Spatial Shocks and Gender Employment Gaps

Evidence from Rising Import Competition in India

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Abstract

Labor demand shocks unfold unevenly across space. I show that the resulting spatial mismatch can disproportionately impact women's employment due to gender-based differences in propensity to commute. My empirical strategy uses rising Chinese import competition in the early 2000s to generate variation in the spatial distribution of work within commuting zones in India. Using municipality-level data containing the universe of non-farm jobs, I show that rising imports caused firms to expand in the urban core and contract in the rural periphery. In areas where firms reduced hiring, women's employment was significantly lower than men's after 10 years. I show that while men started commuting across the rural-urban boundary to take up jobs in expanding sectors, women either switched to locally available jobs in agriculture or dropped out of the labor force. In line with the fact that women rely more on public modes of transport, I find smaller gender gaps in commuting zones with better bus connectivity at baseline. I find similar negative impacts for women regardless of marital status and education level, suggesting that results are not driven by household-level constraints or increasing demand for skilled labor. My findings are consistent with the presence of gendered commuting frictions stemming from a lack of comfortable and safe commuting options for women in India. In the last part of the paper, I use a spatial general equilibrium model to show that relaxing such gendered commuting frictions would have mitigated the observed decline in female labor force participation in India between 2001 and 2011 by 30%, increasing total output by 0.4%.

JEL Classification: F16, J01, J16
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1 Introduction

Women have shorter average commutes than men (Le Barbanchon et al., 2021; Petrongolo and Ronchi, 2020). While gender commuting gaps can arise from household-level constraints that disproportionately impact women, they also reflect the presence of gendered commuting frictions. The latter may be particularly important in developing countries, where poor public transport links (Borker, 2024) and a lack of public safety (Chakraborty et al., 2018; Siddique, 2022) further impede women's ability to commute.[1] In the presence of gendered commuting frictions, it is natural to ask whether the uneven growth of labor demand across space constitutes a barrier to women's work. For instance, do women find it harder than men to work in expanding sectors because new jobs are concentrated in urban areas outside their native village? Answering this question is key for understanding constraints to women's employment in developing countries, with potentially aggregate welfare consequences (Hsieh et al., 2019).

Studying how commuting frictions affect labor market reallocation across space is challenging for at least three reasons. First, it requires exogenous variation in labor demand *within* local labor markets, ideally at a large scale, which is rare. Second, households typically migrate from areas that lose jobs to those that gain jobs, mitigating the importance of commuting over time. Finally, comprehensive data on the spatial distribution of economic activity and workers' relevant local labor markets are typically hard to come by, especially in developing countries.

In this paper, I study the differences in the labor market reallocation of men and women in response to the increasing concentration of work in urban areas within local labor markets in India. My empirical strategy exploits the rapid increase in Chinese imports following China's entry into the WTO in 2001 (Autor et al., 2013) to generate a 'first stage'. I show that trade exposure reallocated labor demand in non-farm sectors from the rural periphery to the urban core over time. In areas where firms reduced hiring, women's employment was significantly lower than men's after 10 years.[2] My results are consistent with the presence of gendered commuting frictions that prevent women from taking up work far from home. In the last part of the paper, I build a spatial general equilibrium model to quantify the role of such frictions in driving the observed decline in female

[1] In India, women spend only 8 minutes on employment-related travel per day, compared to men's 36 minutes (MoSPI, 2020). The corresponding statistic in OECD countries is 22 minutes for women and 33 minutes for men (OECD, 2016).

[2] I find little evidence of significant population movements within or across local labor markets during this time, indicating a muted migration response. Previous work on the local labor market impacts of rising Chinese import penetration across a range of contexts has also found a similarly sluggish migration response (Autor et al., 2021; Mansour et al., 2022).

labor force participation (LFP) in rural areas during a time of rapid structural transformation and economic growth. I calibrate the model using village-level data from 2001 and 2011 and use it to perform policy counterfactuals. I find that the observed decline in female LFP in India during this time would have been mitigated by 30% if gendered commuting frictions were relaxed, corresponding to an additional one million women in the labor force in 2011. A back-of-the-envelope calculation suggests that the resulting improvement in the allocation of women's talent across space would have increased total output by 0.4%.

I proceed in three steps, beginning with data construction. The main dataset consists of administrative census data containing the universe of workers, non-workers, and non-farm firms (including in the informal sector) across nearly all 600,000 municipalities (i.e. villages and towns) in India between 1990 and 2013. Combined with consistent identifiers and municipality boundaries from the SHRUG (Asher and Novosad, 2020), this data allows me to construct a comprehensive picture of the changing spatial distribution of economic activity across India during a period of rapid growth and structural transformation. The natural concept of local labor markets in my setting are geographical commuting zones (CZs), defined as non-overlapping clusters of municipalities within which people live and work. However, there exists no off-the-shelf definition of CZs in India due to the lack of commuter flow survey data.[3] I construct CZs as catchment areas of 'job centers', defined as municipalities with relatively high non-farm job density at baseline, linked to a hinterland by commuting ties using a method similar to Cattaneo et al. (2021).[4] Intuitively, this method predicts optimal CZ boundaries by minimizing total travel time to job centers from surrounding municipalities along the national road network.[5] This approach yields a total of 2,385 non-overlapping CZs covering all of India. Each CZ is characterized by a densely populated urban core, typically corresponding to a medium-to-large town, with an increasingly rural hinterland. The median CZ had a population of 300,000 people in 2001. To my knowledge, no prior study has constructed CZs for India.

In the second step, I proceed with the main empirical analysis. Following the literature on

[3] Most previous studies in India use districts as de facto CZs. However, with a median population of 2 million people in 2001, districts in India are likely too large to represent individual CZs in practice. For comparison, the median CZ in the US had only 115,000 people in 2000.

[4] This is similar to the core-periphery conception of local labor markets in the urban economics literature, such that commuters from the periphery gravitate towards the core to work in non-farm sectors (Fujita et al., 1999).

[5] The 2011 census shows that the vast majority of work trips in India ($\sim 95\%$) are undertaken via roads, with rail and water transport constituting only a small fraction of work trips. Road data come from the Census of India (2001) and contains information on the location of all roads in the country including National highways, State highways, local paved roads, and local unpaved roads. I allow travel speeds to vary by type of road when estimating minimum travel times.

the local labor market impacts of trade liberalization, I treat individual CZs as self-contained sub-economies with no factor mobility across their boundaries (Topalova, 2010; Borjas and Ramey, 1995). I construct a CZ-level shift-share measure of changing Chinese import penetration, by combining industry-level variation in national Chinese import growth following China's entry into the WTO in 2001 ('shifts') with initial differences in industry structures across CZs ('shares') (Bartik, 1991; Topalova, 2007). The main challenge to identification is confounding stemming from unobserved demand and technology shocks in India that can drive both imports from China and local employment in India. To isolate variation in Chinese imports arising from purely supply-side shocks local to the Chinese economy, I instrument rising Chinese imports to India with rising Chinese imports to a set of ten Latin American countries over the same time period (Autor et al., 2013; Acemoglu et al., 2016).[6] My setting thus corresponds to a shift-share Instrumental Variable (SSIV) design with a quasi-random assignment of shocks while exposure shares are allowed to be endogenous (Borusyak et al., 2022).

I conduct two sets of analyses. First, I estimate the CZ-level impacts of rising Chinese imports by regressing changes in labor market outcomes for men and women at the municipality level on CZ-level changes in Chinese import penetration. Second, to study heterogeneity of impacts across rural and urban areas within CZs, I interact the CZ-level import penetration measure with a categorical variable capturing how far each municipality is located in relation to the urban core of its host CZ. I control for district-level time trends along with a rich set of start-of-period controls at the CZ and municipality levels across all regression specifications.

I establish three key results. First, I show that rising Chinese imports caused firms in the non-farm sectors to expand in urban centers and contract in the surrounding rural areas within CZs between 1998 and 2013, with the largest negative impacts seen in areas furthest away from urban centers. In models with heterogeneous firms, monopolistic competition, and endogenous markup as in Melitz (2018), import competition can lead to an intensive margin reallocation from less productive to more productive firms.[7] I provide evidence showing that a higher share of workers in rural areas was employed in low-productivity informal sector firms compared to urban areas at

[6] I pick Argentina, Brazil, Chile, Colombia, Costa Rica, Mexico, Paraguay, Peru, Uruguay, and Venezuela for building the instrument following (Chakraborty et al., 2024). These countries are not major trade partners of India but import a similar basket of goods. I find a strong first stage (F-stats are typically$\geq$70) and similar estimates across OLS and IV specifications. Even without the IV strategy, the increase in Chinese imports to India during my period of study - 1998 and 2013 - are plausibly exogenous because they are primarily driven by internal reforms in China and boosted in 2001 by China's entry into the WTO (Branstetter and Lardy, 2006).

[7] Chakraborty et al. (2024) finds that rising Chinese import penetration reallocated manufacturing employment from informal to formal sector firms, increasing aggregate labor productivity increased by 3.19% between 2001 and 2005.

baseline. As such, my findings likely reflect how this process of creative destruction unfolded across space.

Second, using worker census data, I find that a 1 percentage point increase in Chinese import penetration between 2001 and 2011 caused a 1.3% decrease in non-farm employment rate at the CZ level. Looking at heterogeneity by gender, I find that this negative impact is largely driven by women. This result is somewhat surprising since women only constituted 17% of manufacturing employment at baseline. To understand this result further, and guided by my firm-level results on the spatial reallocation of non-farm firms within CZs, I study how the gender gaps in non-farm employment vary across rural and urban areas within CZs.

My third key result shows that the observed CZ-level gender gaps in non-farm employment are entirely driven by municipalities located in the rural hinterland, with the largest gender gaps appearing in rural municipalities located furthest away from urban centers. These are the same areas where non-farm firms reduced hiring the most. I find no gender gaps in the urban core, where firms expanded hiring due to rising Chinese imports.

I argue that the key driving mechanism explaining these results is the presence of binding commuting frictions that prevent women from working far from home.[8] Rising Chinese imports caused both men and women to lose jobs in non-farm sectors in rural areas in the short run. Non-farm firms expanded hiring in urban areas over time, but only men started commuting across the rural-urban boundary to take up these new jobs. Women took up locally available jobs in agriculture or dropped out of the labor force instead. This is what appears in the data as a persistent employment gap in non-farm sectors as a result of rising Chinese imports between 2001 and 2011.

I provide four pieces of evidence in support of this mechanism. First, I provide direct evidence of differences in the commuting responses of women and men due to the China shock. Using rich individual-level survey data from multiple rounds of National Sample Survey (NSS) data, I construct a district-level measure of the share of workers who reported commuting across the rural-

[8] Such gender-specific commuting frictions can stem from, for instance, women's low access to private modes of transport or the threat of sexual harassment while commuting. The latter is perhaps more important in the Indian context. This is because concerns around women's safety are acute in India, particularly in urban centers. In a survey conducted in New Delhi, 95% of women aged 16–49 stated that they felt unsafe in public spaces (UN Women and ICRW, 2013). Borker et al. (2021) finds that concerns around the threat of physical and verbal abuse and harassment while commuting affect women's choice of college in the Delhi University system. Seki and Yamada (2020) studies the roll-out of the Delhi metro system and finds that proximity to a new metro station increased female but not male employment. They argue that safety improvements were a key reason for the observed effects. At the national level, higher levels of perceived crime at the neighborhood level (Chakraborty et al., 2018) or via media reports (Siddique, 2022) are associated with lower rates of female labor force participation in India.

urban boundary for work in 1999, 2004, and 2011. I regress this outcome on a district-level measure of changes in Chinese import penetration using an analogous specification to the CZ-level analysis. I find that a marginal increase in Chinese import penetration led to an increase in the share of men commuting across the rural-urban boundary for work by 13% in the short run (1999 and 2004) and 2% in the long run (1999 to 2011), respectively. I find no similar commuting response for women living in rural areas. Second, if men started commuting across the rural-urban boundary to take up jobs in expanding sectors but women did not, one should expect firms located in urban areas to report hiring more men relative to women over time. This is exactly what I find. Rising Chinese imports caused the female employee share to decline in firms located in urban areas within CZs over time. Moreover, I find no significant impact on the share of women employed in rural firms, suggesting that gender gaps in rural areas are not driven by men crowding out women in rural firms. Third, I conduct a placebo test showing that gender gaps do not appear in non-farm occupations performed inside the home. The overall gender gap is thus entirely driven by the occupations that require individuals to commute away from their place of residence. Finally, I provide suggestive evidence that relaxing gendered commuting frictions can reduce gender gaps. Leveraging the fact that women in India rely on public modes of transport more than men (GoI, 2011), I study heterogeneous impacts across CZs with low and high bus network density at baseline. I find that CZs with better bus connectivity display significantly smaller gender gaps due to the trade shock.

I provide evidence to rule out alternate mechanisms that may also explain observed impacts. First, the commuting mechanism I propose may be confounded by the migration of individuals across space. For instance, the appearance of gender gaps in rural areas may be driven by the migration of productive women (either alone or along with their household) from rural to urban areas over time. This would cause the share of women employed in non-farm sectors to fall in rural areas without the need for commuting frictions to play a role. While I do find a positive impact on population growth in the urban core relative to the rural periphery within CZs, the magnitude of this impact is very small relative to the growth of non-farm jobs in these areas. Moreover, I find no gender differences in migration, suggesting that the mechanism of selective migration among single women is also likely not important.[9] Second, exposure to trade can induce skill-biased technical change (Juhn et al., 2014; Bloom et al., 2016). If expanding firms in urban

[9]This suggests a generally muted role of migration in the process of labor reallocation. Previous studies on the persistent local labor market impacts of the 'China shock' have also found muted migration responses over similar time horizons (Autor et al., 2021).

areas demand more high-skill labor than before, the finding that women did not take up these jobs could reflect the fact that women had relatively lower average levels of educational attainment at baseline. However, analysis of individual-level NSS data shows that rising Chinese imports had similar negative impacts among women in rural areas with different levels of education (below or above primary), suggesting that my results are not driven by increasing demand for skilled workers due to the trade shock.[10] Third, the negative impact on women's employment in non-farm sectors could be driven by rising household incomes in rural areas due to rising Chinese imports. NSS data shows that the opposite holds true. Weekly household earnings declined in rural areas due to rising Chinese imports between 1999 and 2011. Analysis of nightlight data confirms this result. Rural areas experienced a decline in average nightlight luminosity relative to urban areas due to rising Chinese import penetration between 2011 and 2011. Finally, I find similar negative impacts across single and married women. This suggests that observed gender gaps are likely not driven by household-level constraints stemming from norms around child care and household chores that disproportionately impact married women.

In the last part of the paper, I build a general equilibrium Roy (1951) model of occupational choice to quantify the role of gendered commuting frictions in explaining the observed decline in women's labor force participation (LFP) in India since the mid-2000s.[11] The model features N+1 locations, consisting of an urban core and N villages located at varying distances from it. Individuals in each village choose between three occupations - agriculture, local non-farm, and urban non-farm. Urban wages are higher but require individuals to pay a portion of their wage as commuting cost which increases with distance to the urban core. Migration is not allowed. Wages in the urban core and in each village are determined in equilibrium.

I introduce two forces that distort women's labor supply decisions. Men face no such distortions. First, commuting costs are allowed to differ by gender. This acts like an occupation-specific wedge that pushes more women to work locally rather than commute to urban areas. Second, to induce variation in the LFP rate of women, I assume that women's labor supply is subject to household-level income effects. Each individual independently draws a productivity triple from a Frechet distribution that determines how productive they are in each of the three occupations. Households

[10] I also find no significant difference in impacts by education level among men.

[11] Starting from an already low base of 30%, women's LFP rate in India declined by roughly 10 percentage points between 2004 and 2011 (see figure 10), despite rapidly declining fertility and falling gender gaps in skills and wages. The decline is concentrated among married women aged 25-65 in rural areas, and driven by the fact that a large number of women have left agriculture but failed to transition to non-farm sector jobs at rates similar to men. Men's labor force participation remained relatively stable during this time.

then make two decisions to maximize joint utility: (i) whether one or both members work, and (ii) which occupation each member works in.

I calibrate the model using village-level data from 2001 and 2011 and use it to perform policy counterfactuals. I find that relaxing gendered commuting frictions in 2011 would have mitigated the observed decline in female LFP between 2001 and 2011 by 30%. A back-of-the-envelope calculation suggests that this would have increased total output by 0.4%. Positive impacts are due to reduced misallocation of women's talent across space driven by an increase in urban non-farm employment among women living in rural areas located close to urban centers. Details on the model and quantification exercise are provided in appendix B.

Related Literature This paper is related to several lines of research. First, it relates to the large literature on the distributional effects of trade liberalization, especially in developing countries (Topalova, 2010; Goldberg and Pavcnik, 2007; Menéndez et al., 2012; Dix-Carneiro and Kovak, 2019). While numerous studies have documented persistent negative impacts of rising import competition among men with low skill (Gaddis and Pieters, 2017; Dix-Carneiro and Kovak, 2017), evidence on women's labor market outcomes is more mixed.[12] Using data from India, I show that import exposure can have persistent negative impacts on women's employment even when the directly impacted industries are male-dominated.[13] I propose a novel mechanism to explain these results, namely that commuting frictions disproportionately impede women's labor market adjustment across space. In doing so, I provide some of the first empirical evidence from a developing country showing that exposure to trade has the effect of reallocating economic activity from areas in the rural periphery to the urban core (Fujita et al., 1999; Melitz, 2003, 2018). Finally, while previous work on the local labor market impacts of trade liberalization has largely focused on the role of migration frictions across local labor markets in impeding labor reallocation (Borjas and Ramey, 1995; Topalova, 2007; Autor et al., 2013), I highlight the role of commuting frictions by studying variation within local labor markets instead.

Second, this paper contributes to the growing literature on the impact of gender differences in commuting on women's labor market outcomes. Recent work from developed country contexts has

[12] Rising import competition has been found to increase the demand for female labor in some cases by inducing shifts towards more female-friendly sectors (Kis-Katos et al., 2018; Do et al., 2016), skill-biased technical change that lowers demand for physically intensive skills (Juhn et al., 2014), and pro-competitive effects of trade that increase the cost of labor market discrimination (Anukriti and Kumler, 2019; Black and Brainerd, 2004)

[13] In a closely related study from Peru, (Mansour et al., 2022) also find that rising Chinese imports between 1998 and 2008 negatively impacted employment outcomes of women but not men in the decade following China's entry into the WTO in 2001. Their results are consistent with a mechanism in which trade-induced sectoral shifts favored men but not women. In Peru, rising Chinese imports directly impacted both male- and female-dominated manufacturing industries.

shown that women's lower propensity to commute contributes to the gender wage gap (Le Barbanchon et al., 2021; Caldwell and Danieli, 2024; Liu and Su, 2024) and influences job application behavior (Fluchtmann et al., 2024). In the context of a developing country, I show that gender differences in the propensity to commute can cause women to be relatively under-employed in non-farm sector occupations because these jobs tend to be more geographically clustered relative to farm-based jobs.[14] More broadly, my study sheds light on why women tend to be over-represented in agriculture in low- and middle-income countries (Caselli, 2005; Gollin et al., 2014). Using a general equilibrium Roy model with gender-specific frictions and data from sixty-six low-income countries, Lee (2024) finds that women are over-represented in agriculture since they face higher frictions in non-agricultural employment.[15] My results point to gendered commuting costs as a potential source of these frictions.

Third, this paper is related to the large literature on why women's labor force participation (LFP) rate in India has declined relative to men's after 2004. While one strand of the literature points to rising rural household incomes in a patriarchal society to explain the decline (Klasen and Pieters, 2015; Mehrotra and Parida, 2017; Afridi et al., 2019), other studies point to declining local job opportunities for women in rural areas (Chatterjee et al., 2015; Afridi et al., 2022; Chatterjee and Vanneman, 2022; Deshpande and Singh, 2021; Fletcher et al., 2017).[16] I put forward a new explanation that combines a supply-side fact (i.e. women face higher commuting frictions than men) with a demand-side trend (i.e. growth in non-farm sector jobs is urban-biased). The immediate implication is that policies that reduce mobility barriers for women can mitigate the decline in female LFP in India, while also reducing the misallocation of women's talent across space. This differs markedly from explanations that exclusively rely on the role of social norms in driving women's LFP (Fernández, 2013; Goldin, 1995), which are slow-moving and arguably less amenable to policy intervention.

