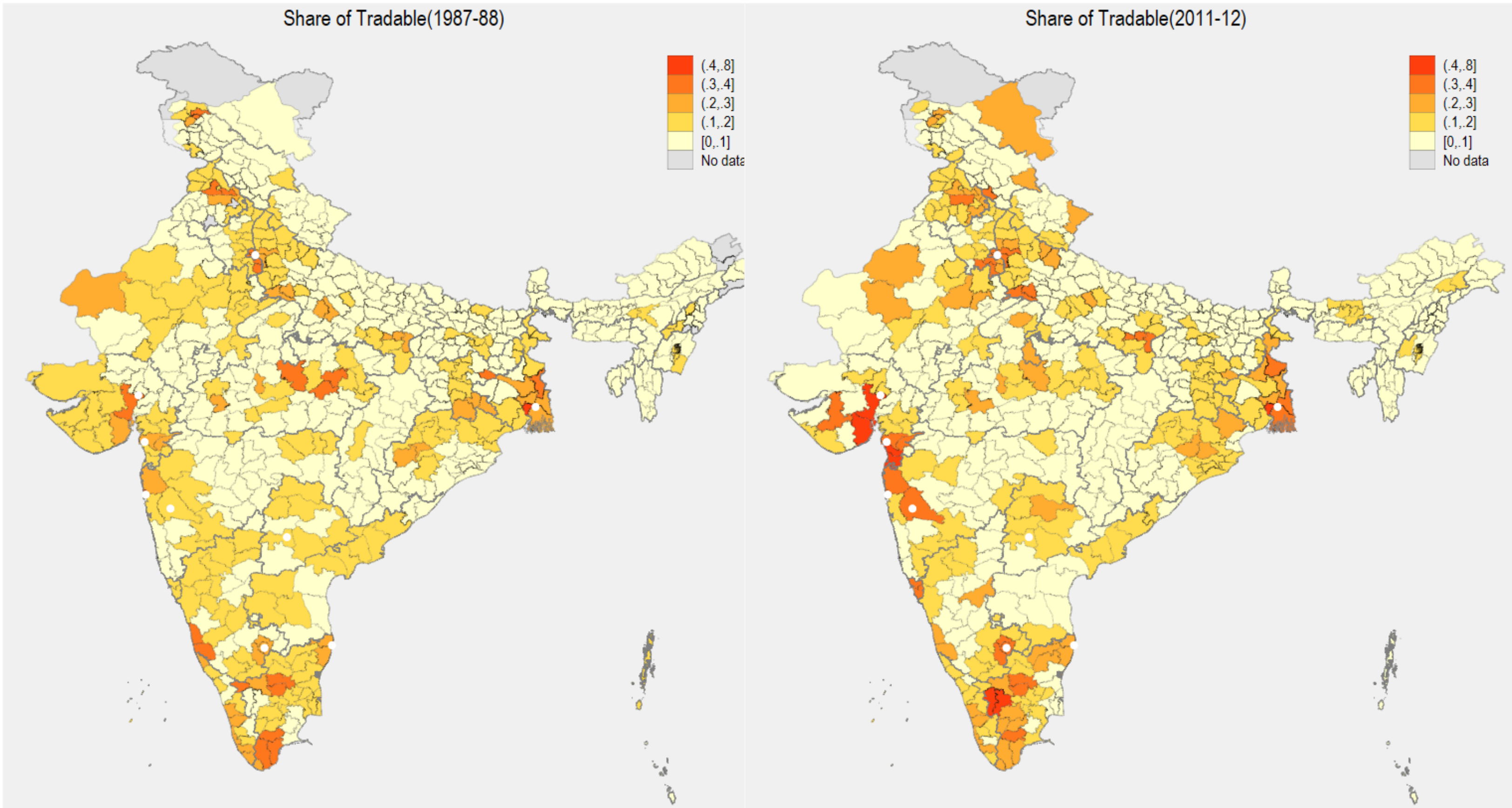
Figure 2: Composition of employment (1987-88 to 2011-12)



Notes: The figure shows the share of total employment in Agriculture, manufacturing, tradable services, and non-tradable services.