Finally, my work is related to the literature studying the impact of changes in commuting costs due to improvements in transportation infrastructure in developing countries. Studies in this literature often find gender-based differences in labor market impacts depending on the type

[14] Looking across 9,400 wards in the UK, Petrongolo and Ronchi (2020) also finds that women tend to be under-represented in industries that are more geographically concentrated.

[15] Similarly, Merfeld (2023) uses individual-level panel data from 29 villages across 17 districts in India to show that women are significantly less likely than men to work in non-farm sectors, despite large non-farm/farm wage gaps within individuals.

[16] Supply-side explanations pointing to the role of rising household incomes are in line with the macro-development literature on the downward part of the 'U-shaped' relationship between women's labor force participation and economic development observed both within and across countries (Boserup, 1970; Goldin, 1995; Ngai et al., 2022).

of infrastructure improvement being studied. For instance, large-scale road-building policies that connect remote rural areas with all-weather roads in India (Asher and Novosad, 2020; Dasgupta et al., 2024) and Uganda (Herzog et al., 2024) induce men to take up non-farm jobs located outside the village but not women. On the other hand, improvements in the quality and safety of public transport increased female but not male employment in Delhi (Seki and Yamada, 2020) and Lima (Martinez et al., 2020). The household-level model I propose (outlined in appendix B) provides a lens to understand these disparate results within a common framework. In the model, building roads (modeled as a secular reduction in commuting costs) induces men to switch from farm to non-farm employment, but not women. This is because men remain the marginal beneficiaries of such policies given the gendered nature of commuting frictions. On the other hand, policies that directly address gender-specific commuting barriers (eg. by providing safer modes of public transport, which women tend to use more than men (Borker, 2024)) are relatively more effective in reducing barriers to women's work.

The rest of the paper is organized as follows. Section 2 describes the data. Section 3 describes my empirical strategy. Section 4 presents results. Section 5 provides evidence on mechanisms. Section 6 provides a discussion of the potential sources of gendered commuting frictions in India. Section 7 presents the quantification exercise. Section 8 concludes.

2 Data

Firm census and population census data. I combine administrative data from multiple census rounds to construct a comprehensive picture of how the spatial distribution of economic activity has evolved across the nearly 600,000 villages and 8,000 towns in India over time. This constitutes my main source of data for firm- and worker-level outcomes.

Data on the location of firms come from the Economic Census (EC). Conducted in 1990, 1998, 2005, and 2013, the EC covers the universe of firms in non-farm sectors (i.e. manufacturing and services), including in the informal sector. Data are available at the firm level and contain information on the number of employees (disaggregated by gender) and four-digit industry code.[17] The 2013 round of the EC lists 58.5 million firms employing 131.3 million workers. The vast majority of firms are small in size, with only 5% of the firms employing more than 5 employees. The median

[17] Each round of the EC uses a different industry code classification scheme. I harmonize industry codes over time using concordance tables provided by the Ministry of Statistics and Programme Implementation (MoSPI) to be in line with three-digit NIC 1998 codes.

firm employs one man and no women. I collapse each round of the EC to the municipality level and calculate the number of firms and total employment (disaggregated by sector and gender) located in each municipality. I exclude firms in agriculture and the public administration and defense sectors since these are not consistently recorded across different rounds of the EC. Excluded sectors accounted for 11% of total non-farm employment in 1998.

Data on the residence of workers come from the Population Census (PC) conducted in 1991, 2001, and 2011. The PC contains information on the total population and the count of workers (disaggregated by gender) living in all municipalities in India. Importantly, it also contains the count of non-workers, as well as workers in agriculture, which is not covered by the EC. This allows me to study how workers adjust to labor demand shocks along all available margins of adjustment at the village level. Unfortunately, the PC does not provide data on population and workers by age group. As such, I use employment-to-population ratios (i.e. total employment divided by total population) as my main outcome of interest rather than the standard ILO definition of employment among individuals aged 15+. Finally, the PC contains data on municipality-level background characteristics like literacy rates, caste composition, under-5 gender ratio, and availability of infrastructure facilities such as access to various types of roads, bus stations, and schools. I use these variables as controls (measured at baseline) to increase the precision of estimates and conduct heterogeneity analysis.

I link the firm and population census data, both across surveys and across time, using time-consistent municipality identifiers provided by the Socioeconomic High-Resolution Rural-Urban Geographic Platform (SHRUG) for India (Asher et al., 2021). This results in a municipality-level panel that contains information on the universe of workers and non-farm jobs in the country over a 15-year period between 1998 and 2013.[18] Table 1 presents descriptive statistics.

Next, I aggregate municipality-level data into geographical local labor markets, which is the level at which my identifying variation is defined. Following the literature on the local labor market effects of trade liberalization (Topalova, 2010; Autor et al., 2013), I define local labor markets as self-contained sub-economies with no factor mobility across their boundaries. I find a relatively muted migration response to rising Chinese imports across CZs so this assumption also seems to hold in practice.[19]

[18]Strictly speaking, the panel is defined at the level of the 'shrid' (i.e. SHRUG ID), which describes a geographical unit that can be mapped consistently across multiple rounds of the Indian population and economic censuses in the SHRUG data. In the vast majority of cases, a shrid maps to exactly one village or town (Asher et al., 2021).

[19]Even ex-ante, the assumption of no labor mobility across local labor markets is not too controversial in the Indian context. India ranked last in a cross-country study of internal migration rates across a sample of 80 countries (Bell

Table 1: Descriptive Statistics: Population Census and Economic Census Data

Population Census Data			Economic Census Data			
	2001	2011		1998	2005	2013
Population	1781.04	2103.12	All non-farm sectors			
	(30773.94)	(37532.86)	Jobs per 1000	52.11	53.62	67.58
Women: employment-to-population ratios				(519.31)	(335.30)	(902.70)
All sectors	34.86	34.10	Female employee share	0.15	0.18	0.27
	(21.21)	(21.54)		(0.17)	(0.18)	(0.20)
Farm sectors	29.57	27.68	Manufacturing sectors			
	(21.52)	(21.83)	Jobs per 1000	16.20	14.68	15.07
Non-farm sectors	5.29	6.41		(446.85)	(224.69)	(393.37)
	(9.18)	(9.38)	Female employee share	0.16	0.17	0.24
Men: employment-to-population ratios				(0.22)	(0.23)	(0.28)
All sectors	52.66	53.89	Service sectors			
	(9.08)	(9.39)	Jobs per 1000	35.92	38.94	52.51
Farm sectors	40.03	39.85		(178.05)	(232.12)	(699.87)
	(14.61)	(15.41)	Female employee share	0.14	0.16	0.27
Non-farm sectors	12.63	14.05		(0.17)	(0.18)	(0.20)
	(11.98)	(13.27)				
Number of municipalities	578,125	576,158	Number of municipalities	437,221	509,178	533,056

Notes: The left side of this table presents descriptive statistics from the 2001 and 2011 rounds of the population census of India. Employment-to-population ratios are calculated by dividing the total number of workers in each sector by the total population, separately for men and women. The right side of this table presents descriptive statistics from the 1998, 2005, and 2013 rounds of the economic census of India. The count of non-farm jobs is normalized with respect to the total population from the closest round of the population census. Standard deviations are in parentheses.

Defining local labor markets as urban-rural catchment areas. The natural concept of local labor markets in my context are geographical 'commuting zones' - non-overlapping clusters of municipalities within which people live and work. Examples include the 709 Commuting Zones for the United States and the 320 Travel to Work Areas for the UK. Commuting Zones (CZs) are typically constructed by applying clustering techniques to commuter flow survey data that contains counts of commuters in a matrix with origins as rows and destinations as columns. However, like many other developing countries, there exists no commuter flow survey data in India. As such, most previous studies use district boundaries as de facto CZs. Using districts as CZs has at least two drawbacks. First, there are few constraints to commuting across administrative borders in India, especially within states. As such, CZs need not adhere to district boundaries. Second, Indian districts are likely too large to represent individual CZs. For instance, while the the median CZ in the US had 115,000 people in 2000, the median district in India had roughly 2 million people in 2001 with 21 districts having more than 5 million people. Moreover, the relevant labor market for workers in India is expected to be even smaller in scope and size than in the US given relatively higher transportation costs.

et al., 2015). Imbert and Papp (2020) find that seasonal migrants in a rural state in India are willing to take a 35% pay cut to work in local public works rather than migrate to urban areas. Munshi and Rosenzweig (2016) argue that insurance provided by strong caste networks keeps people back in rural areas.

To make progress, I define CZs as catchment areas of key urban municipalities linked to a hinterland by commuting ties using an approach similar to Cattaneo et al. (2021). The idea is to characterize each CZ as an urban core and a rural periphery such that commuters from the periphery gravitate towards the core for non-farm employment (Fujita et al., 1999). According to census data, 70% of India's population lived in rural areas in 2001.[20] Much of this population is not connected to big cities by commuting ties. Accordingly, I define CZs as catchment areas of not just big cities, but also of more remote secondary towns.[21] The following algorithm describes this method. More details are provided in appendix A.

1. Define one 'job center' per commuting zone. Rank municipalities in terms of the count of non-farm jobs using data from the 1998 round of the firm census (i.e. before China entered the WTO in 2001). Define the top 0.05% municipalities in each district as 'job centers'.[22] These job centers are assumed to be the focal points of individual commuting zones with strong commuting ties to areas in the surrounding municipalities.

2. Define CZs as catchment areas of job centers. Overlay the national road network to estimate minimum travel times to each job center from nearby municipalities. Allowing for travel speeds to vary by type of road, construct a 'cost surface' that codifies the minimum time needed to move across 2 Km X 2 Km cells in a grid that covers the whole surface of India.[23] Use Dijkstra's least-cost path algorithm to map each municipality to the job center that is closest to it. Allocate all municipalities mapped to the same job center to the same commuting zone.

Defining CZs as catchment areas in this way yields 2,385 non-overlapping CZs with a median population of 300,000 people in 2001 (mean = 410,000 people). I drop municipalities that are located more than 1.5 hours away from their nearest job center (3.1% of the sample) since these areas are

[20] The 2001 census defines rural municipalities as settlements with a population of less than 5,000 people and a population density of less than 400 people Km^2, with at least 75% of the male working population engaged in agriculture.

[21] Gibson et al. (2017) find that the growth of secondary towns has contributed more to rural poverty reduction in India than growth in big cities between 1993–2012.

[22] Defining 'job centers' to be the top 0.05% of municipalities in each district yields a total of 2,385 commuting zones with an average straight-line radius of around 20 Kms. This construction is in line with the observed distribution of travel distance from 2011 census data, which shows that $\sim$ 90% work trips were within 25 Km. Using stricter definitions of 'job centers' - like picking the top 1% or 0.01% of municipalities in each district - delivers qualitatively similar results but yields much smaller or larger CZs on average.

[23] Road network data come from the census of India (2001). I assume average speeds of 60 Km/hr for national highways, 50 Km/Hr for state highways, 30 Km/hr for local paved roads, and 20 Km/hr for local unpaved roads. I assume individuals can traverse across areas without roads at walking speed (5 Km/hr).

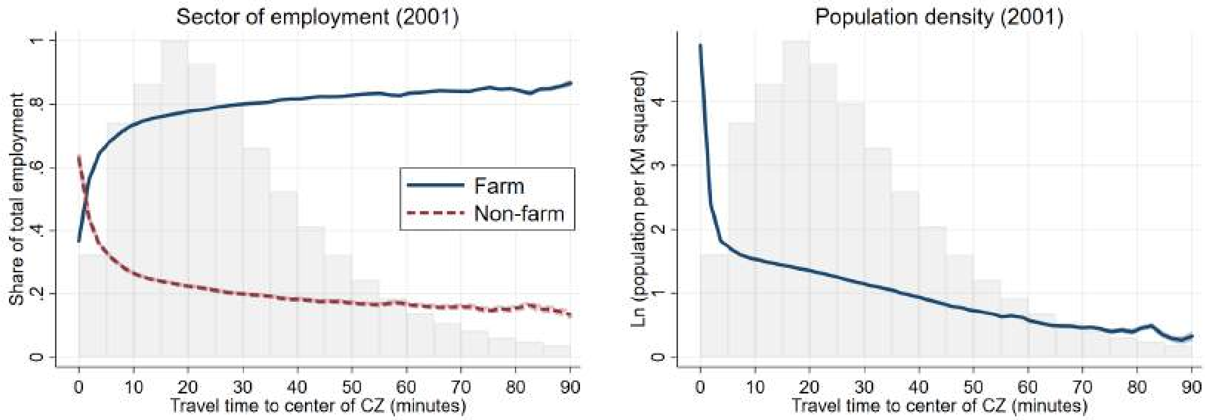
unlikely to be connected to job centers by daily commuting networks. While I do not restrict CZ boundaries to lie within state or district boundaries, they rarely cut across these administrative boundaries in practice (see figure A1b). This is likely driven by the fact that both administrative boundaries and the national road network are jointly determined by the underlying geographical features.

Note that I do not directly observe commuter flows into job centers from surrounding areas. However, two aspects of my setting imply that they are likely to be important commuter destinations in reality. First, job centers typically correspond to medium-to-large-sized towns, including most district and state capitals, with a median population of 25,000 in 2001 (mean = 90,000). Economic activity was highly concentrated in these 2,385 municipalities at baseline, accounting for only 23% of India's population but 53% of its non-farm jobs.[24] Second, job centers are also highly persistent over time - 85% of places ranked one in terms of non-farm jobs within their districts in 1998 were also ranked one in 2013.

Each CZ is characterized by an urban core surrounded by an increasingly rural periphery. Figure 1 shows that the average employment share in non-farm sectors and population density falls smoothly with increasing distance to the urban center. For ease of exposition, I divide municipalities into travel time quintiles, each containing 20% of the total sample. Municipalities located within 10 mins to the center of their host CZ are defined as the 'urban core'. The remaining group of municipalities, located at 10-20 mins, 20-30 mins, 30-40 mins, or 40-90 mins away from the center are defined as the increasingly 'rural periphery'.

[24]Figure 11 shows that non-farm job density (defined as jobs per 1000 population) was twice in the job center relative to areas in the rural periphery at baseline.

Figure 1: Characterizing commuting zones: population census data



Notes: This graph uses municipality-level data from the 2001 round of the population census to show how municipality characteristics vary within CZs by increasing distance to the center of their host CZ. The panel on the left plots employment shares in farm and non-farm sectors as a flexible function of travel time to the center of the CZ. The panel on the right plots a similar function of population density, measured as the natural log of total population divided by municipality area in KM^2. The underlying count of villages by travel time is represented in the form of a histogram in grey.

Trade data from UN COMTRADE. To construct my measure of Chinese import penetration, I use data on the annual value of trade flows for all country pairs from the UN COMTRADE database at an annual frequency between 1998-2013. Trade data are available by industry, disaggregated up to the level of 6-digit codes in the International Standard Industrial Classification (ISIC) rev 3. I collapse these data to the 3-digit level (N$\sim$115 industries) since these correspond one-to-one with National Industry Classification (NIC) 1998 codes used by the Indian EC.

Other data sources. While the municipality-level panel data I construct allow me to analyze the impacts of rising Chinese import penetration at a fine level of spatial disaggregation, they do not contain information on worker characteristics, commuting patterns, wages, or unemployment. I therefore complement my main analysis with nationally representative survey data from multiple rounds of the National Sample Survey (NSS). Representative at the district level, NSS data contains rich individual-level information on individual workers' employment, earnings, location of residence (urban/rural), location of workplace (urban/rural), as well as worker characteristics such as age, gender, education, marital status, religion, and social group. Finally, I use nationally representative firm survey data to construct estimates of total production at the industry level, which I use to construct my import penetration measure. Information on formal sector output comes from the 1994 round of the Annual Survey of Industries (ASI) and informal sector output from the NSSO's 1994 round of the survey of unorganized manufacturing enterprises.

3 Empirical strategy

3.1 Background on the employment impacts of the 'China shock'

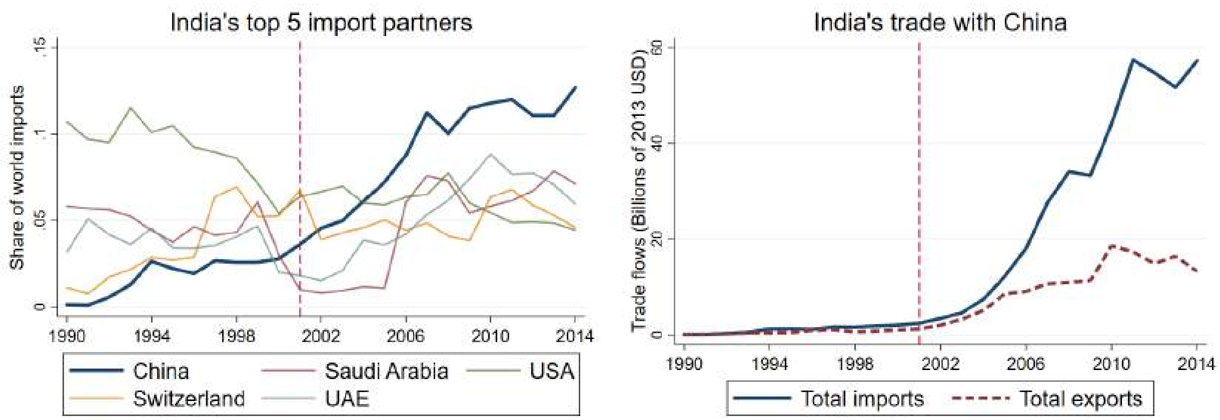
Following seminal work by Autor et al. (2013) in the US, a growing literature has studied the local labor market impacts of rising Chinese manufacturing boosted by China's entry into the WTO in 2001 (i.e. the 'China shock') across several developed countries. A common finding in this literature is that individuals living in CZs facing greater Chinese import competition experience persistent negative employment impacts, pointing to significant labor market frictions that impede the reallocation of displaced workers across CZs and industries.[25] I expand on this literature in two main ways. First, I study the spatial instance of trade exposure within rather than across CZs using fine-grain administrative data. This allows me to highlight the role of heterogeneous commuting frictions in determining the process of labor reallocation across space, which is an under-studied margin of adjustment. Second, I add to the relatively small literature on the labor market impacts of the China shock in developing countries, which has largely focused on Latin American countries thus far. Different from studies based in developed countries, these studies typically find muted employment impacts of rising Chinese imports due to the presence of a large informal sector that acts as a ready buffer for displaced workers in such contexts (Dix-Carneiro and Kovak, 2019; Ponczek and Ulyssea, 2022).

I study the case of India, a large developing country and China's immediate neighbor. The left panel of figure 2 shows that China quickly became India's top importing partner after it entered into the WTO in 2001, with its share of total Indian imports growing by a factor of 90 between 1992 and 2007. For comparison, Chinese import share in the US grew only by a factor of 11 over the same time period (Autor et al., 2013). The right panel of figure 2 shows that the value of Chinese imports to India was low and flat between 1990-2000, followed by a period of rapid increase coinciding with China's entry into the WTO in 2001 (Branstetter and Lardy, 2006). Further, the rapid rise in the value of Chinese imports to India during this time was not matched by an increase in Indian exports to China. Indeed, India's overall trade surplus (total exports - total imports) steadily worsened starting from the early 2000s, driven in large part by India's rising trade deficit with China. The 'China shock' in India's case can thus be characterized as a rapid increase in the value of Chinese goods imported by Indian firms to largely satisfy local demand. The product mix

[25] See, for example, Balsvik et al. (2015) for Norway, Utar (2018) for Denmark, De Lyon and Pessoa (2021) for the UK, and Citino and Linarello (2022) for Italy.

of Chinese imports in India shifted from largely consisting of raw materials to relatively capital-intensive finished goods between 2001 and 2011 (see figure 14).[26]

Figure 2: India's trade



Notes: This graph uses annual bilateral trade data for India and its trading partners from the UN-COMTRADE database. The panel on the left plots India's imports from its top-5 trade partners (defined in 1990) as a share of world imports in each year. The panel on the right reports the value of India's annual trade with China (imports and exports) in billions of 2013 US dollars. The dotted red line marks 2001, the year in which China entered the WTO.