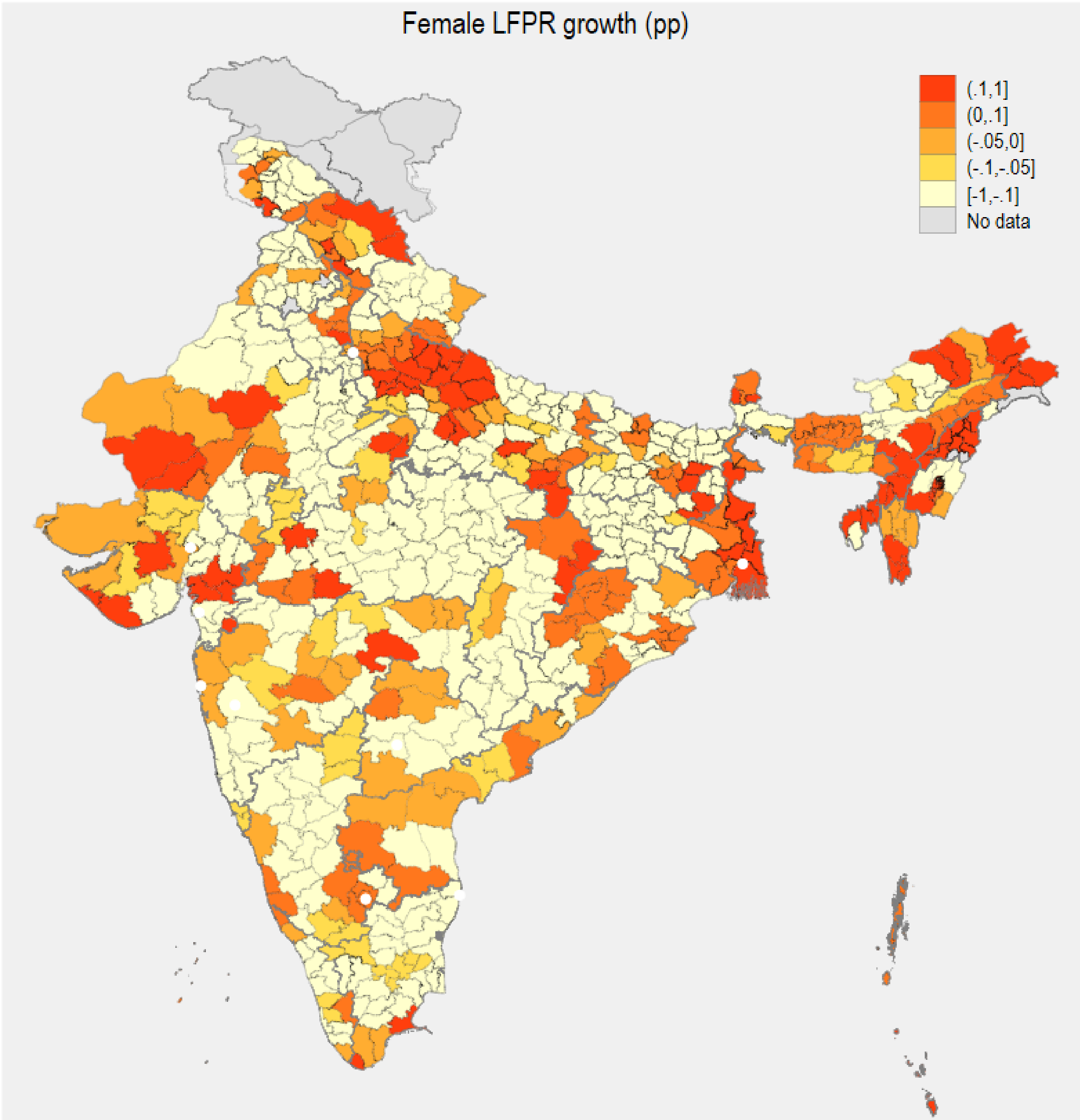
Figure 3: Geographical variation in share of tradable in total employment