Given the rapid increase in the share and value of Chinese imports starting in the early 2000s, one might expect to find significant labor market impacts across local labor markets in India. Yet, previous studies on the impacts of rising Chinese import penetration between 1999 and 2012 across districts in India have found muted impacts on overall employment and wages (Saha, 2024; Shi, 2024), and no differential wage impacts by skill level (Deb and Hauk, 2020). I improve on this previous literature by exploiting richer variation stemming from the use of municipality-level census data, which enables me to define local labor markets at a finer level of geographical disaggregation than districts. While I also find muted impacts on overall employment at the level of CZs, I point to significant heterogeneity of impacts across gender, employment sectors (farm and non-farm), and type of area (urban core or rural hinterland). The commuting mechanism I highlight points to a potential explanation for why rising Chinese imports reduced women's wages relative to men between 1999 and 2012 (Saha, 2024; Deb and Hauk, 2020).

[26]In the early 2000s, India's imports from China were more heavily concentrated in raw materials, with organic chemicals (18%) and minerals and fuels (15%) being the top imported goods in 2001. By 2011, the top import sectors had shifted to more capital-intensive goods, with industrial machinery (22%) and electrical equipment (20%) being the top imported goods.

3.2 Constructing a measure of Chinese import penetration

Following Autor et al. (2016), I use a shift-share argument to construct a measure of predicted Chinese import exposure in CZ c at time t by apportioning changes in industry-level import penetration at the national level to each CZ according to its local industry employment structure at baseline:

$$IP_{ct}^{China\to India} = \sum_j \left(\frac{L_{cj,1998}}{L_{c,2001}}\right)\left(\frac{IM_{jt}^{China\to India}}{Y_{j,1994} + IM_{j,1994} - EX_{j,1994}}\right) \tag{1}$$

This equation makes clear that across-CZ variation in the import penetration measure stems from variation in (i) CZ-level industry employment structure at the start of the study period and (ii) industry-level growth in Chinese imports over time relative to the initial size of domestic industry. The first term in Equation 1 corresponds to the 'share', and is calculated as the ratio of the start of period employment in industry j of CZ c (measured by $L_{cj,1998}$) and the total employment in CZ c (measured by $L_{c,2001}$).[27] The second term is the level of Chinese import penetration in million USD at time t and corresponds to the 'shift'. Import penetration is calculated as the observed level of Chinese imports in industry j at time t ($IM_{jt}^{China\to India}$), normalized by the total absorption of industry j before the start of my study period, calculated as domestic production ($Y_{j,1994}$) plus imports ($IM_{j,1994}$) less exports ($EX_{j,1994}$) in 1994. Industries are at the NIC 3-digit level (N$\sim$115).

A potential threat to estimation is omitted variable bias stemming from unobserved demand and technology shocks starting at the same time as China's entry into the WTO in 2001 that can affect both local employment and imports from China. To isolate variation in Chinese imports to India stemming entirely from supply-side shocks in China, I follow (Autor et al., 2016) in using the growth and composition of average Chinese imports to other countries as an instrument for growth in Chinese imports to India in an Instrumental Variable (IV) strategy:

$$IV_{ct}^{China\to India} = \sum_j \left(\frac{L_{cj,1998}}{L_{c,2001}}\right)\left(\frac{IM_{jt}^{China\to Other}}{Y_{j,1994} + IM_{j,1994} - EX_{j,1994}}\right) \tag{2}$$

I follow Chakraborty et al. (2024) in selecting ten Latin American countries - Argentina, Brazil, Chile, Colombia, Costa Rica, Mexico, Paraguay, Peru, Uruguay, and Venezuela - to be in the group of IV countries. Selecting this particular group of countries has two main advantages. First, Latin

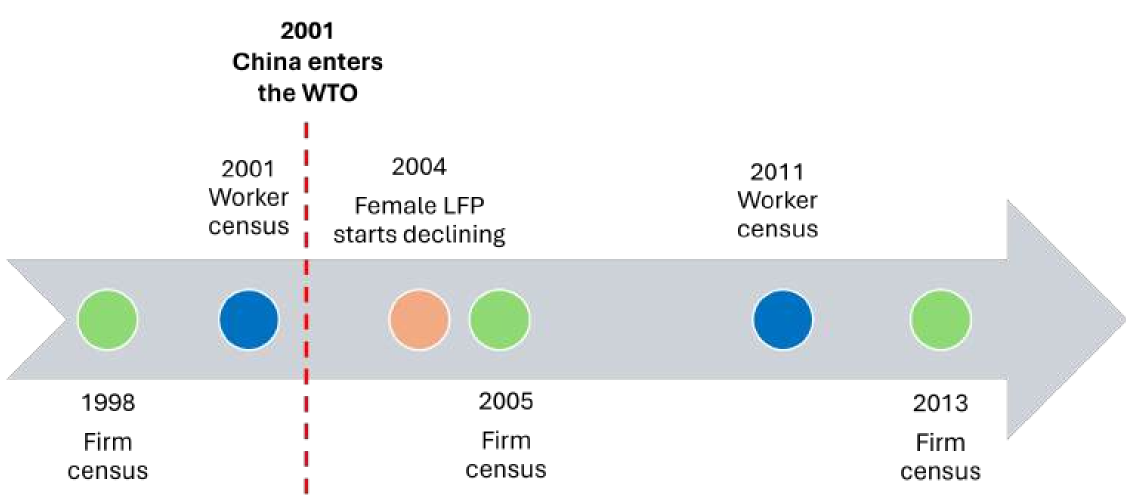
[27] $L_{cj,1998}$ is taken from the 1998 round of the EC and $L_{c,2001}$ is taken from the 2001 round of the PC. This is because the PC does not contain employment disaggregated by industry codes, while the EC does not include employment in agriculture.

American countries imported a similar basket of goods and experienced a similar rise in Chinese import penetration during the study period (see figure 12). This lends itself to a strong first stage - OLS and IV estimates are consistently similar in magnitude and size, with first-stage Kleibergen-Paap F-stats typically being > 70. Second, since these countries had minimal trade with India before and during the period of study (see figure 13), there is little scope for Indian exporters to experience negative impacts due to increased competition from China in these destination markets. This provides support for the exclusion restriction holding in practice.

3.3 Outcome variables

The key outcome of interest is the employment-to-population ratios of men and women at the village level measured in the 2001 and 2011 rounds of the population census. The secondary outcome of interest - counts of non-farm jobs at the municipality level - is measured in 1998, 2005, and 2013 of firm census data. Figure 3 shows the timing of the shock in relation to the measurement of outcomes. It also marks 2004 as the year in which women's labor force participation started declining in rural areas at the aggregate level. As China entered the WTO in 2001, I have at least one observation at baseline for each source of outcome data. For outcomes measured in the firm census, I track changes across two sets of time periods - between 1998 and 2005 (short run) and between 1998 and 2013 (long run). For outcomes measured in the population census, I observe changes only over the long run (2001 to 2011).

Figure 3: Timing of shock and measurement



3.4 Empirical specification

I use municipality-level panel data to fit models of the following form:

$$Y_{v(cd)t} = \beta IP_{c(d)t-1} + \delta_{dt} + \boldsymbol{\eta}\mathbf{X} + \epsilon_{v(cd)t} \quad (3)$$

where $Y_{v(cd)}$ corresponds to outcome Y in village v at time t. As described in the data section, each village is nested within a CZ c, which is further nested within a district d. My main explanatory variable ($IP_{c(d)t-1}$) is the level of Chinese import penetration in CZ c at time $t-1$.[28] I include district $\times$ year fixed effects (denoted by δ_{dt}) to control for time trends at the level of districts. Since I use data from two time periods, this is equivalent to a specification in first differences with district-level fixed effects.[29] The identifying variation is thus at the level of year $\times$ CZ within districts. The coefficient of interest β captures the impact of a marginal increase in Chinese import penetration over time on village-level outcomes. The vector $\mathbf{X}$ contains a rich set of start-of-period controls for labor force and demographic composition that might independently affect outcomes of interest. At the CZ level, I control for women's employment rate, caste composition, under-five sex ratios, and literacy rates amongst men and women measured in the 2001 population census. Crucially, I also control for the employment share in manufacturing at the CZ level measured in 1998 and 1990 to account for differential trends stemming from initial industry structure at the CZ level (Borusyak et al., 2022).[30] At the municipality level, I control for the start-of-period population and the baseline value of the outcome of interest. Standard errors are clustered at the district level to account for spatial correlations across CZs.

A key focus of my analysis is to study how CZ-level impacts of rising Chinese imports manifest across rural and urban areas *within* CZs. As described in Section 2, a good proxy for the 'ruralness' of a given municipality is how far it is located from its nearest job center (i.e. the center of its host CZ). As such, to study within-CZ heterogeneity of impacts along this dimension, I add to the basic specification in equation 3 an interaction term capturing how far municipality v is from the center of its host CZ measured as a categorical variable:

[28] I use a lagged measure of Chinese import penetration to alleviate endogeneity concerns related to anticipatory responses to Chinese import competition.

[29] I estimate all regressions in levels to maximize power since village-level data does not constitute a balanced panel.

[30] Even when manufacturing shocks are random, regions with higher manufacturing employment will tend to have systematically different values of the instrument, leading to bias when these regions also have different unobservables. Borusyak et al. (2022) show that controlling for the regional lagged manufacturing shares restores quasi-experimental variation in manufacturing shocks.

$$Y_{v(c,d)t} = \beta IP_{c(d)t-1} + \gamma_i(IP_{c(d)t-1} \times \delta_i^{travel}) + \delta_{it}^{travel} + \delta_{dt} + \boldsymbol{\eta}\mathbf{X} + \epsilon_{v(cd)t} \quad (4)$$

where δ_i^{travel} is a categorical variable denoting travel time in minutes with $i \in (0-10, 10-20, 20-30, 30-40, 40-90)$. These travel time intervals split the total sample of municipalities into five roughly equally sized categories. I include fixed effects at the level of travel time categories × year (denoted by δ_{it}^{dist}) to account for differential time trends at this level. The base category corresponds to the 'urban core', defined as the group of municipalities located within 0-10 mins of their nearest job center. γ_i captures the additional impact of a marginal increase in Chinese import penetration on municipality-level outcomes by how far municipalities are located in relation to the urban core.

4 Results

I begin by describing the impact of rising Chinese import penetration on outcomes measured in population census data. I then move on to discuss impacts on outcomes measured in firm census data. Finally, I discuss heterogeneity in worker-level impacts across rural and urban municipalities within CZs.

4.1 Impacts on workers: CZ level

Table 2 reports the impact of rising Chinese import penetration across CZs between 2001 and 2011 on non-farm employment using municipality-level data. Each panel estimates equation 3 separately for women (panel A), men (panel B), and all individuals (panel C) respectively. Column 1 controls only for district-level time trends. Columns 2 and 3 add CZ- and village-level controls respectively. IV estimates are presented in column 4.

The OLS estimate of -5.6 in column 3 of panel A indicates that a one percentage point increase in Chinese import penetration between 2001 and 2011 led to a decline in women's employment-to-population ratio in non-farm sectors by 5.6%. The estimated coefficient is relatively stable in sign and magnitude across different specifications, including the IV estimate of -5.8 in column 4. This underscores the stability of this statistical relationship. The impact on men's non-farm employment was much smaller in comparison. The estimated coefficient for men is only -0.8% in

Table 2: Impact of Chinese imports on employment in non-farm occupations (2001-2011)

Dependent variable: 100 × employment-to-population ratio

	I. Non-Farm employment			
	OLS			IV
	(1)	(2)	(3)	(4)
Panel A: Women				
Chinese IP	-8.302***	-4.438***	-5.637***	-5.871***
	(1.358)	(1.257)	(1.212)	(1.695)
KP F stat				83.18
R-squared	0.066	0.067	0.078	0.013
Observations	906,393	898,739	898,739	898,739
Panel B: Men				
Chinese IP	-1.824***	-0.887***	-0.805***	-0.451
	(0.307)	(0.276)	(0.277)	(0.316)
KP F stat				83.77
R-squared	0.033	0.033	0.046	0.014
Observations	1,037,172	1,028,616	1,028,616	1,028,616
Panel C: Overall				
Chinese IP	-2.737***	-1.276***	-1.339***	-0.895**
	(0.440)	(0.379)	(0.374)	(0.417)
KP F stat				83.81
R-squared	0.034	0.034	0.046	0.013
Observations	1,047,498	1,038,926	1,038,926	1,038,926
District × Year FE	✓	✓	✓	✓
CZ controls		✓	✓	✓
Village controls			✓	✓

Note: This table presents the estimated impact of a marginal increase in Chinese import penetration between 2001 and 2011 across CZs in India on employment in non-farm occupations. Each panel presents results from separate regressions estimated using municipality-level data for women, men, and all individuals, respectively (see equation 3). Estimates are weighted by municipality-level populations measured in 2001. The specification in column 1 controls for district-level time trends. Column 2 adds CZ-level controls. Column 3 adds village-level controls. Column 4 presents IV estimates (see section 3 for details). CZ-level controls include the start-of-period female employment rate, caste composition, under-five sex ratio, male and female literacy rates from the 2001 census, and manufacturing employment shares measured in 1998 and 1990. Village-level controls include the natural log of population in 2001 and the start-of-period value of the outcome variable. Total observations reflect the number of municipalities × two time periods (2001 and 2011). Women have fewer observations than men due to the fact that around 10% of villages had no women employed in non-farm sectors in 2001. Results are similar when these villages are also removed from the men's sample. Significance levels are denoted by: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$. Standard errors clustered at the district level are in parentheses.

column 3 of panel B. The IV estimate of -.5% in column 4 is even smaller in magnitude and not significant at the 90% level. I conclude that the observed decline of 1.3% in the rate of overall employment in non-farm sectors due to rising Chinese imports (reported in panel C) was driven largely by women.[31]

How large is this negative impact on women's non-farm employment? The average change in Chinese import penetration between 2001 and 2011 was around 1.5 percentage points so the point estimate of -5.6% for women translates to an average impact of -8.4% (5.6×1.5). The average growth in women's employment in non-farm sectors was +22% during this time, going from 5.29 in 2001 to 6.41 in 2011 (see table 1). As such, the impact of rising Chinese imports went against a secular positive trend in the opposite direction.[32] It is important to note at this point that my empirical strategy is silent on the impact of exposure to trade on levels. Instead, it focuses on estimating relative impacts across low- and high-exposure CZs. As such, the implied impact of -8.4% on women's non-farm employment should not be interpreted as the impact on the overall share of women employed in non-farm sectors due to rising Chinese imports.

Taken together, these results show that rising Chinese imports between 2001 and 2011 reduced employment in non-farm sectors among women but not men, which further increased the existing gender gap in non-farm employment. The observed impacts go against secular trends that were moving in the opposite direction. This result is somewhat surprising given that rising imports impacted largely male-dominated industries. What explains this? In the next subsection, I analyze impacts on outcomes measured in firm census data to shed light on this question.

4.2 Impacts on firms

In this section, I describe the impact of rising Chinese import penetration on outcomes measured in firm census data from 1998, 2005, and 2013. These data contain information on the location of the universe of non-farm firms in the country, including in the informal sector. As such, they deliver a good proxy for the changing spatial distribution of labor demand in these sectors. My main outcome of interest is municipality-level non-farm job density defined as the count of non-farm jobs per 1000 population.

I begin by describing impacts on overall non-farm job density estimated using equation 3. Short

[31] Table 5 in the appendix reports impact on farm-based and overall employment. I find an increase in overall employment among men due to rising Chinese imports. This is driven by the fact that men entered farm-based occupations to compensate for lost income from non-farm occupations. I do not find a similar pattern of substitution from non-farm to farm-based employment among women.

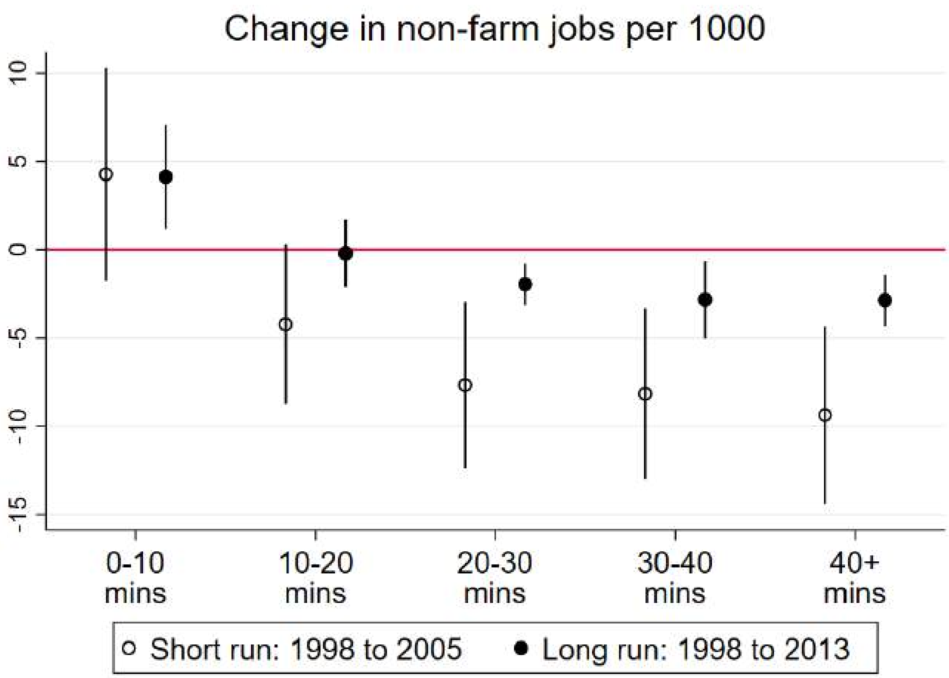
[32] Table 3 presents pre-trends. Women in areas more exposed to Chinese import penetration between 2001 and 2011 saw significantly faster growth in non-farm employment relative to men between 1991 and 2001. This implies gender gaps in non-farm employment were closing in more exposed areas in the past. Post-2001 exposure reversed this trend.

run (1998-2005) and long run (1998-2013) impacts are reported in separate panels of table 4. The OLS estimate of -6.8 in column 3 of panel a corresponds to the change in non-farm job density in response to one percentage point increase in Chinese import penetration between 1998 and 2005. The IV estimate of -19.6 in column 5 is much larger in magnitude (F-stat$\sim$40), suggesting that the OLS estimate is biased downwards. The average change in the outcome over this time was +1.5, going from 52.1 in 1998 to 53.6 in 2005 (see table 1), so these impacts are relatively large in magnitude. Long run (1998-2013) impacts are reported in panel b. Both OLS (0.06) and IV estimates (-0.7) are relatively small and not significant at the 10% level, suggesting that the observed negative impacts in the short run disappeared completely over time.

I now turn to a discussion of how these impacts manifested across rural and urban areas within CZs. As discussed in section 2, areas located 0-10 minutes away from the center of the CZ correspond to the urban core with high population density and high employment in non-farm sectors at baseline. Areas located outside of the urban core correspond to the increasingly rural periphery with falling population density and increasing share of farm employment. Figure 4 reports heterogeneous impacts across these areas within CZ using equation 4 estimated using OLS. Short run (1998-2005) and long run (1998-2013) impacts are estimated using separate regressions (see columns 4 and 6 of table 4 for the full set of results). The figure makes it clear that overall negative impacts in the short run are largely driven by areas located in the rural periphery, with the largest negative impacts seen in areas located 40+ minutes away. There was an expansion in non-farm jobs in the urban core, but this effect is not statistically significant at the 10% level. In the long run, negative impacts in rural areas were mitigated and there was a significant positive impact in the urban core.[33] Figure 17 shows this within-CZ reallocation of non-farm jobs was driven both by an increase in average firm size in urban areas and a reduction in average firm size in rural areas in the long run. I find relatively small negative impacts on the count of non-farm firms in rural areas and no significant impact on the number of firms in the urban core during this time.

[33] To guard against concerns related to a higher instance of missing information in firm census data relative to population census data, I triangulate my results with analysis of nightlight luminosity at the village level. Nightlight data are available for most villages and serve as an effective proxy for economic activity, especially in non-farm sectors (Asher et al., 2021). Figure 23 presents these results. In line with the pattern observed in firm census data, I find that a marginal Chinese import penetration between 2001 and 2011 increased nightlight luminosity by 3% in areas located in the urban core while reducing it by 4% in rural areas located furthest away (40+ minutes) from urban job centers.

Figure 4: Impact of Chinese imports on non-farm job density within CZs (OLS estimates)



Notes: This figure shows the heterogeneous impacts of rising Chinese import penetration on the number of non-farm jobs per 1000 population at the municipality level by how far municipalities are located to their nearest urban center within CZs as defined in section 2. Estimates of short-run impacts (1998 and 2005) and long-run impacts (1998-2013) come from two separate regressions that fit models of the form presented in Equation 4 using OLS. All models include controls for time trends at the level of districts and four travel time bands, as well as time-invariant CZ- and municipality-level controls measured at baseline (see text for details). Data on job counts from 1998, 2005, and 2013 (taken from firm census data) has been normalized by population data from the closest population census round (2001 population census for 1998 and 2005, and 2011 population census for 2013).

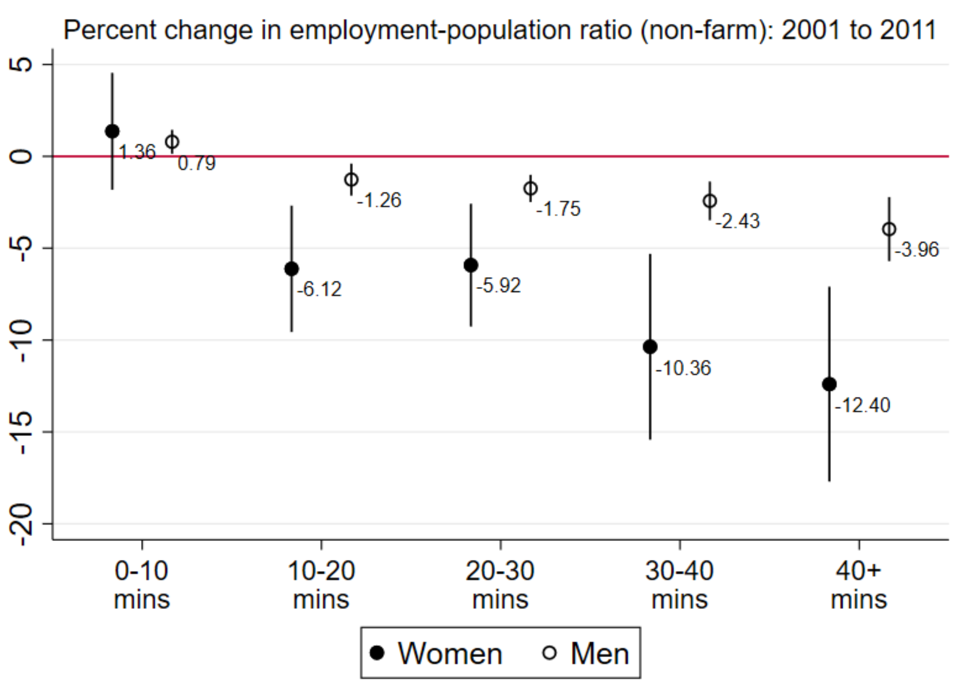
These results show that rising Chinese import penetration between 1998 and 2013 across CZs in India had the effect of shifting non-farm job density from areas in the rural periphery to the urban core within CZs while having no significant impact at the level of individual CZs. The implied impact on non-farm job density was -11.3 in areas located 40+ minutes away and +6.8 in the urban core. The average change in the non-farm job density during this time was +10 (going from 49.6 to 59.6) in areas located 40+ minutes away and +18.7 (going from 85.2 to 66.5) in the urban core. As such, rising Chinese imports further contributed to the increasing concentration of non-farm job density in urban areas which was already underway across CZs in India.

4.3 Impacts on workers: heterogeneity within CZs

Motivated by the finding that rising Chinese import penetration shifted labor demand in non-farm sectors from rural to urban areas within CZs over time, I return to the analysis of worker outcomes with a focus on within-CZ heterogeneity.

I estimate heterogeneous impacts on non-farm employment across rural and urban areas within CZ using equation 4. Figure 5 summarizes these results (see table 6 for details). Impacts for men and women are estimated using separate regressions. Figure 5 shows that the negative impact on women's non-farm employment at the CZ level is driven entirely by areas in the rural periphery, with the largest impacts seen in areas located furthest away (30+ minutes). While men's non-farm employment also declined in areas located in the rural periphery, it increased in the urban core. This explains the overall null impact on men's non-farm employment at the CZ level. Comparing impacts across men and women, the figure makes it clear that women's employment in non-farm sectors declined at a much faster rate than men's across areas located in the rural periphery, with the largest gender gaps appearing in areas located furthest away (30+ minutes). However, there was no significant gender differences in the impact on non-farm employment in areas located in the urban core.

Figure 5: Impact of Chinese imports on employment in non-farm sectors (2001-2011)



Notes: This figure shows the heterogeneous impacts of rising Chinese import penetration between 2001 and 2011 on municipality-level employment in non-farm occupations within CZs. The x-axis corresponds to a categorical variable that captures how far municipalities are located to the center of their host CZ as defined in section 2. Estimates along with 95% confidence intervals come from two models that fit equation 4 separately for men and women using OLS. Estimates are weighted by municipality-level population measured in 2001. Regressions include controls for time trends at the level of districts and global travel time bands, as well as time-invariant CZ- and municipality-level controls measured at baseline (see text for details). Standard errors are clustered at the district level.

Figure 15 in the appendix summarizes heterogeneous impacts for women and men across non-farm, farm, and overall employment. I find muted impacts on overall employment rates since both men and women compensated for lost income from non-farm occupations by entering agriculture instead. However, in areas located furthest away, the negative impact on women's non-farm employment was so large that their overall employment rate also declined.

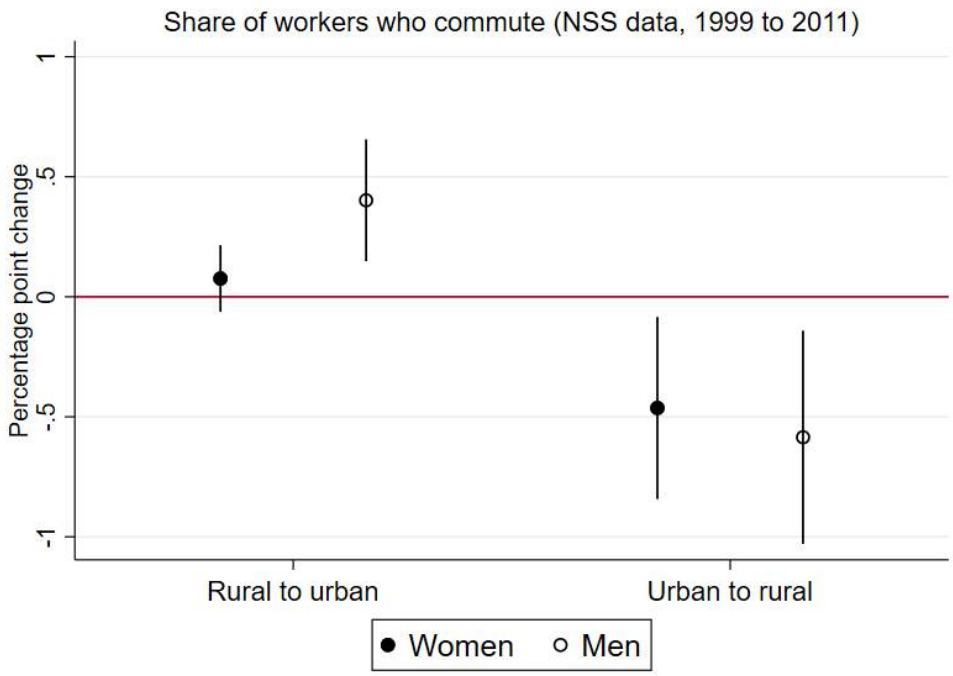
5 Mechanisms

5.1 Gender differences in propensity to commute

I argue that my results are consistent with the following mechanism. Rising Chinese imports displaced both men and women from non-farm occupations in rural areas between 2001 and 2011. Displaced men either switched to agriculture or started commuting longer distances to take up work in nearby urban areas where non-farm firms expanded hiring due to rising Chinese imports. While displaced women also switched to agriculture, they were less likely than men to commute to urban areas to continue working in non-farm occupations. The large negative impact on women's non-farm employment in rural areas is thus explained by women's lower propensity to commute. I provide four pieces of evidence that support this interpretation of the data.

First, I provide direct evidence showing that men in rural areas started commuting to urban areas in response to rising Chinese imports but women did not. I use rich individual-level information from the 1999, 2004, and 2011 rounds of nationally representative National Sample Survey (NSS) data to construct an indicator variable capturing whether workers report commuting across the rural-urban boundary for work in the last week. Since NSS data are representative only at the level of districts, I construct a district-level analogue of my CZ-level measure of rising Chinese import penetration. Using the specification outlined in equation 4, I regress my individual-level measure of commuting on this district-level measure of Chinese import penetration with an interaction term capturing within-district heterogeneity of impacts across individuals living in rural and urban areas. Each regression includes controls for time trends at the level of states and area of residence (urban/rural), district-level manufacturing employment share at baseline, as well as time-varying individual-level controls for caste, religion, age, age squared, education level, and marital status. Standard errors are clustered at the level of states to account for spatial correlation across districts. I run separate regressions for the sample of men and women. Results are shown in figure 6. I find that a marginal increase in Chinese import penetration is associated with a 0.05 percentage point increase in the share of men commuting across the rural-urban boundary for work between 1999 to 2011. I find no similar commuting response among women living in rural areas.[34] In line with the finding that rising imports caused non-farm firms to contract in rural areas, both men and women living in urban areas reduced commuting to rural areas during this time.

Figure 6: Impact of Chinese imports on the share of workers who commute



Notes: This figure reports the estimated impact of rising Chinese import penetration across districts in India on the share of workers who report commuting across the rural-urban boundary using individual-level data from the 1999 and 2011 rounds of nationally representative NSS data. The district-level measure of Chinese import penetration is constructed using a shift-share argument analogous to the CZ-level measure (see section 3). Heterogeneous impacts by area of residence (urban/rural) are estimated using equation 4. Impacts for men and women are estimated using two separate regressions by OLS. Both regressions include controls for (i) time trends at the level of states and area of residence (urban/rural), (ii) district-level manufacturing employment share at baseline, as well as (iii) time-varying individual-level controls for caste, religion, age, age squared, education, and marital status. Standard errors are clustered at the state level. Estimates are weighted by survey weights.

Second, if men started commuting to work in urban areas but women did not, one should expect to see a decrease in the share of female employees in urban firms due to the trade shock. Moreover, to rule out the possibility that men simply crowded out women's employment in rural firms during this time, there should be no decrease in female employment share in rural firms. To test this claim, I estimate equation 4 to capture heterogeneity of impacts on female employment share across non-

[34]In 1999, 2.6% of male and 0.7% of female workers residing in rural areas reported commuting to urban areas for work. A 0.05 percentage point increase thus translates to a 2% increase between 1998 and 2005. Impacts were larger in the short run (1999-2004), with men increasing commuting by 13%. Women showed no impact also in the short run.

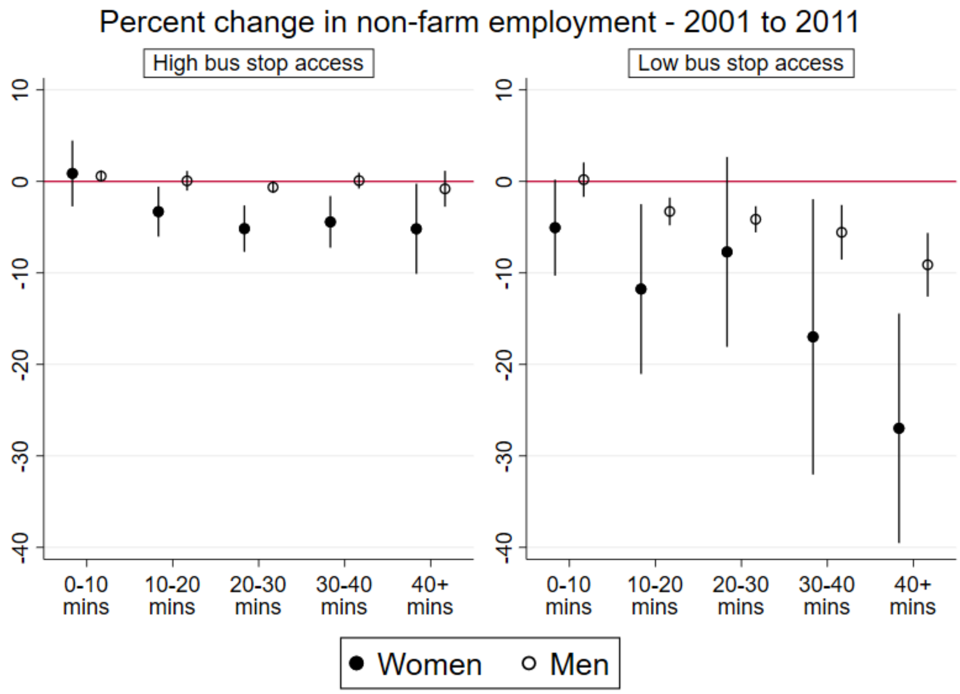
farm firms located in rural and urban areas within CZs. Results are shown in figure 19. I find that a marginal increase in Chinese import penetration reduced the female employment share in the urban core by 1 percentage point in the short run (1998-2005) and 0.3 percentage points in the long run (1998-2013). There was no significant change in the female employment share in rural areas during this time. Figure 18 confirms that this pattern is driven by the fact that while both men and women were fired from firms located in rural areas, only men were hired in expanding firms located in urban areas.

Third, I conduct a placebo test showing that no gender gaps appear in non-farm occupations that don't require commuting. Using the specification outlined in equation 4, I regress changes in employment-to-population ratios in household-based non-farm employment and other non-farm employment on my measure of rising Chinese import penetration at the CZ level with an interaction term capturing heterogeneity of impacts across rural and urban areas within CZs.[35] Results are shown in figure 16. I find that overall gaps in non-farm employment in the rural hinterland are largely driven by other non-farm employment. There are no significant gender gaps in household-based employment across rural or urban areas.

Finally, I provide suggestive evidence that relaxing gendered commuting frictions can reduce gender gaps. Using the fact that women in India rely on public modes of transport more than men (GoI, 2011), I estimate impacts separately for CZs with low and high bus network density at baseline, conditioning on the quality of the general road network (measured as the share of villages with a paved road). Results are shown in figure 7. I find that CZs with better bus connectivity at baseline display significantly smaller gender gaps due to the trade shock.

[35] The population census records two types of non-farm occupations - household-based occupations and 'other' occupations. The latter is a residual category capturing all non-farm jobs performed outside the household. These may or not require commuting outside of one's native village.

Figure 7: Heterogeneity by access to bus network



Notes: This figure shows the heterogeneous impacts of rising Chinese import penetration across CZs with below- and above-median bus access where bus access is measured at the CZ level as the share of villages that had access to a bus stop as measured in 2001 census data. Estimates along with 95% confidence intervals come from two models that fit equation 4 separately for men and women using OLS. Estimates are weighted by municipality-level population measured in 2001. All regressions include controls for time trends at the level of district and travel time bands, as well as time-invariant CZ- and municipality-level controls measured at baseline (see section 3 for details).

5.2 Evidence against alternate mechanisms

In this section, I provide evidence against three competing mechanisms that may also explain observed impacts.

First, the commuting mechanism I propose may be confounded by the migration of individuals across space. For instance, the appearance of gender gaps in rural areas may be driven by the migration of productive women (alone or along with their households) from rural to urban areas over time. To test this mechanism, I estimate the heterogeneous impact of rising Chinese imports on municipality-level population growth between 2001 and 2011 using the specification outlined in equation 4. Results are shown in figure 20. While I do find a positive impact on population growth in the urban core relative to the rural periphery within CZs, the magnitude of this impact is very small (point estimate=+0.03%) relative to the growth of non-farm jobs in these areas. This explains why I find a significant increase in non-farm job density (defined as the count of jobs per

1000 population) in the urban core due to rising Chinese imports. Further, I find no evidence for gender differences in population growth in the urban core, suggesting that the selective migration of productive single women from rural to urban areas is also not a key driver of my main result. Overall, this evidence points to a relatively muted role of migration in the process of labor market adjustment due to rising Chinese imports, even over a period of 10 years.[36] This provides further support for the relative importance of commuting in my setting.

Second, exposure to trade can induce skill-biased technical change (Juhn et al., 2014; Bloom et al., 2016). If expanding firms in urban areas demand more high-skill labor than before, the appearance of gender gaps in rural areas could reflect the fact that women had lower levels of average educational attainment than men at baseline.[37] To test this mechanism, I estimate the heterogeneous impact of rising Chinese imports on non-farm employment in rural areas across individuals with low (primary or below) and high (above primary) levels of education using rich individual-level survey data from the 1999 and 2011 rounds of the NSS. Results are shown in figure 21. I find similar negative impacts among women with different levels of education, suggesting that my results are not driven by increasing demand for skilled workers due to the trade shock.[38] These findings are in line with previous work showing rising Chinese imports induced little skill-biased technical change among Indian firms. For instance, Deb and Hauk (2020) finds that rising Chinese imports between 1999 and 2012 had no impact on wage gaps between skilled and unskilled workers. (Chakraborty et al., 2024) finds that although rising Chinese imports increased the share of formal sector employment, the probability of displaced workers being employed in expanding formal enterprises does not vary by education level.

Third, the negative impact on women's employment in non-farm sectors could potentially be driven by rising household incomes in rural areas. This is unlikely since I find that individuals entered low-wage agriculture to adjust to the trade shock, which suggests that household incomes were impacted negatively rather than positively. Nonetheless, since cheaper goods from China likely reduced consumer prices, the impact on real household incomes is ambiguous. To test this mechanism, I estimate the heterogeneous impact of rising Chinese imports across rural and urban areas on household-level measures of per capita consumption (a measure of real household incomes)

[36] This result is in line with the facts that (i) India has generally low rates of internal migration (Bell et al., 2015) and (ii) previous studies on the persistent local labor market impacts of rising Chinese import penetration have also found a similarly sluggish migration response across a range of contexts (Autor et al., 2021; Mansour et al., 2022).

[37] At baseline, 46% of men aged 15-65 had completed primary education compared to only 27% of women (NSS, 1999).

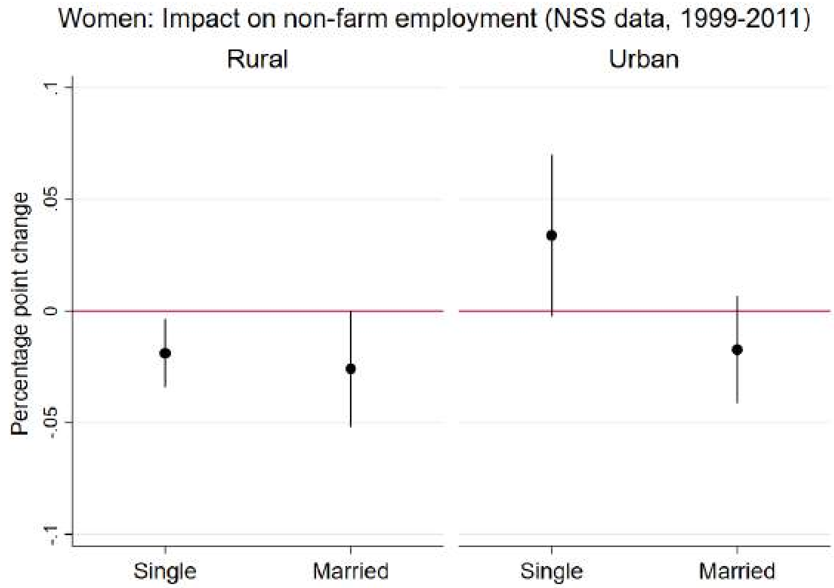
[38] I also find no significant difference in impacts by education level among men, although the impact estimate amongst men with high education is positive and significant.

and total earnings of household members in the past week (a measure of nominal earnings) using individual-level NSS data from 1999 and 2011. Results are shown in figure 22. I find that while rising Chinese imports led to an increase in both household earnings and per capita consumption amongst households living in urban areas, there was a significant negative impact on household earnings and no impact on per capita consumption in rural areas. These results are somewhat noisy given that NSS data are only representative at the district level. As such, I complement this analysis by also estimating the heterogeneous impact of rising Chinese imports within CZs on average nightlight luminosity, which provides a proxy for relative per capita consumption at the municipality level. Results are shown in figure 23. I find that a marginal Chinese import penetration reduced average night light luminosity in rural areas located furthest away (40+ mins) from urban job centers by 4% between 2001 and 2011 while increasing it by 3% in areas located in the urban core (within 0-10 mins). Taken together, these results suggest that household incomes in rural areas did not rise due to rising Chinese imports. As such, this cannot be a major driver of the observed negative impacts on women's employment rates.