(a) 1987-88 (b) 2011-12



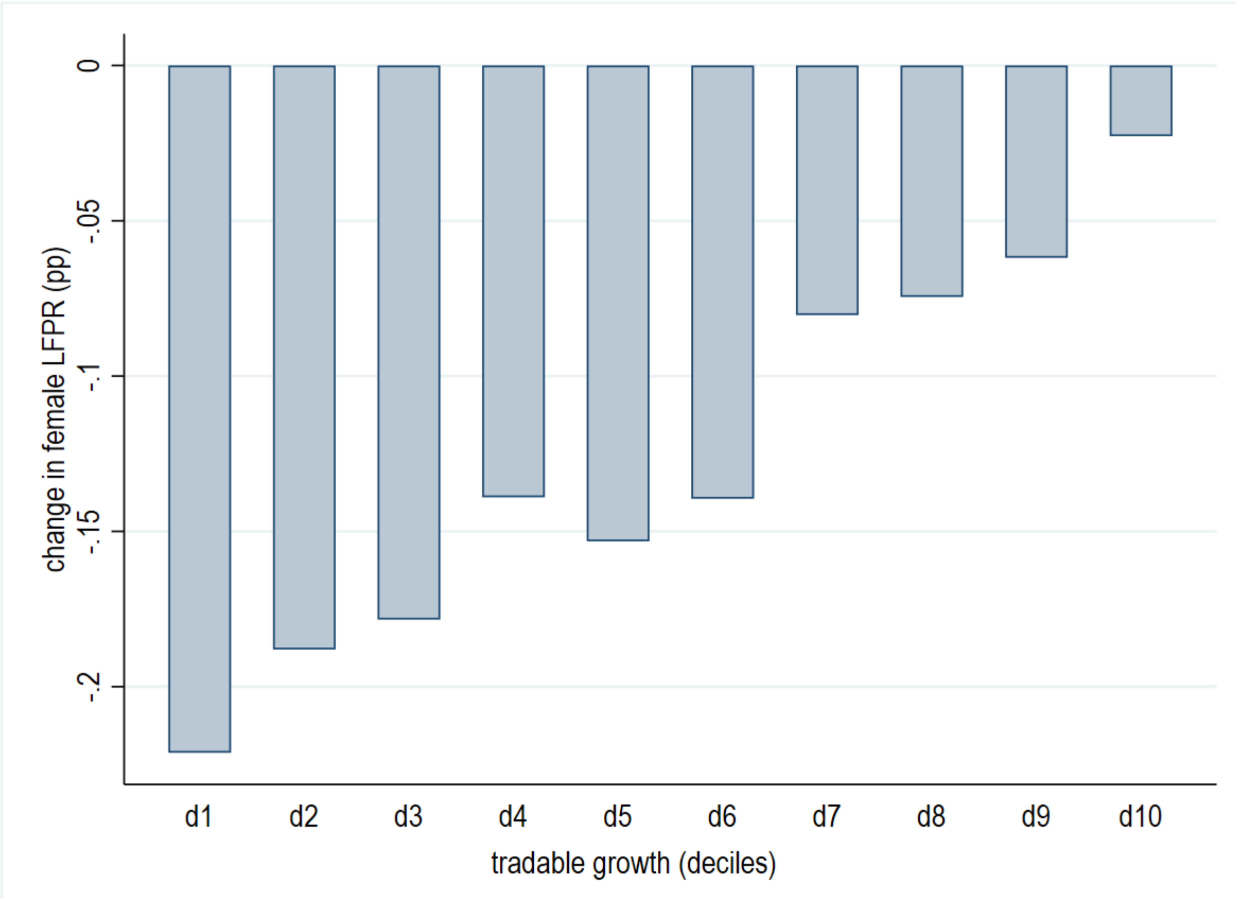
Notes: The figure shows the share of tradable (manufacturing and tradable services combined) in total employment in each district for 1987-88 and 2011-12.