6 Discussion

My results are consistent with gender differences in the propensity to commute. But why are women less amenable to commuting than men? One common explanation relates to the role of household-level constraints stemming from social norms around child care and household chores that disproportionately impact married women. To test this explanation, I use individual-level NSS data to estimate the heterogeneous impact of rising Chinese imports on the employment rates of single and married women in non-farm occupations using the specification outlined in equation 4. Results are shown in figure 8. I find similar negative impacts for single and married women in rural areas. In urban areas, however, I find that single women were significantly more likely to enter non-farm occupations relative to married women. Taken together, these findings suggest that both household-level constraints and commuting frictions constitute key barriers to women's work in India. While the former prevents married women from taking up non-farm employment even when job access improves (as is the case in urban areas), the latter prevents women from taking up employment outside one's village regardless of marital status.

Figure 8: Impact of Chinese imports on women's non-farm employment by marital status (1999-2011)



Notes: This figure reports the estimated impact of rising Chinese import penetration across districts in India on the share of single and married women aged 15-60 employed in non-farm sectors in the last week. It uses individual-level data from the 1999 and 2011 rounds of nationally representative NSS data. The district-level measure of Chinese import penetration is constructed using a shift-share argument analogous to the CZ-level measure (see section 3). Heterogeneous impacts by marital status are estimated using OLS as in equation 4. Impacts for individuals living in urban and rural are estimated in separate regressions. Both regressions include controls for (i) time trends at the level of states and marital status, (ii) district-level manufacturing employment share at baseline, and (iii) time-varying individual-level controls for caste, religion, age, age squared, and years of education.

The fact that negative impacts on women's employment in rural areas do not vary by marital status suggests that gender differences in the propensity to commute reflect frictions that affect single and married women equally. Such gendered commuting frictions could stem from, for instance, women's low access to private modes of transport combined with the threat of sexual harassment in public spaces across labor markets in India.[39] Previous work has shown these factors constitute a key barrier to women's employment in India, especially in urban areas. For instance, in a survey conducted in New Delhi, 95% of women aged 16–49 stated that they felt unsafe in public spaces (UN Women and ICRW, 2013). At the national level, higher levels of perceived crime at the neighborhood level (Chakraborty et al., 2018) or via media reports Siddique (2022) are associated with lower rates of female labor force participation. In line with this evidence, policies that improve the

[39] Strictly speaking, it is not possible to separate the role of commuting 'frictions', which I view as external constraints that can be potentially mitigated by policy action, from inherent gender differences in commuting preferences. There is evidence for the latter from developed countries, where concerns around public safety are arguably lower than in India. For instance, even amongst single individuals without kids, women in France (Le Barbanchon et al., 2021) and Denmark (Bütikofer et al., 2024) have a shorter maximum acceptable commute than comparable men.

comfort and safety of public modes of transport have been shown to disproportionately improve women's employment outcomes. For instance, Seki and Yamada (2020) studies the roll-out of the Delhi metro system and finds that proximity to a new metro station increased female but not male employment.

7 Quantification

It is natural to ask whether gendered commuting frictions constitute a barrier to women's work more generally. This question is especially pertinent in the case of India, where women's labor force participation (LFP) in rural areas declined by 20 percentage points between 2004 and 2012 during a period of rapid urban-biased economic growth (Deshpande and Singh, 2021). How much of the observed decline in female LFP in rural areas would have been mitigated if gendered commuting frictions were relaxed? Answering this counterfactual question requires a model.

I proceed in three steps. First, I build a spatial general equilibrium Roy (1951) model of occupational choice. The model features N+1 locations, consisting of an urban core and N villages located at varying distances. Individuals in each village choose between three occupations - agriculture, local non-farm, and urban non-farm. Urban wages are higher but require individuals to pay a portion of their wage as an iceberg commuting cost. I introduce two forces that distort women's occupational decisions. First, to capture gendered commuting frictions, I allow commuting costs to differ by gender. Second, to model household constraints stemming from social norms around childcare and household chores that disproportionately impact women, I assume that households receive some exogenous utility from women staying at home. This generates a household-level income effect: women exit the labor force when the male wage is sufficiently high. I assume that men supply labor inelastically.[40] In the beginning, each individual independently draws a triple from a Frechet distribution with a given shape parameter that determines how productive they are in each of the three occupations. Households then make two decisions to maximize joint utility: (i) whether one or both members work, and (ii) which occupation each member works in. Wages in each village and in the urban core are determined in equilibrium. More details are provided in appendix B.

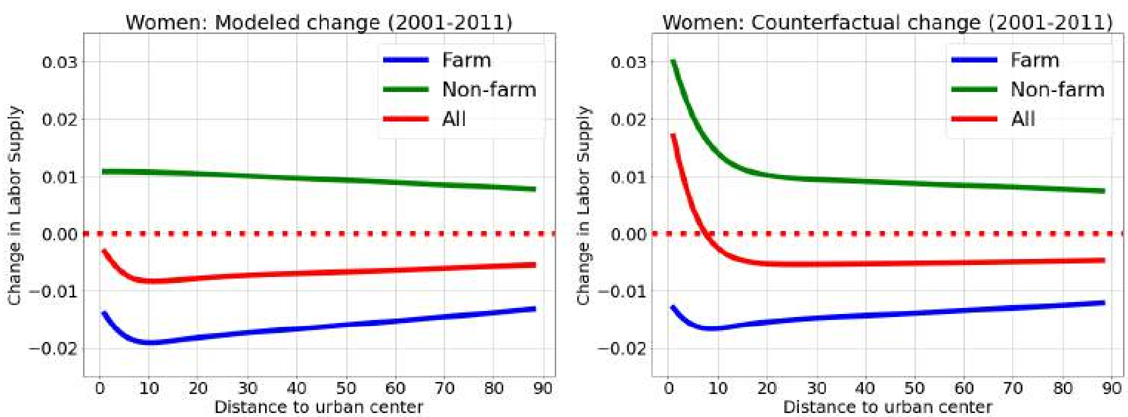
Second, I calibrate the model using municipality-level data from the 2001 and 2011 rounds of the

[40] While gendered commuting frictions act as an occupation-specific wedge between wage and marginal product that induces potential misallocation of women's talents into rural occupations, household-level optimization generates variation in the share of women in the labor force.

population census. Results of the calibration are provided in table B1 in the appendix. Estimated values of relative wages align closely with previous work on rural-urban wage gaps in India (Munshi and Rosenzweig, 2016; Baysan et al., 2024). Further, figure B4 shows that the model does a good job of reproducing the key untargeted moment of the village-level changes in female labor force participation between 2001 and 2011 within CZs.

Finally, I use the calibrated model to simulate how female LFP would have evolved in the absence of gendered commuting frictions. I do this by setting commuting costs to be the same across men and women while keeping the remaining parameter values fixed at their levels in 2011. I let wages adjust to their new equilibrium level, and back out the counterfactual female LFP rate implied by the model in 2011. I then compare the counterfactual change with the actual change in female LFP between 2001 and 2011 implied by the model parameters. Results are reported in figure 9.

Figure 9: Impact of removing gendered commuting frictions on change in female LFP between 2001 and 2011



Notes: This figure compares the change in female labor supply between 2001 and 2011 implied by the model parameters (panel on the left) with the counterfactual change when gendered commuting frictions are switched off in 2011 (panel on the right). See appendix B for details.

The left panel of figure 9 shows that the observed decline in total female LFP between 2001 and 2011 (shown in red) is driven by a large drop in farm employment (shown in blue) without a commensurate increase in non-farm employment (shown in green). The decline is largest in villages located close to urban centers. The right panel of figure 9 presents the counterfactual change in female LFP. It shows that, in the absence of gendered commuting frictions, the decline in women's LFP would have been mitigated in areas located close to urban centers by making it easier for women in these areas to work in urban non-farm sectors.

The model implies that the observed decline in female LFP between 2001 and 2011 would have been mitigated by 30% in the absence of gendered commuting frictions. This corresponds to an additional 1 million women in the labor force in 2011. A back-of-the-envelope calculation suggests that this would have increased total output by 0.4%.

8 Conclusion

I study the impact of the increasing concentration of labor demand in urban areas stemming from rising exposure to international trade on gender employment gaps in India. Using municipality-level panel data containing the universe of workers and non-farm firms in the country, I show that rising exposure to Chinese import competition starting in the early 2000s shifted non-farm firms from areas in the rural periphery to the urban core within CZs over time. In areas where firms contracted, women's employment in non-farm occupations was lower than men's after ten years. Gender employment gaps are driven entirely by non-farm sector jobs performed outside the home. I find no gender gaps in areas where firms expanded. Household incomes declined in areas that lost jobs, so the observed negative impacts on women's employment cannot be explained by an income effect. I find minimal impacts on population growth both within and across CZs during this time, indicating a relatively muted role for migration in the process of labor market adjustment.

I argue that my results are consistent with the following mechanism. While men displaced by rising Chinese imports started commuting across the rural-urban boundary to work in expanding non-farm occupations, women either switched to locally available employment in agriculture or dropped out of the labor force instead. In line with the fact that women rely more on public modes of transport in India, I find smaller gender gaps in commuting zones with better bus connectivity at baseline. I find similar negative impacts for women regardless of marital status and education level, suggesting that results are not driven by household-level constraints or increasing demand for skilled labor. My findings point to the presence of gendered commuting frictions that impede women's ability to work far from home. Such frictions are consistent with women in India having relatively low access to private modes of transport and facing a high threat of sexual harassment in public spaces, factors that have been identified by previous work as key barriers to women's work in the country.

In the last part of the paper, I quantify the relative importance of such gendered commuting frictions in explaining the observed steep decline in female LFP rates in India between 2001 and

2011. Using a spatial general equilibrium model calibrated to village-level data, I estimate that relaxing gendered commuting frictions would have mitigated the observed decline in female LFP during this time by 30%. The resulting improvement in the allocation of women's talent across space would have increased total output by 0.4%.

My results highlight a general mechanism —gendered commuting frictions —through which the changing spatial distribution of labor demand can exacerbate existing employment gender gaps. In future work, I intend to use the machinery developed in this paper to study the impact of other shocks like localized impacts of climate change, plant closures etc. in driving gender employment gaps. I expect this mechanism to be especially relevant in contexts similar to India, where existing gender commuting gaps are large and rates of household migration are low.

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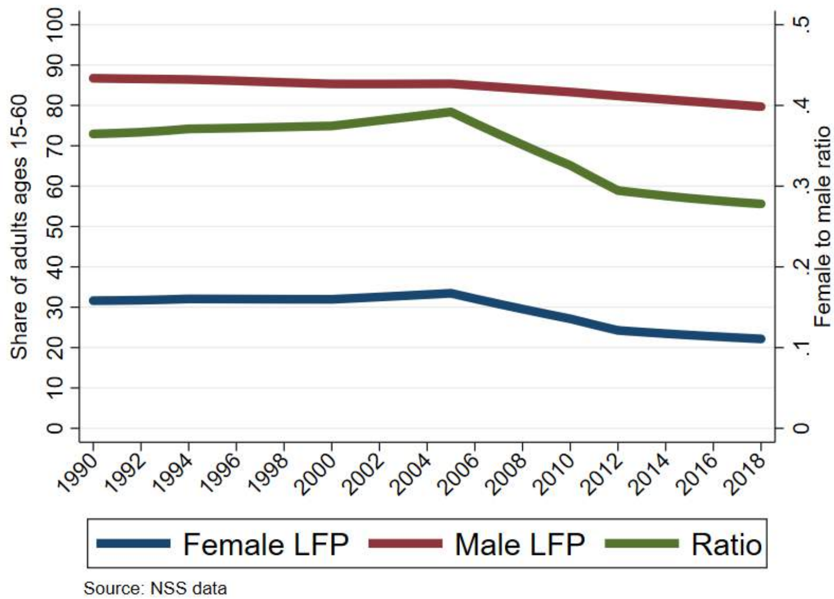
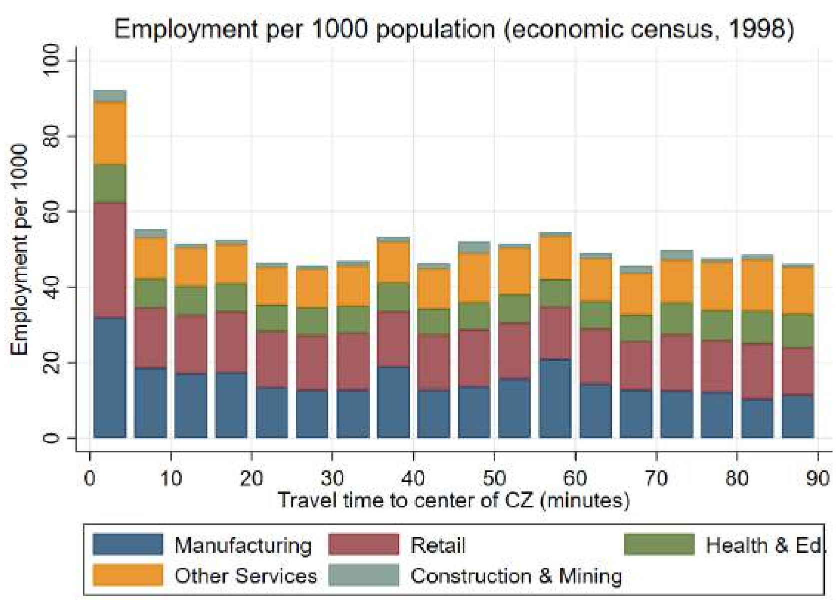
Additional Figures

Figure 10: Rates of labour force participation in India



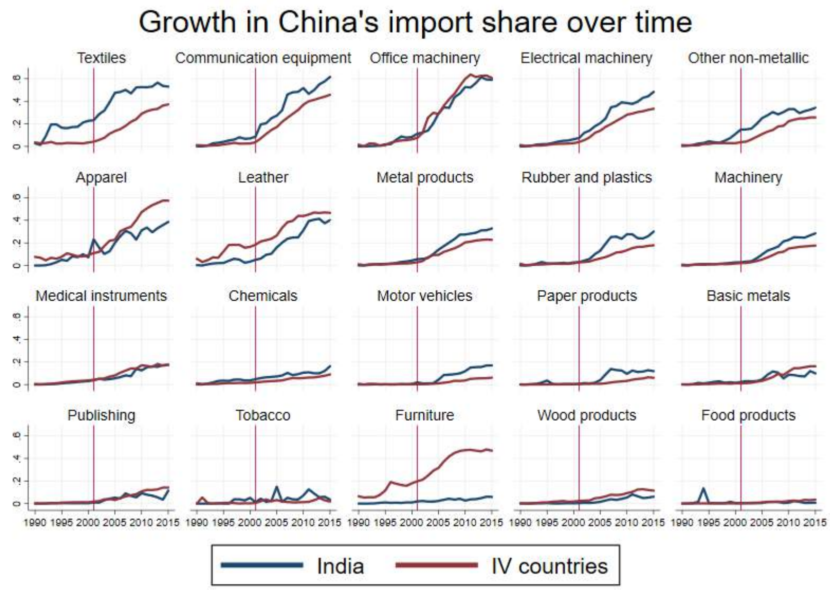
Source: World Development Indicators, modeled ILO estimates based on NSS surveys.

Figure 11: Characterizing commuting zones: economic census data



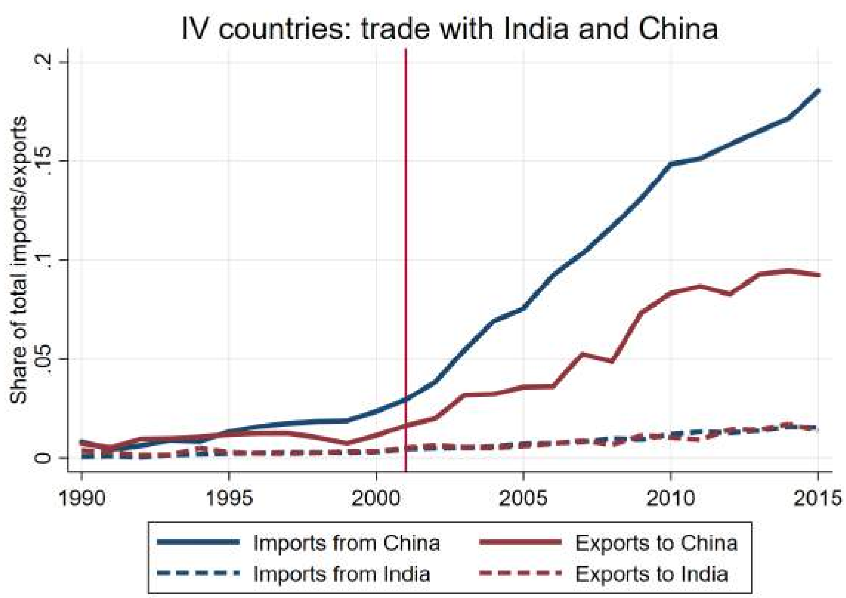
Notes: This graph shows how average job density across different non-farm sectors varies within CZs by increasing distance to the nearest urban center as defined in section 2. Job density is defined as the total number of jobs in the 1998 round of the economic census per 1000 population measured in the 2001 population census.

Figure 12: Trade with China: India and IV countries



Notes: This figure shows Chinese manufacturing imports in India and the average across IV countries as a share of world imports at the two-digit level. IV countries include Argentina, Brazil, Chile, Colombia, Costa Rica, Mexico, Paraguay, Peru, Uruguay, and Venezuela. *Source:* UN-COMTRADE database.

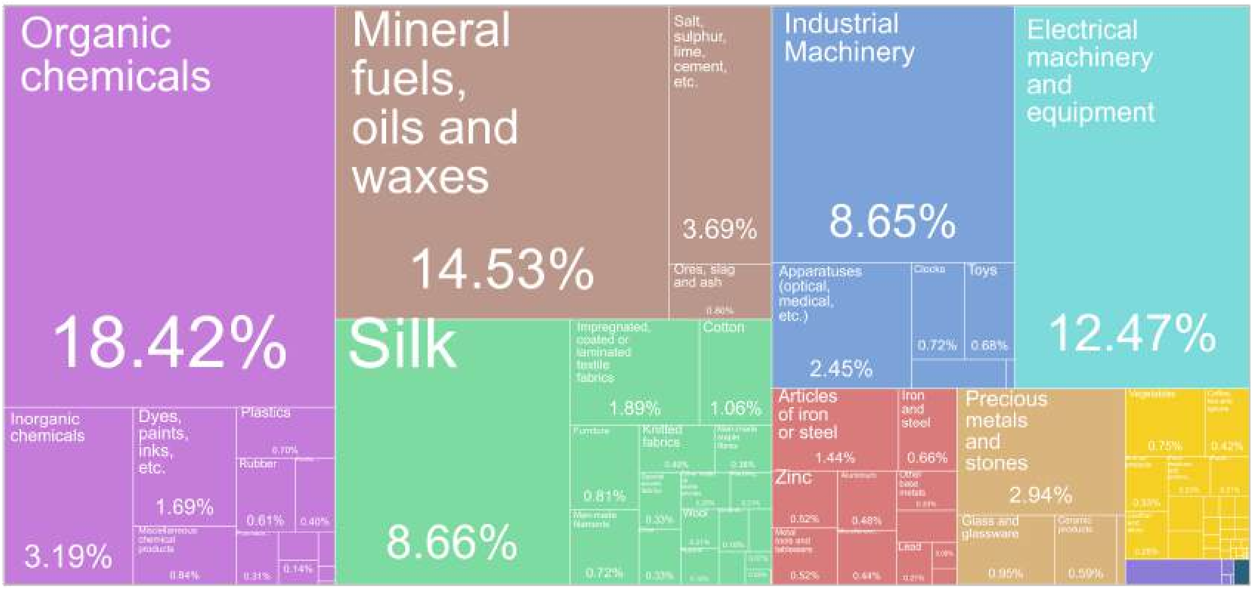
Figure 13: IV countries: trade with China and India



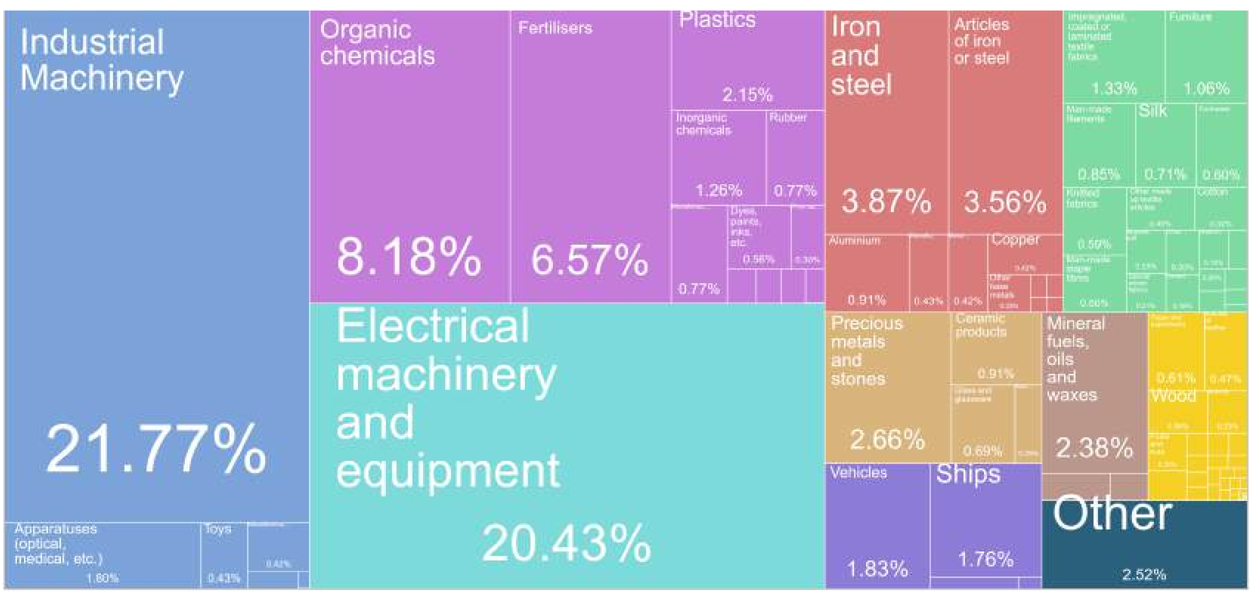
Notes: This figure shows average trade flows for IV countries with China and India as a share of world trade. IV countries include Argentina, Brazil, Chile, Colombia, Costa Rica, Mexico, Paraguay, Peru, Uruguay, and Venezuela. *Source:* UN-COMTRADE database.

Figure 14: Change in Chinese import mix

(a) Chinese imports to India in 2001

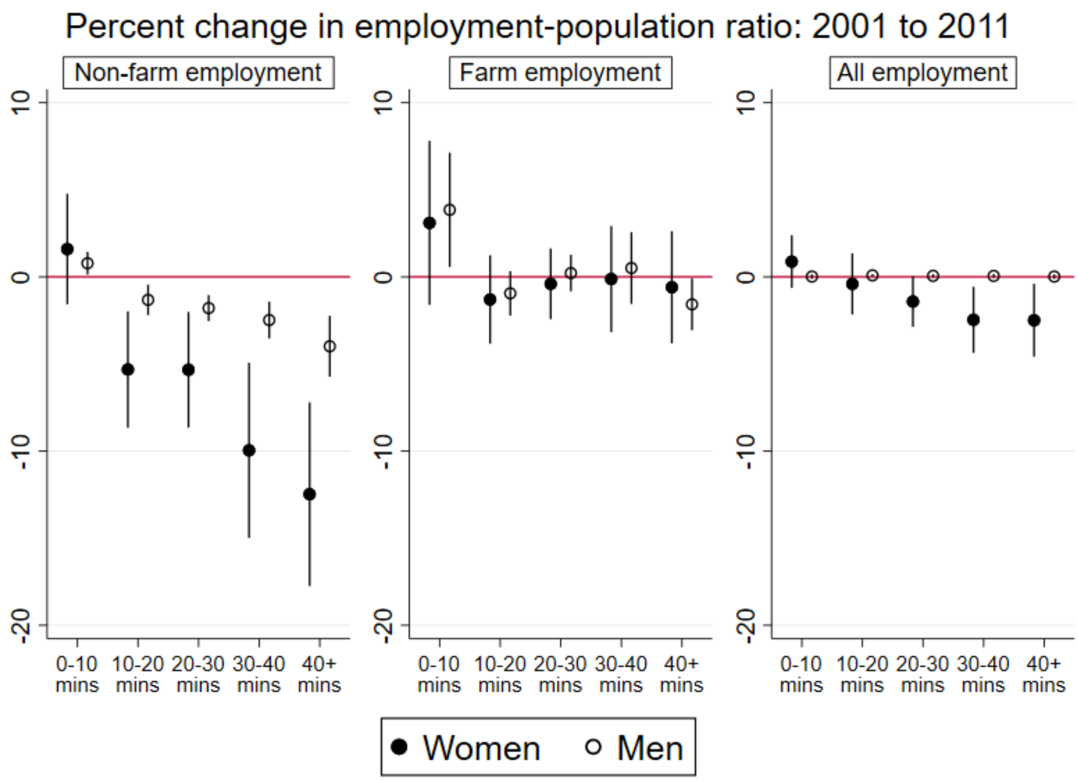


(b) Chinese imports to India in 2011



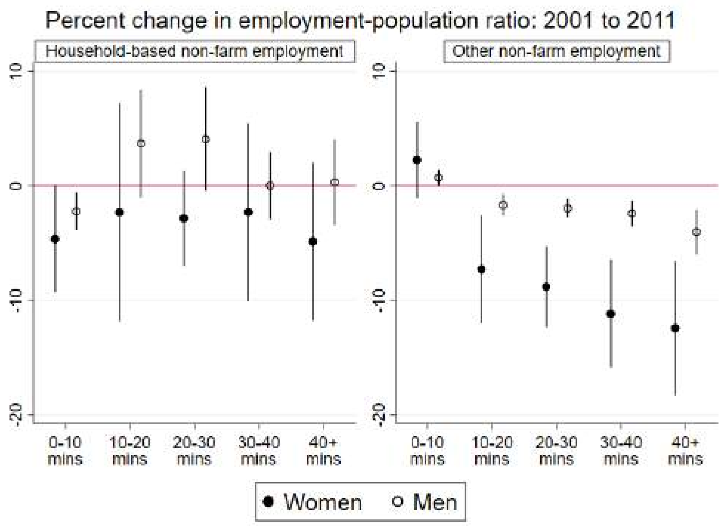
Notes: This figure shows how the import mix of Chinese manufacturing imports to India changed between 2001 (panel a) and 2011 (panel b). Sector-wise shares of total imports are at the 2 digit HS 1992 level. Total imports from China grew from \$1.8 Billion in 2001 to \$51.2 Billion in 2011. *Source*: The Atlas of Economic Complexity, Harvard Growth Lab

Figure 15: Impact of Chinese imports across all employment margins (2001-2011)



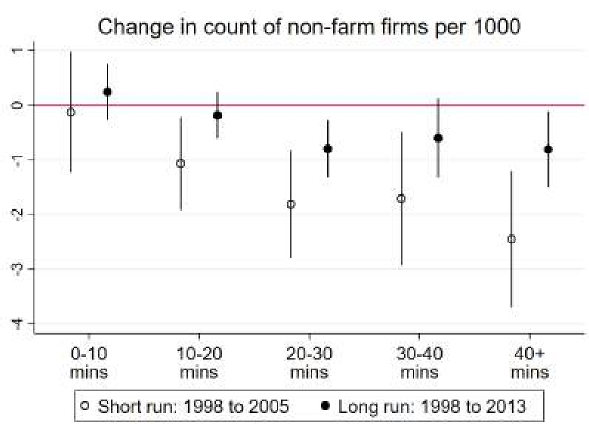
Notes: This figure shows the heterogeneous impacts of rising Chinese import penetration between 2001 and 2011 on municipality-level employment by how far municipalities are located to their nearest urban center within CZs as defined in section 2. Impacts for men and women are estimated within the same model by fitting equation 4 using OLS. The three sub-figures report estimates from separate models for non-farm employment, farm employment and overall employment, respectively. All regressions include controls for time trends at the level of districts, gender, and travel time bands, as well as time-invariant CZ- and municipality-level controls measured at baseline (see text for details).

Figure 16: Impact of Chinese imports on employment in household-based jobs vs other jobs (2001-2011)

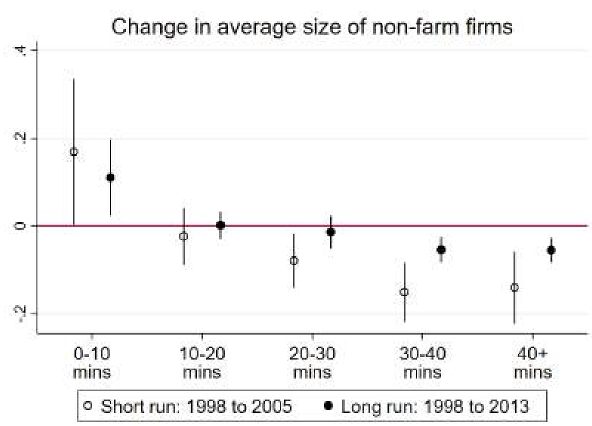


Notes: This figure shows the heterogeneous impacts of rising Chinese import penetration across Indian CZs between 2001 and 2011 on employment in non-farm sectors by how far municipalities are located to their nearest urban center as defined in section 2. Impacts for men and women are estimated by OLS using separate regressions as in equation 4. 'Other' non-farm employment is a residual category, calculated as the difference between all non-far work and household-based non-farm work, that captures non-farm work performed outside the home. Such work may be performed within or outside the village. All regressions include controls for time trends at the level of districts and travel time bands, as well as time-invariant CZ- and municipality-level controls measured at baseline (see text for details).

Figure 17: Impact of Chinese imports on firms counts and average size



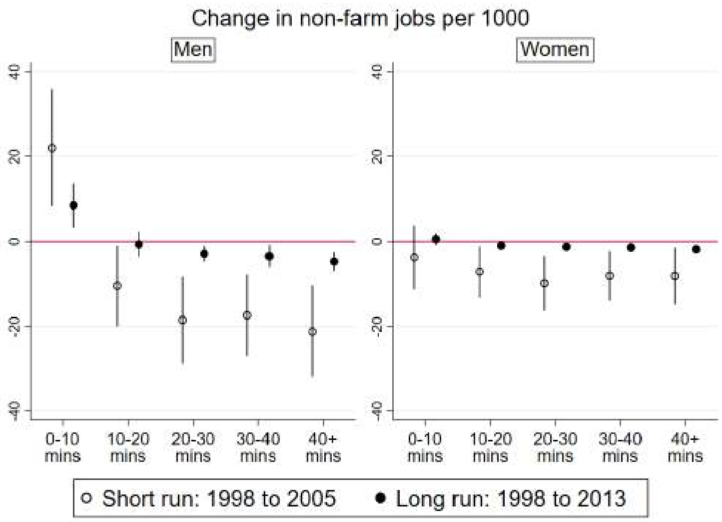
(a) Impact on firm counts



(b) Impact on firm size

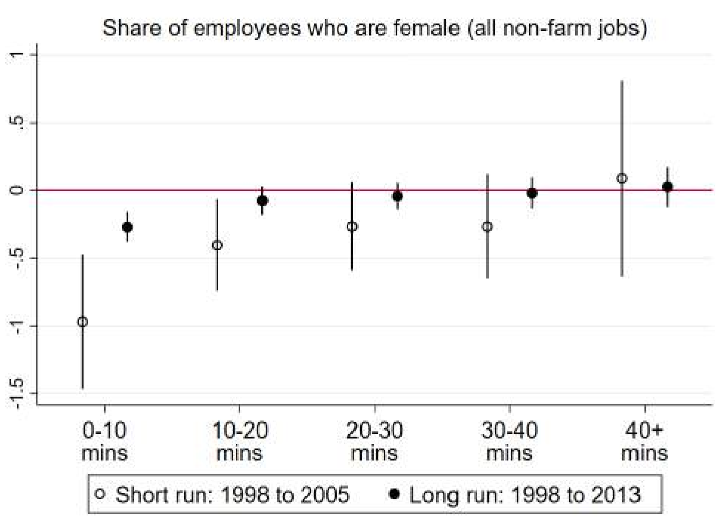
Notes: This figure shows the heterogeneous impacts of rising Chinese import penetration across Indian CZs on the number and size of non-farm firms by how far municipalities are located to their nearest urban center as defined in section 2. Impacts for the short run (1998-2005) and the long run (1998-2013) are estimated by OLS using separate regressions as in equation 4. All regressions include controls for time trends at the level of districts and travel time bands, as well as time-invariant CZ- and municipality-level controls measured at baseline (see text for details).

Figure 18: Impact of Chinese imports on non-farm jobs per 1000: men and women



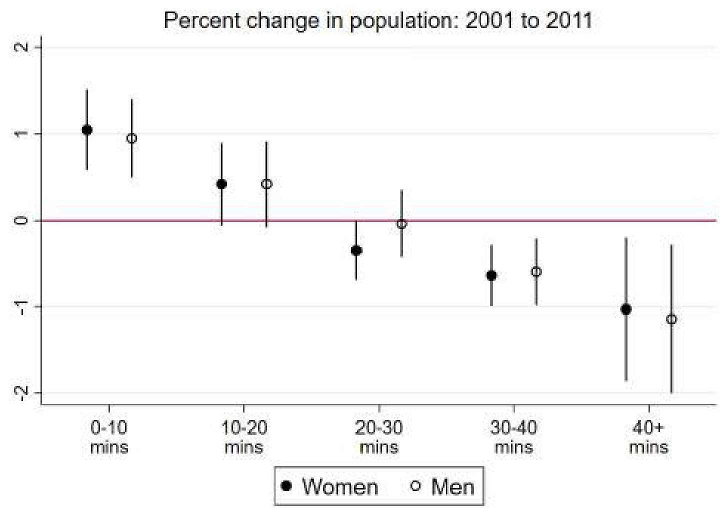
Notes: This figure shows the heterogeneous impacts of rising Chinese import penetration across CZs in India on the number of non-farm jobs at the municipality level by how far municipalities are located to their nearest urban center as defined in section 2. For each municipality, male (female) employment is measured as the ratio of total male (female) employees in firm census data per 1000 men (women) in population census data. Impacts for men and women, as well as over the short-run (1998 and 2005) and long-run (1998-2013), are estimated using four separate regressions like in equation 4 by OLS. All regressions include controls for time trends at the level of district and travel time bands, as well as time-invariant CZ- and municipality-level controls measured at baseline (see section 3 for details).

Figure 19: Impact of Chinese imports on female employment share



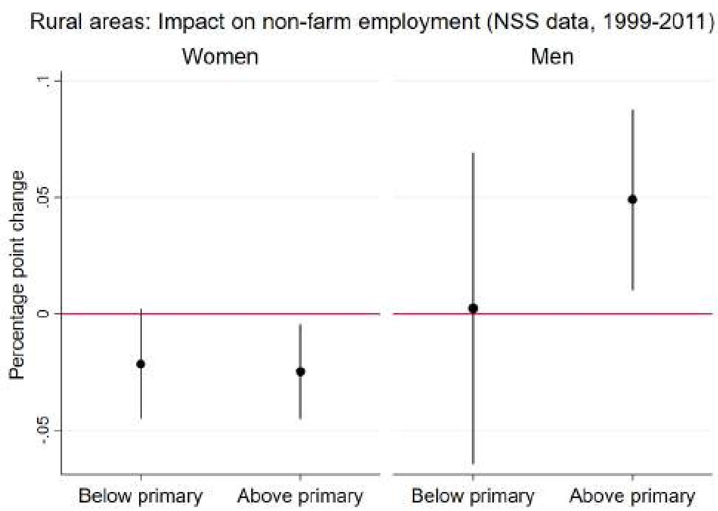
Notes: This figure shows the heterogeneous impacts of rising Chinese import penetration across CZs in India on municipality-level female employee share by how far municipalities are located to their nearest urban center as defined in section 2. Female employee share is measured as the ratio of female employees to all employees in firm census data, which contains the universe of non-farm jobs in each municipality of India in 1998, 2005, and 2013. Short-run (1998 and 2005) and long-run (1998-2013) impacts are estimated using two separate regression like in equation 4 by OLS. All regressions include controls for time trends at the level of district and travel time bands, as well as time-invariant CZ- and municipality-level controls measured at baseline (see section 3 for details).

Figure 20: Muted impact on population growth



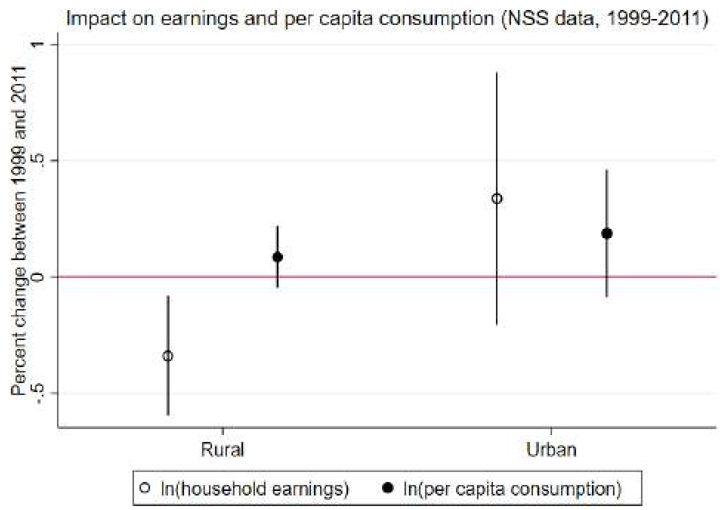
Notes: This figure shows the heterogeneous impacts of rising Chinese import penetration across CZs in India between 2001 and 2011 on the population growth by how far municipalities are located to their nearest urban center as defined in section 2. Impacts for men and women are estimated by OLS using separate regressions (see equation 4). All regressions include controls for time trends at the level of district and travel time bands, as well as time-invariant CZ- and municipality-level controls measured at baseline (see section 3 for details).