Figure 4: Change (pp) in female LFPR between 1987-88 and 2011-12



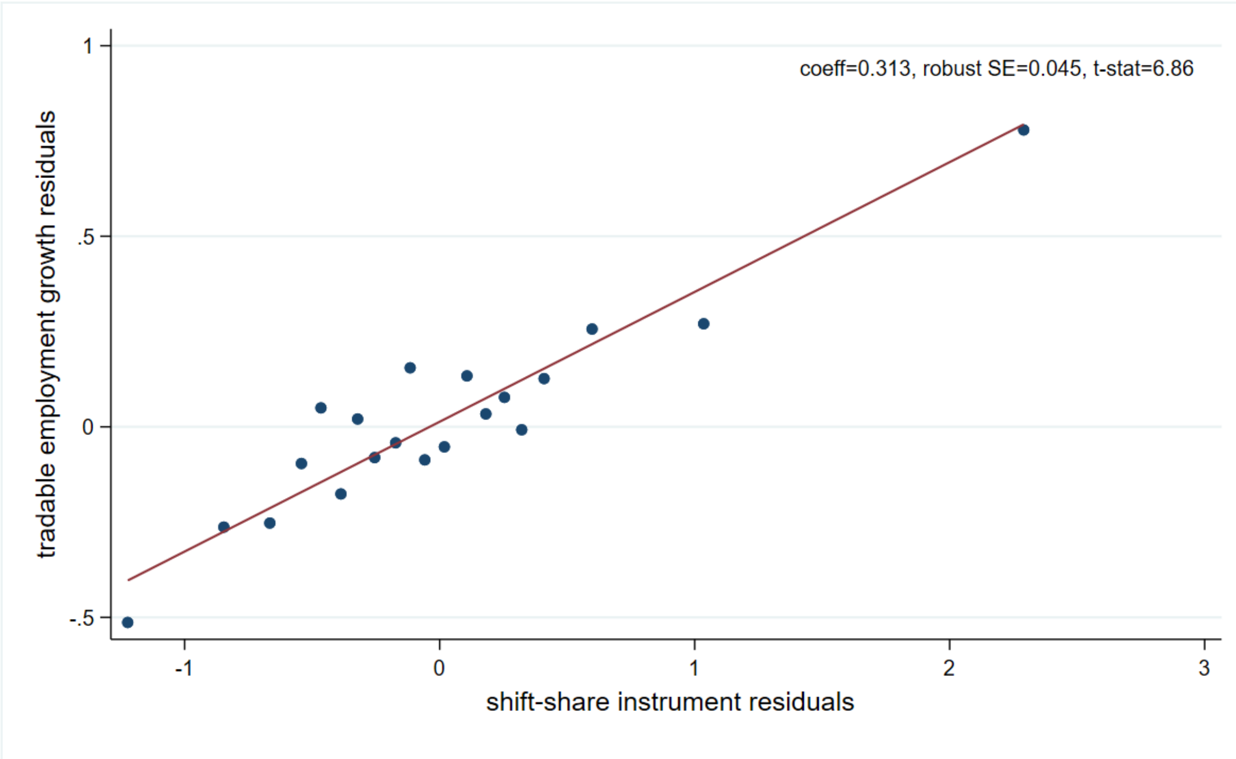
Notes: The figure shows the change in female LFPR (in percentage points) between 1987-88 and 2011-12 in each district.