Figure 21: Impact of Chinese imports on women's non-farm employment by education level (1999-2011)



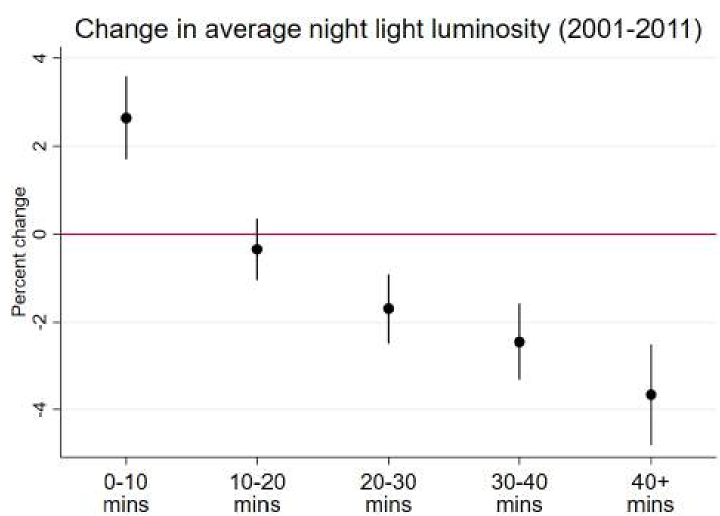
Notes: This figure reports the estimated impact of rising Chinese import penetration across districts in India on the share of individuals living in rural areas aged 15-60 who report being employed in non-farm sectors in the previous week. It uses individual-level data from nationally representative NSS survey rounds conducted in 1999 and 2011. The independent variable is a district-level measure of Chinese import penetration constructed using a shift-share argument analogous to the CZ-level measure (see section 3). Heterogeneous impacts by education level are estimated using equation 4 by OLS, with separate regressions for men and women. Both regressions include controls for (i) time trends at the level of states and education level (below or above primary) (ii) district-level manufacturing employment share at baseline, as well as (iii) time-varying individual-level controls for caste, religion, age, age squared, and marital status.

Figure 22: Impact of Chinese imports on household earnings and per capita consumption (1999-2011)



Notes: This figure reports the estimated impact of rising Chinese import penetration across districts in India on the natural log of weekly household earnings and per capita consumption. It uses household-level data from the 1999 and 2011 rounds of nationally representative NSS data. The independent variable is a district-level measure of Chinese import penetration constructed using a shift-share argument analogous to the CZ-level measure (see section 3). Heterogeneous impacts by area of residence (urban/rural) are estimated using equation 4 by OLS, with separate regressions for household earnings and per capita consumption. Both regressions include controls for (i) time trends at the level of states and urban/rural areas, (ii) manufacturing employment share at baseline, as well as (iii) time-varying household-level controls for caste and religion.

Figure 23: Impact of Chinese imports on average night light luminosity (1998-2013)



Notes: This figure shows the heterogeneous impacts of rising Chinese import penetration between 1998 and 2013 across CZs in India on average night light luminosity by how far municipalities are located to their nearest urban center as defined in section 2. Impacts are estimated using equation 4 by OLS. The regression includes controls for time trends at the level of district and travel time bands, as well as time-invariant CZ- and municipality-level controls measured at baseline (see section 3 for details), including a control for whether each municipality was electrified in 2001 or not.

Additional Tables

Table 3: Imports from China (2000s) and Changes in Employment-to-Population Ratios (2000s vs 1990s)

Dependent variable: 100 × percent change in employment-to-population ratio

	I. Women			II. Men			III. All		
	Non-farm	Farm	All	Non-farm	Farm	All	Non-farm	Farm	All
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Current period (2001-2011)									
Δ Chinese IP	-5.418***	-2.521	-5.234***	-2.271***	0.509	-0.190	-4.881***	-0.507	-1.061***
	(2.072)	(1.657)	(1.856)	(0.654)	(0.576)	(0.258)	(0.914)	(0.777)	(0.397)
Pre-exposure (1991-2001)									
Δ Chinese IP	26.280***	-5.239*	9.630	-1.198	-0.355	0.569***	-1.596	-0.682**	0.485**
	(7.023)	(3.094)	(6.701)	(0.863)	(0.231)	(0.127)	(1.068)	(0.324)	(0.211)
Level in 1991 (main workers)	1.610	18.37	19.98	8.580	43.61	52.20	5.220	31.47	36.69
Level in 2001 (main workers)	3.020	14.74	17.76	10.95	32.88	43.82	7.100	24.09	31.19
Level in 2011 (main workers)	3.500	14.12	17.62	11.01	29.85	40.86	7.360	22.20	29.56

Notes: This table presents correlations between changes in CZ-level Chinese import penetration between 2001-2011 and decadal changes in employment-to-population ratios of men and women constructed using municipality-level census data from 1991, 2001, and 2011. To ensure comparability across census rounds, this table reports the ratio of 'main workers' to the total population rather than all workers. Main workers are those who worked for more than 6 months in the previous year. Panel A presents correlations with contemporaneous changes (2001-2011). Panel B reports correlations with lagged changes (1991-2001). All regressions control for district-level time trends. No other controls are included. Significance levels are denoted by: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$. Standard errors clustered at the district level are in parentheses.

Table 4: Impact of rising Chinese imports on non-farm jobs per 1000 population

Dependent variable: change in non-farm jobs per 1000 population

	OLS				IV	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Short run (1998 to 2005)						
Chinese IP	17.220***	-2.105	-6.852*	8.344	-19.597***	10.346
	(4.331)	(4.932)	(3.491)	(5.448)	(7.534)	(9.668)
× (10-20 mins travel)				-16.195***		-29.977***
				(5.190)		(8.753)
× (20-30 mins travel)				-21.748***		-43.066***
				(5.332)		(9.318)
× (30-40 mins travel)				-22.946***		-46.852***
				(5.652)		(10.470)
× (40-90 mins travel)				-24.611***		-46.557***
				(5.586)		(10.241)
KP F stat					34.25	7.630
R-squared	0.008	0.009	0.011	0.011	0.004	0.005
Observations	890,842	886,747	729,170	729,170	729,170	729,170
Panel B: Long run (1998 to 2013)						
Chinese IP	3.540***	0.100	-0.062	4.515***	-0.692	4.513**
	(0.662)	(0.832)	(0.655)	(1.623)	(0.689)	(1.772)
× (10-20 mins travel)				-4.733***		-5.171**
				(1.753)		(2.081)
× (20-30 mins travel)				-6.527***		-7.363***
				(1.734)		(2.033)
× (30-40 mins travel)				-7.506***		-8.726***
				(1.952)		(2.160)
× (40-90 mins travel)				-7.457***		-7.968***
				(1.733)		(1.941)
KP F stat					121.7	20.58
R-squared	0.004	0.004	0.011	0.011	0.005	0.005
Observations	912,115	907,913	744,863	744,863	744,863	744,863
District × Year FE	✓	✓	✓	✓	✓	✓
CZ controls		✓	✓	✓	✓	✓
Village controls			✓	✓	✓	✓
Travel time bands × Year FE				✓		✓

Notes: This table presents estimated impacts of rising Chinese imports on firm outcomes using municipality-level data from the 1998, 2005 and 2013 rounds of the firm census. The average non-farm jobs per 1000 population was 52 in 1998, 53.5 in 2005, and 67.4 in 2013. Panel A reports short-run impacts (1998-2005). Panel B reports long-run impacts (1998-2013). All regressions control for district-level time trends. CZ-level controls include manufacturing employment share in 1998 as well as women's employment rate, caste composition, under-five sex ratios, and literacy rates among men and women in 2001. Village-level controls include the natural log of population in 2001, and the lagged value of the outcome variable (measured in 1990). Column 1 presents estimates of equation 3 while controlling only for district-level time trends. Column 2 adds CZ-level controls. Column 3 adds village-level controls. Column 4 presents estimates of equation 4 to study heterogeneity of impacts by travel time bands within CZs. It adds controls for time trends at the level of travel time bands. Columns 5 and 6 present IV analogues of columns 3 and 4, respectively (see text). Total observations reflect the total number of municipalities (N=531,403) × two time periods. Significance levels are denoted by: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$. Robust standard errors clustered at the district level are in parentheses.

Table 5: Impact of rising Chinese imports across Indian CZs on employment (2001-2011)

Dependent variable: 100 × percent change in employment-to-population ratio between 2001 and 2011

	II. Farm employment				**III. All employment**			
	OLS			IV	OLS			IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Women								
Chinese IP	1.993	1.452	1.676	0.304	-0.123	-0.109	-0.241	0.631
	(1.713)	(1.702)	(1.715)	(1.392)	(0.543)	(0.558)	(0.535)	(0.571)
KP F stat				83.84				83.77
R-squared	0.041	0.040	0.058	0.020	0.045	0.045	0.074	0.031
Observations	1,059,155	1,051,297	1,051,297	1,051,297	1,079,856	1,071,464	1,071,464	1,071,464
Panel B: Men								
Chinese IP	4.419***	2.986**	3.128***	2.833***	0.205***	0.085*	0.208***	0.293***
	(1.095)	(1.176)	(1.175)	(1.055)	(0.046)	(0.044)	(0.046)	(0.067)
KP F stat				83.86				83.70
R-squared	0.076	0.077	0.091	0.018	0.054	0.054	0.115	0.066
Observations	1,091,386	1,082,780	1,082,780	1,082,780	1,095,889	1,087,249	1,087,249	1,087,249
Panel C: Overall								
Chinese IP	4.260***	2.898**	3.064***	2.762***	0.496***	0.312***	0.407***	0.578***
	(1.068)	(1.152)	(1.159)	(0.986)	(0.096)	(0.094)	(0.099)	(0.131)
KP F stat				83.98				83.92
R-squared	0.051	0.052	0.061	0.012	0.061	0.063	0.141	0.085
Observations	1,092,802	1,084,192	1,084,192	1,084,192	1,096,045	1,087,405	1,087,405	1,087,405
District × Year FE	✓	✓	✓	✓	✓	✓	✓	✓
CZ controls		✓	✓	✓		✓	✓	✓
Village controls			✓	✓			✓	✓

Note: This table presents the estimated impact of a marginal increase in Chinese import penetration between 2001 and 2011 across CZs in India on farm employment and overall employment at the municipality level. Each panel presents results from separate regressions for women, men, and all individuals respectively (see equation 3). Within each type of job (farm or overall), successive columns add controls at CZ and village level. Column 3 adds village-level controls. Columns 4 and 8 present corresponding IV estimates (see text for details). All specifications control for district-level time trends. CZ-level controls include the start-of-period female employment rate, caste composition, under-five sex ratio, and male and female literacy rates from the 2001 census, along with manufacturing employment shares measured in 1998 and 1990. Village-level controls include the natural log of population in 2001 and the start-of-period value of the outcome variable. The total number of observations reflects the number of municipalities × two time periods (2001 and 2011). Significance levels are denoted by: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$. Standard errors clustered at the district level are in parentheses.

Table 6: Impact of rising Chinese imports on employment: within-CZ heterogeneity (OLS)

Dependent variable: 100 × percent change in employment-to-population ratio between 2001 and 2011

	All		**Women**		**Men**	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Non-farm occupations						
Δ Chinese IP	-0.704**	0.858**	-1.248**	0.137	-0.180	0.495*
	(0.284)	(0.434)	(0.585)	(0.839)	(0.184)	(0.286)
× (10-20 mins travel)		-1.138***		-0.923		-0.354
		(0.422)		(0.800)		(0.315)
× (20-30 mins travel)		-1.365***		-1.125		-0.643**
		(0.422)		(0.937)		(0.276)
× (30-40 mins travel)		-1.959***		-2.236*		-0.813**
		(0.580)		(1.233)		(0.398)
× (40-90 mins travel)		-3.564***		-3.330***		-1.754***
		(0.697)		(1.197)		(0.486)
R-squared	0.059	0.059	0.079	0.079	0.057	0.058
Observations	1,038,926	1,038,926	898,739	898,739	1,028,616	1,028,616
Panel B: Farm occupations						
Δ Chinese IP	0.305*	0.168	0.582	-0.898	0.218**	0.187
	(0.165)	(0.293)	(0.564)	(0.846)	(0.097)	(0.204)
× (10-20 mins travel)		0.000		0.000		0.000
		(0.000)		(0.000)		(0.000)
× (20-30 mins travel)		0.213		0.945		0.002
		(0.165)		(0.639)		(0.151)
× (30-40 mins travel)		-0.078		2.301**		-0.075
		(0.320)		(1.050)		(0.220)
× (40-90 mins travel)		0.451		2.992**		0.150
		(0.334)		(1.298)		(0.208)
R-squared	0.037	0.037	0.057	0.058	0.038	0.039
Observations	1,084,192	1,084,192	1,051,297	1,051,297	1,082,780	1,082,780
District × Year FE	✓	✓	✓	✓	✓	✓
CZ controls	✓	✓	✓	✓	✓	✓
Village controls	✓	✓	✓	✓	✓	✓
Travel time bands × Year FE		✓		✓		✓

Notes: This table presents the estimated impact of a marginal increase in Chinese import penetration between 2001 and 2011 across CZs in India on employment-to-population ratios at the municipality level. Each panel presents results from separate regressions for non-farm, farm, and overall employment respectively (see equation 4). All specifications control for district-level time trends, CZ-level controls, and village-level controls. Columns 2, 4 and 6 add controls for time trends at the level of travel time bands (see text for details). CZ-level controls include the start-of-period female employment rate, caste composition, under-five sex ratio, and male and female literacy rates from the 2001 census, along with manufacturing employment shares measured in 1998 and 1990. Village-level controls include the natural log of population in 2001 and the start-of-period value of the outcome variable. The total number of observations reflect the number of municipalities × two time periods (2001 and 2011). Women have fewer observations than men due to the fact that around 10% of villages had no women employed in non-farm sectors in 2001. Significance levels are denoted by: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$. Standard errors clustered at the district level are in parentheses.

Appendices

A Constructing commuting zones for India

This appendix describes how I construct non-overlapping Commuting Zones (CZs) for India. Given my focus on commuting across the urban-rural boundary, I define CZs as catchment areas of urban centers linked to a hinterland by commuting ties. My method of defining CZs is similar to Cattaneo et al. (2021, 2022), who construct a global dataset of urban-rural catchment areas. One major point of difference between their approach and mine is that while I use municipality-level census data to define CZ centers as areas with a relatively high number of non-farm jobs, they define centers as areas with a minimum population density of 1,500 inhabitants per KM^2. I proceed in two steps.

First, I define the focal points of individual CZs to be the top 0.05% of municipalities in each district in terms of non-farm job counts in the 1998 round of the economic census of India (i.e. before China entered the WTO in 2001). These 2,385 municipalities are my candidate 'job centers' - areas which may be attractive to commuters living in surrounding municipalities looking to work in non-farm sectors. The typical job center typically corresponds to a medium- or large-sized urban municipality (including all district and state capitals) with an average population of 90,000 in 2001 (median=25,000). Economic activity is highly concentrated in these areas, with 51% of all non-farm jobs in 1998 being performed in these 2,385 job centers alone. Figure A1a shows an example of how job centers were selected in practice, focusing on areas at the border of three states in Eastern India.

In the second step, I overlay the national road network from the census of India (2001) to estimate minimum travel times to each job center from surrounding municipalities.[41] I assume individuals can travel at average speeds of 60 Km/hr, 50 Km/Hr, 30 Km/hr and 20 Km/hr along National highways, State highways, local paved roads and local unpaved roads, respectively. In areas without roads, I assume individuals can traverse at walking speed (5 Km/hr). Estimating

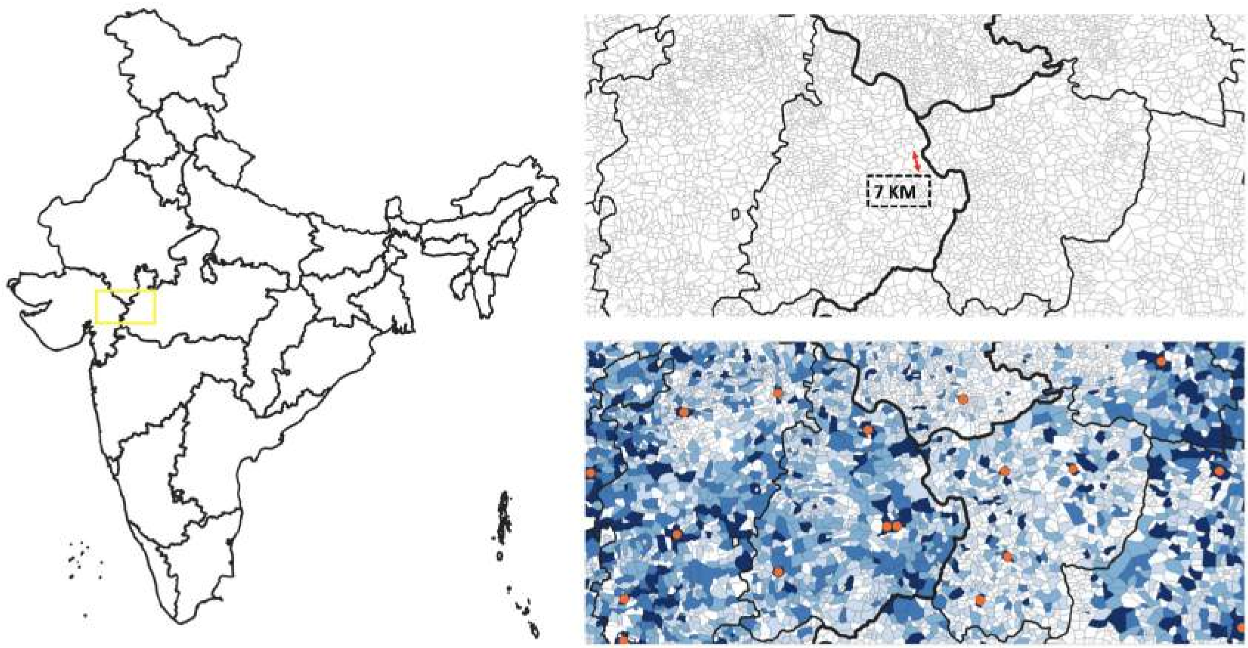
[41] I make use of the road network in 2001 to reduce endogeneity concerns stemming from the possibility that openness to trade after 2001 may have induced improvements in transport infrastructure. In general, the period of my study between 2001 and 2011 coincides with rapid road building and road upgradation in the country. For instance, while nearly half of India's 600,000 villages lacked access to a paved road in 2001, 25% of these villages had received a road under the Pradhan Mantra Gramin Sadak Yojana (PMGSY) by 2012 (Asher and Novosad, 2020). I argue that such road-building policies do not constitute a major threat to my identification strategy or data construction. First, I show that rising Chinese imports are uncorrelated with road building at the CZ-level between 2001 and 2011. This allays concerns that observed impacts are partially driven by road building induced by the trade shock. Second, the position and rough size of individual CZs are largely determined by the location of 'job centers', which are highly persistent over time. Finally, while new and faster rural roads reduce absolute travel times, they likely leave the ranking of how far each municipality is to its nearest job center unchanged within CZs. My analysis of within-CZ heterogeneity relies only on relative travel times being the same over time.

travel times between municipalities pairs along the actual road network in a country as large as India is very computationally intensive. To simplify the problem, I partition the surface of India into a grid with cells of size 2 Km X 2 Km. I assign each cell a single value of commuting cost, given by the fastest way one can traverse across the cell given the different roads available within it. Finally, given this 'cost surface', I use Dijkstra's least-cost path algorithm to map each municipality to the job center that is closest to it. Municipalities mapped to the same job center are allocated to the same CZ. Figure A1b shows how this was implemented in practice. While I impose no restrictions on CZ boundaries to lie within state or district boundaries, they rarely cut across these administrative boundaries in practice. This is likely driven by the fact that both administrative boundaries and the national road network are jointly determined by underlying geographical features.