Figure 5: Change in female LFPR vs tradable growth



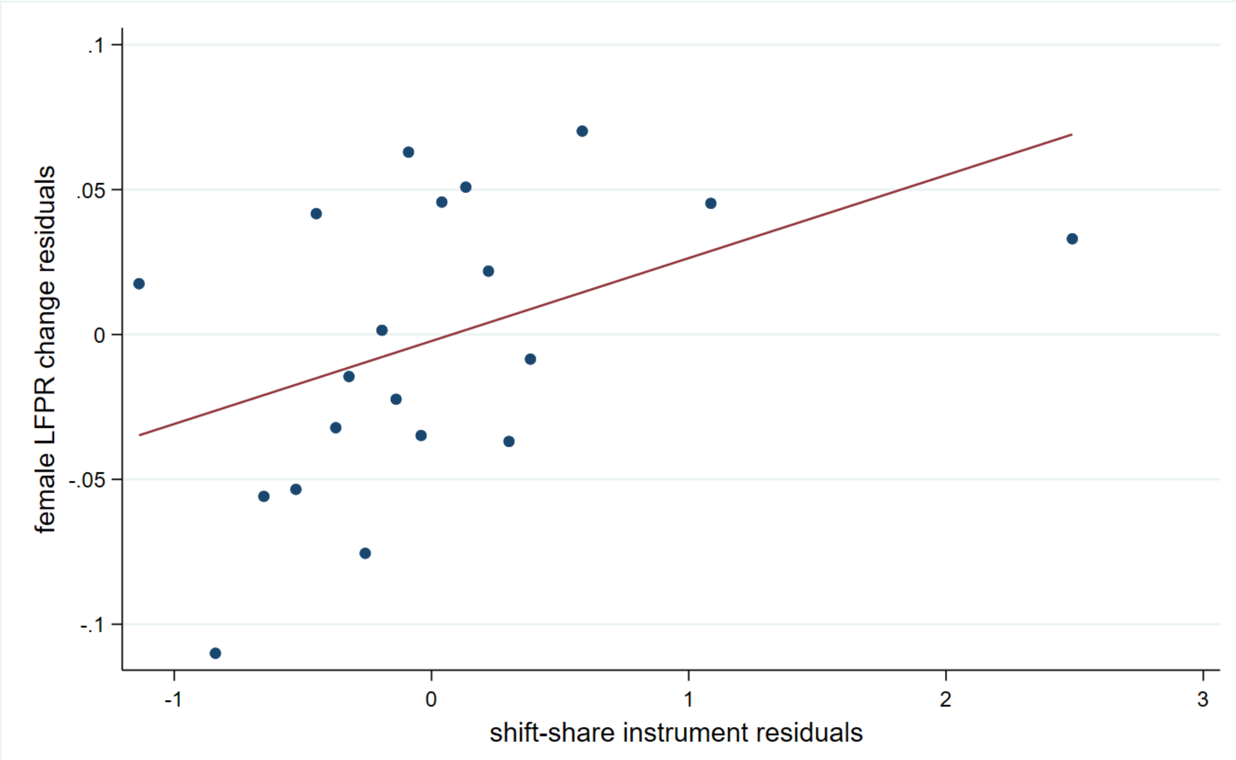
Notes: The figure shows the relationship between tradable growth and change in female LFPR. I divide the districts into 10 deciles based on growth in tradable employment and estimate the change in female LFPR for each decile. The decile d1 is the group of districts with the lowest growth in tradable employment and d10 has districts with the highest tradable employment growth. The y-axis shows the average change in female LFPR for districts in each decile.

Figure 6: IV first stage



The figure plots the relationship between tradable growth residuals (y-axis) and shift-share instrument residuals (x-axis). First, I regress both the variables on state dummies and controls to obtain their residual values. This is a scatter bin plot between these residuals.

Figure 7: Change in female LFPR vs instrument (predicted tradable growth)



The figure plots the relationship between female LFPR change residuals (y-axis) and shift-share instrument residuals (x-axis). First, I regress both the variables on state dummies and controls to obtain their residual values. This is a scatter bin plot between these residuals.

Appendix Figures and Tables

Table A.1: Impact of tradable employment growth on sectoral change

	(1)	(2)	(3)	(4)	(5)	(6)
	Δ agri employment		Δ tradable employment		Δ non-tradable employment	
	OLS	IV	OLS	IV	OLS	IV
Change in tradable	-0.125***	-0.0848***	0.111***	0.0711***	0.0140	0.0137
	(0.0147)	(0.0273)	(0.00786)	(0.0133)	(0.0139)	(0.0224)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	358	358	358	358	358	358
R-squared	0.397	0.274	0.702	0.592	0.326	0.118

Note: This table corresponds to the regression results of Equation (1) with the following dependent variables. The dependent variables are the change in share of employment in the "sector" in total district employment between 1987-88 and 2011-12; where the sector is agriculture in Columns (1) and (2), tradable in Columns (3) and (4), and non-tradable in Columns (5) and (6). The main explanatory variable "change in tradable" is the standardized value of absolute change in tradable employment in the district divided by total employment in the district in 1987-88. All regressions include state fixed effects controls similar to Column (2) of Table 5 for male and female combined sample. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A.2: Impact on female LFPR, individual-level analysis

	(1)	(2)	(3)	(4)	(5)	(6)
		OLS			IV	
Change in tradable	-0.0339***	0.0271***	0.0189***	-0.0227***	0.0227***	0.0430***
	(0.0044)	(0.0048)	(0.0047)	(0.0035)	(0.0040)	(0.0047)
Female LFPR (1987-88)		0.320***	0.191***		0.287***	0.229***
		(0.0157)	(0.0187)		(0.00930)	(0.0103)
Individual controls			Yes			Yes
Household level controls			Yes			Yes
District level controls			Yes			Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	113,615	113,615	113,615	113,615	113,615	113,615
R-squared	0.058	0.069	0.108	0.000	0.009	0.047

Note: This table corresponds to the regression results of Equation (3). Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A.3: Robustness check: employment measurements

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS				2SLS			
VARIABLES	LFPR (UPSS)	LFPR (UPS)	WPR (UPSS)	WPR (UPS)	LFPR (UPSS)	LFPR (UPS)	WPR (UPSS)	WPR (UPS)
change in tradable	0.0935***	0.0541***	0.0880***	0.0482***	0.105***	0.100***	0.0765**	0.0717**
	(0.0218)	(0.0172)	(0.0211)	(0.0167)	(0.0335)	(0.0322)	(0.0302)	(0.0294)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	358	358	358	358	358	358	358	358
R-squared	0.313	0.298	0.330	0.322	0.329	0.346	0.326	0.349

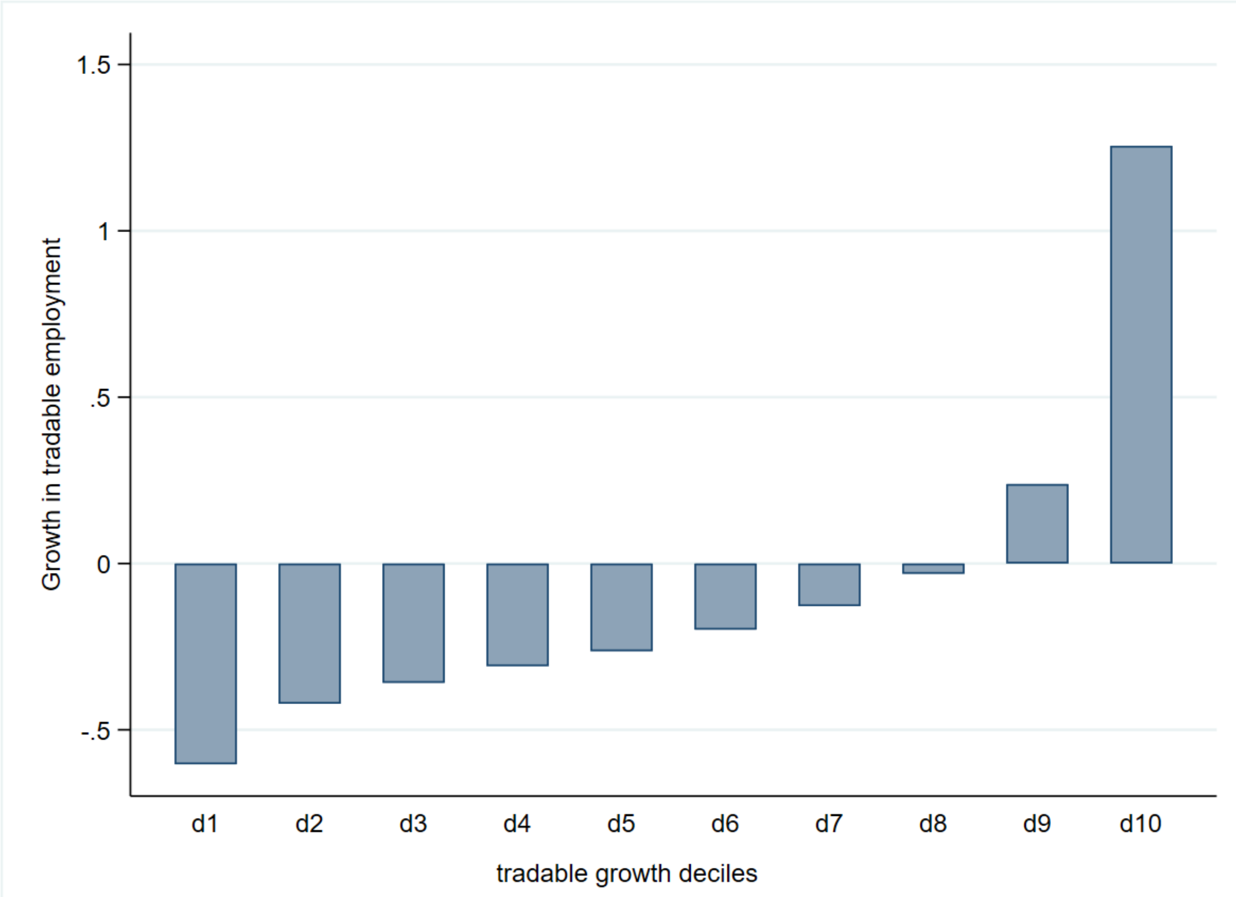
Note: This table corresponds to the regression results of Equation (3) using IV. The dependent variable is the change in female LFPR in percentage points. The main explanatory variable "change in tradable" is the standardized value of absolute change in tradable employment in the district divided by total employment in the district in 1987-88. All the controls are similar to the Column (3) Table 6. The Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A.4: Robustness checks: Changing tradable classification

	(1)	(2)	(3)	(4)
	2SLS estimates			
change in tradable	0.137***	0.119***	0.0846**	0.114**
	(0.0298)	(0.0289)	(0.0341)	(0.0445)
change in non-tradable				-0.0106
				(0.0141)
Δ age-group shares		Yes	Yes	Yes
Δ caste shares		Yes	Yes	Yes
Δ religion shares		Yes	Yes	Yes
Δ married share		Yes	Yes	Yes
Δ education levels			Yes	Yes
Δ household consumption			Yes	Yes
Δ urban share			Yes	Yes
State FE	Yes	Yes	Yes	Yes
Observations	358	358	358	358
R-squared	0.057	0.071	0.062	0.064

Note: This table corresponds to the regression results of Equation (1) with IV. The dependent variable is the change in female LFPR in percentage points. The main explanatory variable "change in tradable" is the standardized value of absolute change in tradable employment in the district divided by total employment in the district in 1987-88. The "change in non-tradable" variable is also defined in a similar way. All regressions include state fixed effects. All controls are in percentage point change values between 1987-88 and 2011-12. Age groups, caste-groups, religious groups and education level controls have multiple sub-categories as mentioned in Table 1. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

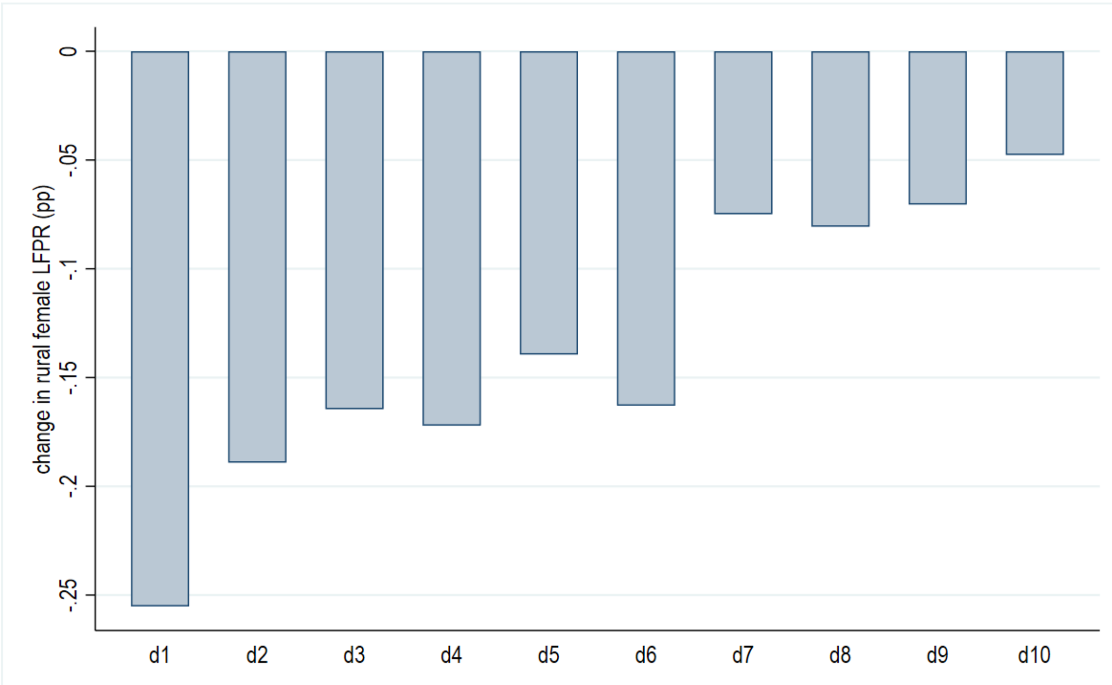
Figure A.1: Employment growth in the tradable sector (1987-88 to 2011-12)



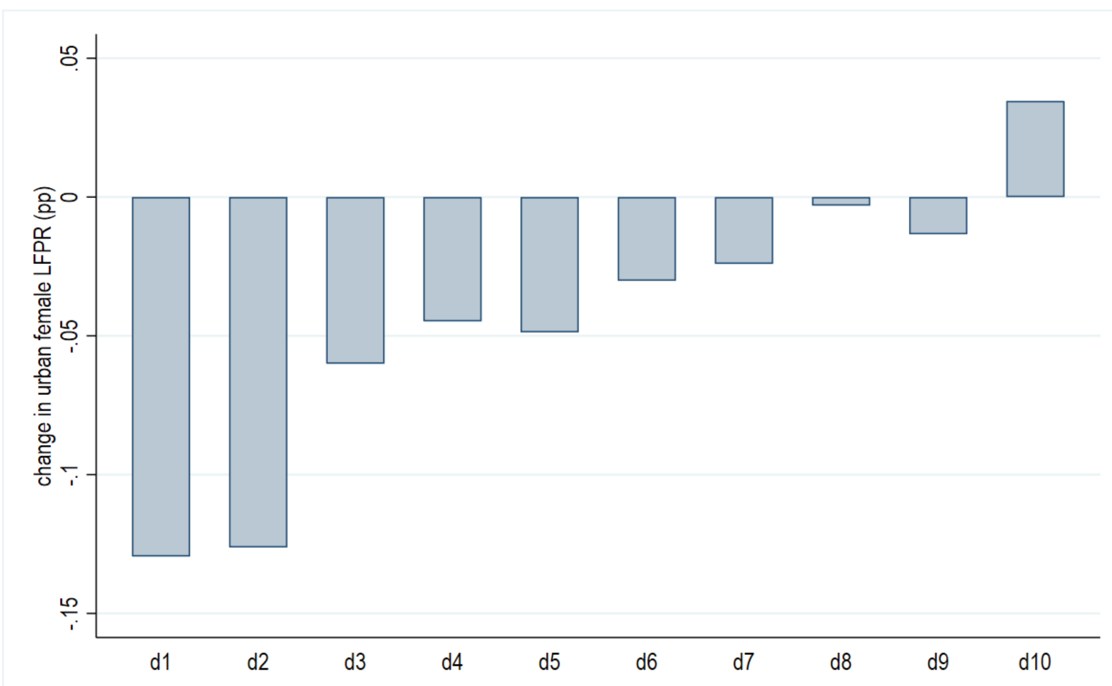
Notes: The figure shows the absolute employment growth in tradable per worker in districts. I divide the districts into 10 deciles based on growth in tradable sector employment. The decile d1 is the group of districts with the lowest growth in tradable employment and d10 has districts with the highest tradable employment growth. The y-axis shows the average change in tradable sector employment for districts in each decile.

Figure A.2: Change in female LFPR vs tradable growth

(a) Rural



(b) Urban



Notes: The figure shows the relationship between tradable growth and change in female LFPR. I divide the districts into 10 deciles based on growth in tradable employment and estimate the change in female LFPR for each decile separately by rural-urban. The decile d1 is the group of districts with the lowest growth in tradable employment and d10 has districts with the highest tradable employment growth. The y-axis shows the average change in female LFPR for districts in each decile.