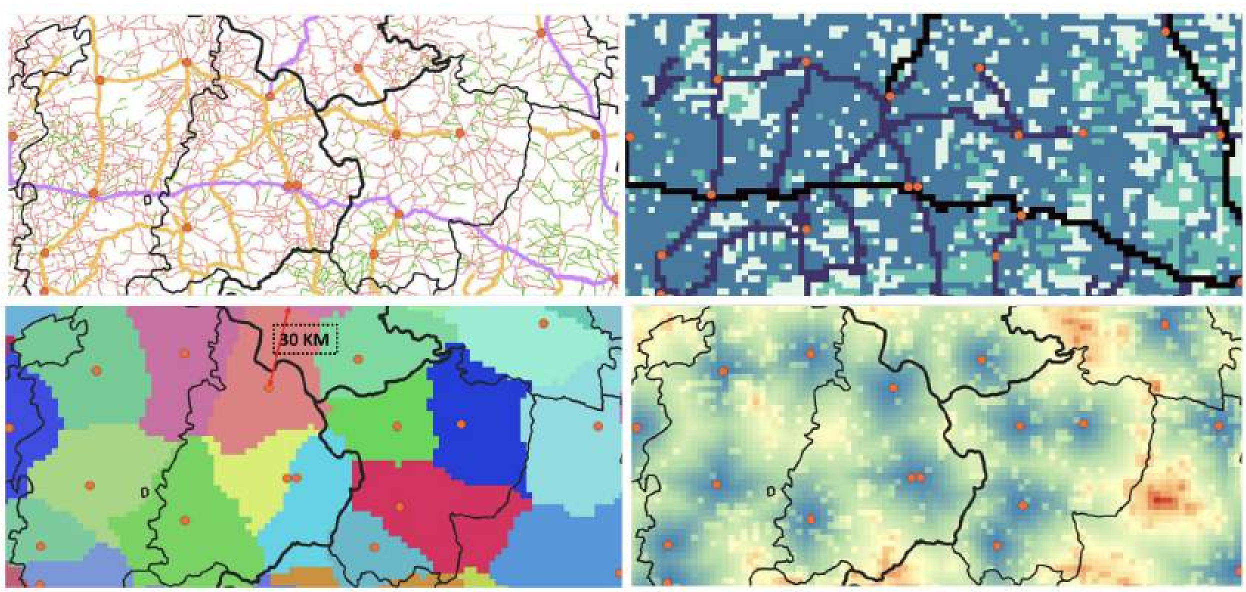
Having defined CZ boundaries, I also construct a measure of how far each municipality is from its closest job center. I drop municipalities that are located more than 1.5 hours away from their nearest job center (3.1% of the sample) since these areas are unlikely to be connected to these areas by daily commuting networks. In section 2, I provided evidence showing that CZs typically consist of a dense urban core surrounded by an increasingly rural hinterland, as indicated by smoothly falling population density and rising employment in agriculture with increasing distance to the center of each CZ. Figure A2 presents further descriptive evidence in this regard. It plots the average within-CZ distribution of population (in green) and non-farm jobs (in blue) at baseline with increasing distance to the job center in each CZ. The light grey histogram at the back shows the distribution of municipalities by how far they are located to the centroid of their nearest job center. Red lines mark categories of travel time that divide the total sample of municipalities into five intervals, each containing roughly 20% of the total sample. Figure A2 shows that economic activity in non-farm sectors is heavily concentrated around the urban core of CZs - while nearly 50% of all non-farm jobs of CZs lie within 10-minutes from the job center, only 30% of CZ population lives within this travel time band.

Figure A1: Constructing commuting zones for India as urban-rural catchment areas

(a) Picking job centers

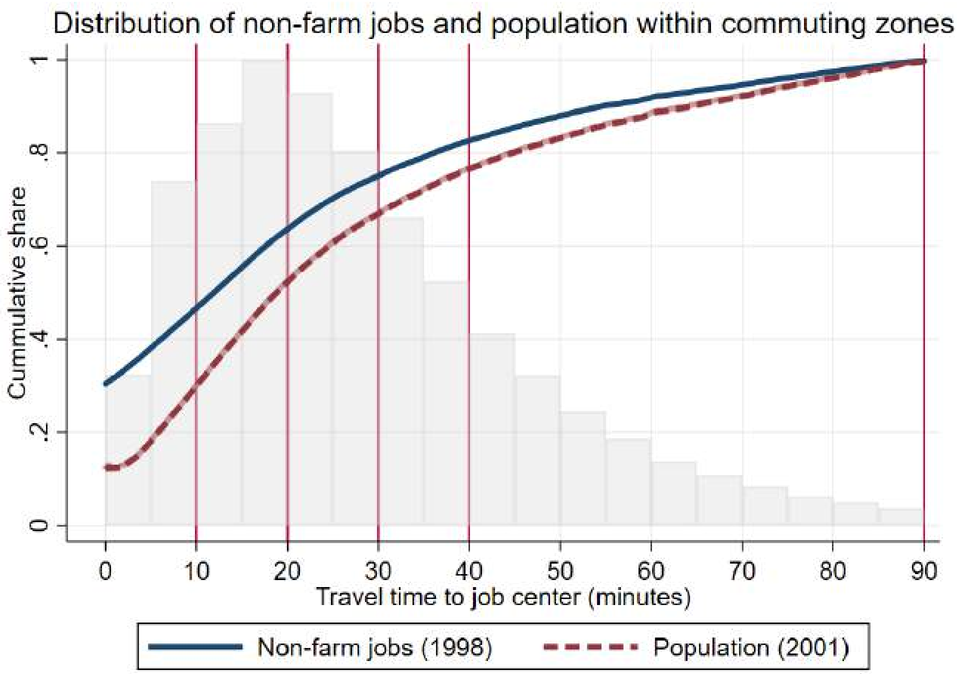


(b) Creating catchment areas



Notes: This figure describes how I construct non-overlapping commuting zones for India. Panel a shows how focal points of individual commuting zones are identified. The figure on the right of panel a shows municipality-level boundaries in grey. District boundaries are shown in black. Darker shades of blue represent municipalities with a relatively higher count of non-farm jobs in 1998; orange dots mark 'job centers' - the top 0.05% of municipalities in each district on this metric. Panel b shows catchment areas of job centers are constructed. The figure on the top-left shows the national road network, with different types of roads shown in Purple (National highways), Yellow (State highways), Red (local paved roads) and Green (local unpaved roads), respectively. The figure on the top right codifies the road network into a cost surface represented as a grid with a 2 Km X 2 Km resolution. The figure on the bottom-left shows the optimal CZ boundaries constructed using Dijkstra's algorithm. Municipality-level measures of travel time to the center of each CZs are shown in the figure on the bottom right. See the text for more details. *Source:* SHRUG (Asher and Novosad, 2020) for consistent municipality-level identifiers and shape files. Economic Survey of India (1998 round) for data on the count of non-farm jobs. Survey of India (2001) for the national road network.

Figure A2: Distribution of non-farm jobs and population within CZs at baseline



Notes: This graph shows the average cumulative distribution of non-farm jobs and population within CZs by increasing travel time to the center of CZ. The underlying count of villages by travel time is represented in the form of a histogram in grey. *Source:* Data on non-farm jobs from the 1998 economic census. Data on population from the 2001 population census.

B A model of household decisions with commuting costs

B.1 Model setup

I analyze occupational choices for men and women using a Roy (1951) model, integrating household-level optimization with a spatial model of commuting based on Balboni et al. (2021). The model features N+1 locations: an urban core (c) surrounded by N villages (v_j) each located at distance d_j from the urban core. The set of villages is denoted by $\mathcal{V} = \{v_1, ., v_j, ..v_N\}$. Each location offers both farm and non-farm employment opportunities. Farm wages are assumed to be equal across locations, eliminating the incentive to commute to farm work. I assume that households can only choose where to work (either locally or by commuting) but not where to live (i.e., no migration is allowed). All jobs produce a single final consumption good whose price is one. Trade within the commuting zone is assumed to be frictionless.

B.1.1 Labor supply

The economy is populated by a unit mass of households, each comprising of one man and one woman. Individuals living in the village choose between three occupations: farm work, local non-farm work, and urban non-farm work. Urban wages are higher but require individuals to pay a portion of their wage as commuting cost that differs by gender. Commuting cost is assumed to vary inversely with distance d_j.

In the beginning, each individual $i \in (m, f)$ in the household independently draws a productivity triple $\sigma^i = (\sigma_a^i, \sigma_v^i, \sigma_c^i)$ from a Frechet distribution with shape parameter θ corresponding to the individual's productivity in each of the three occupations. All individuals receive wage equal to marginal product. The effective wages for individual i is thus given by:

$$w(\sigma^i) = \begin{cases} \sigma_a^i \cdot w_a & \text{for Agriculture} \\ \sigma_v^i \cdot w_j & \text{for Village non-farm work} \\ \sigma_c^i \cdot c_j^i \cdot w_c & \text{for City non-farm work, with } c_j^i < 1 \end{cases}$$

where c_j^i denotes iceberg commuting cost of individual i living in village j. w_a and w_c denote wages in agriculture and in the non-farm sector in the city, respectively. The local non-farm wage in each village is denoted by w_j.

I introduce three forces that distort the allocation of women across occupations (Hsieh et al., 2019). Men face no such distortions. First, I allow for gender differences in commuting costs, modeled as $c_j^f = c_j^m \times \lambda$; where $\lambda \in [0, 1]$. This acts as a wedge that reduces women's effective wage in urban non-farm occupations relative to men. It captures frictions stemming from poor access to private modes of transport among women or the risk of sexual harassment in public spaces.

Second, I allow for gender wage discrimination or stigma women may face from working in non-farm occupations outside the home (across both rural and urban areas) (Goldin, 1995). This is modeled as women receiving $\mu\times$ men's non-farm wage where $\mu \in [0, 1]$. This allows us generate a better fit with the observed data, which shows that women's participation in the non-farm sector is systematically lower than men's across both rural and urban areas.

Third, I explicitly model household constraints stemming from social norms around childcare and household chores that disproportionately impact women by assuming that households receive some exogenous utility (L) from women staying at home. This generates a household-level income effect: when the male wage is sufficiently high, women may exit the labor force. Household utility is thus modeled as:

$$U_h(.) = \begin{cases} \log(w^m + w^f), & \text{if both members work} \\ \log(w^m) + L, & \text{if only the man works} \end{cases}$$

where w^m and w^f represent the effective market wage for men and women (f denotes 'female'). The woman works if:

$$\log(w^m + w^f) \geq \log(w^m) + L$$

which simplifies to:

$$\frac{w^f}{w^m} \geq e^L - 1; \quad \text{Let } e^L - 1 = k$$

$$\implies w^f \geq k \cdot w^m$$

This implies that women work in our model only if the wage they can get exceeds a constant multiple of their husband's wage.

While the third force generates variation in the share of women in the labour force, the first and second forces act as occupation-specific wedges between wages and marginal products that induce potential misallocation of women's talents into rural occupations.

Employment Likelihoods

The maximum wage men can get depends only on their productivity draw:

$$w^m(\sigma) = \max\{\sigma_a^m w_a, \sigma_v^m w_j, \sigma_c^m c w_c\}$$

The maximum wage women can get additionally depends on λ and μ:

$$w^f(\sigma) = \max\{\sigma_a^f w_a, \sigma_v^f \mu w_j, \sigma_c^f \mu \lambda c w_c\}$$

Recall that $\lambda = 1$ corresponds to the case where women face the same commuting cost as men. $\mu = 1$ corresponds to the case when there is no wage discrimination against women working in non-farm occupations. Individuals choose to work in the sector that pays them the highest wage. Given that productivities are independently drawn from a Frechet distribution with shape parameter θ, I can derive closed-form employment likelihoods in each sector for men and women.

The likelihood of men working in a non-farm occupation in village j (summing over local non-farm and city non-farm) is:

$$Men_j(nonfarm) = \frac{w_j^\theta + w_c^\theta}{w_a^\theta + w_j^\theta + (cw_c)^\theta}$$

The likelihood of women working in a non-farm occupation in village j (summing over local non-farm and city non-farm) is:

$$Women_j(nonfarm) = \frac{\mu^\theta \left(w_j^\theta + (\lambda c w_c)^\theta\right)}{k^\theta(w_a^\theta + w_j^\theta + (cw_c)^\theta) + \left[w_a^\theta + \mu^\theta(w_j^\theta + (\lambda c w_c)^\theta)\right]}$$

Finally, the labor force participation (LFP) rate of women in village j is:

$$Women_j(LFP) = 1 - \left[\frac{k^\theta \left(w_a^\theta + w_j^\theta + (cw_c)^\theta\right)}{k^\theta \left(w_a^\theta + w_j^\theta + (cw_c)^\theta\right) + \left[w_a^\theta + \mu^\theta \left(w_j^\theta + (\lambda c w_c)^\theta\right)\right]}\right]$$

B.1.2 Labor demand

There are N+1 non-farm sector firms, one in each location. Labor is the sole factor of production:

$$Y_j = A_j F(L_j) \quad \text{Where } F'(.) > 0 \text{ and } F''(.) < 0$$

The productivity term A_j is fixed. Male and female labor are assumed to be perfect substitutes. All firms produce the same product, whose price is one. I denote the labor demand elasticity with ϵ_d:

$$\epsilon_d = \frac{\partial L_j}{\partial w_j} < 0 \quad \forall j$$

B.1.3 Equilibrium

Fix parameters ϵ_d, θ, k, λ, μ, and costs of commuting c_j for every village. An equilibrium is a vector of non-farm wages in every location that ensures that the labor markets clear in each village $j \in (1, ...N)$:

$$L_j = (F_j + M_j)R_j$$

and also in the city:

$$L_c^n = \sum_j (F_j(city) + M_j(city))R_j$$

Where R_j is the population of village j, and the functions F and M correspond to productivity-weighted labor units ("effective labor") supplied by men and women to the village (F_j, M_j) or to the city $(F_j(city), M_j(city))$. I use 'exact hat' methods to simultaneously solve supply and demand responses in order to estimate wages and labor force participation rates in equilibrium (Monte et al., 2018).

I assume that agricultural wages do not respond to market fundamentals. This implies that the agricultural wage is fixed. Any worker who want to work in agriculture can get a job at this fixed wage.

B.2 Calibration

One key shortcoming of the my setting is that I don't observe wages at the village level. Instead, I estimate wages from the data. For tractability, I assume that w_j is a linear function of c_j given by $w_j = w_{v0} + (w_{v1} \times d_j)$. The model thus features nine global parameters - $\theta, \epsilon_d, k, \lambda, \mu, w_c, w_{v0}, w_{v1}$

and w_a. I set $w_a = 1$ as a normalization. I fix the Frechet shape parameter θ to be 3 following Franklin et al. (2024), and the elasticity of labor demand ϵ_d to be -1 following Lichter et al. (2015).

I calibrate the remaining six parameters of the model using municipality-level data from the 2001 and 2011 rounds of the population census. I use four observables for each village: distance to nearest urban center (d_j; measured in terms of travel time), non-farm employment for men ($Men_j(nonfarm)$), non-farm employment for women ($Women_j(nonfarm)$), and the labor force participation of women ($Women_j(LFP)$).[42] Figure B3 shows these values in 2001. Results of the corresponding calibration are provided in table B1.

Figure B3: Village-level observables in 2001 data

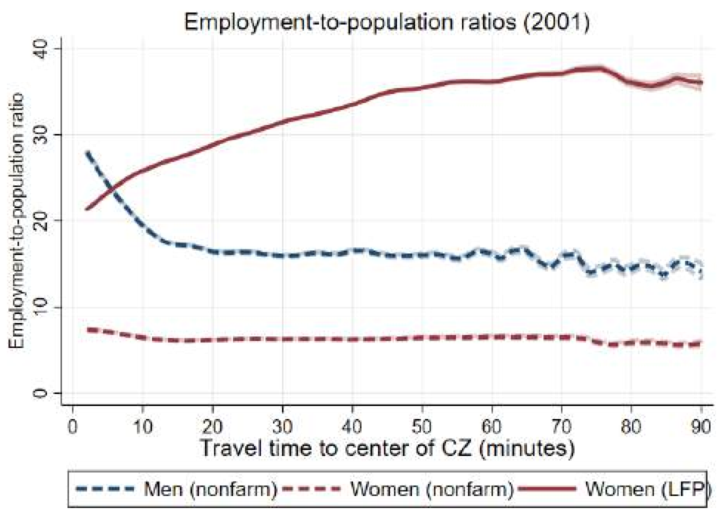


Table B1: Calibration to 2001 data

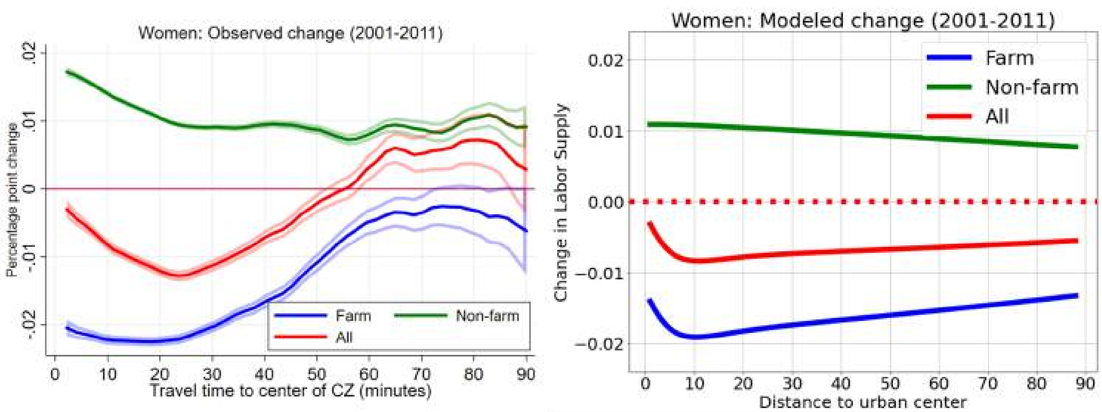
Parameter	Value	Source	Interpretation
θ	3	(Franklin et al., 2024)	Frechet shape parameter, usually between 2 and 4
α	-1	(Lichter et al., 2015)	Elasticity of labor demand, usually between -0.5 to -1.2
w_a	1	Normalization	wage in agriculture is fixed at 1
w_c	1.369	Calibration	City wage is 37% higher than farm wage
w_{v_0}	1.236	Calibration	Wage in the closest village 24% higher than farm wage
w_{v_1}	-0.002	Calibration	Village wage drops by 0.2% with increasing distance
λ	0.771	Calibration	Women pay 33% higher commuting cost than men
μ	0.508	Calibration	Women's non-farm wage is lower by 50% relative to men
k	0.995	Calibration	Women work if $w_f \geq 0.99\ w_m$

Estimated relative wages align closely with previous work on the rural-urban wage gap in India. For instance, the estimated value of the non-farm wage in the city (+37% relative to the farm

[42] I use only the non-farm employment for men since I assume in the model that men always work.

wage) is in line with Munshi and Rosenzweig (2016), who find that the urban wage is between 25-47 percent higher than the rural wage. Moreover, the estimated value of the non-farm wage in the village (+24% relative to the farm wage) aligns closely with evidence from Baysan et al. (2024), who find that agricultural laborers in rural areas increase earnings by 23% when switching to non-agricultural work close by. Finally, I check whether the model can reproduce the key untargeted moment of changes in female LFP over time. In figure B4, the left panel shows changes observed in the data and the right panel shows the changes implied by the calibrated model. The model does a good job of reproducing the general pattern of changes in female labor supply across villages within commuting zones between 2001 and 2011.

Figure B4: Urtargeted moment: change in female labor supply between 2001 and 2011



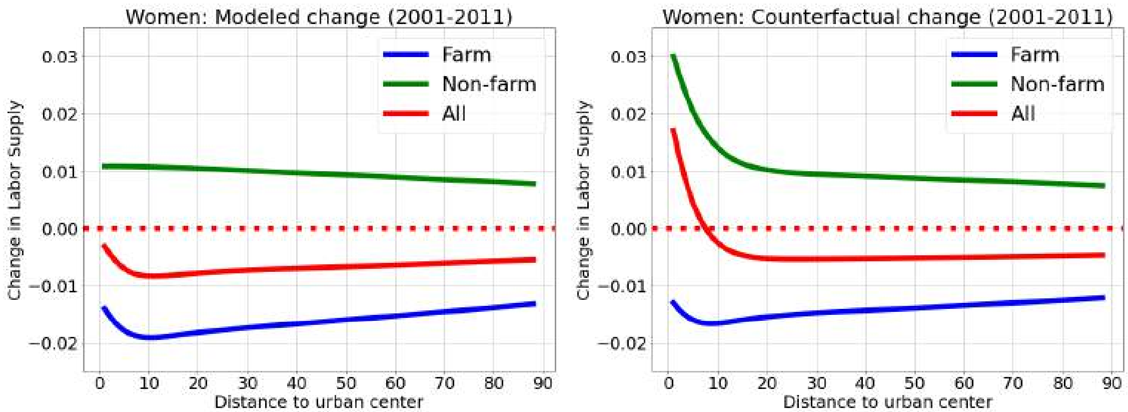
B.3 Policy counterfactuals

Having estimated the model, I now proceed to conduct policy counterfactuals.

I begin by asking: how much of the observed decline in aggregate female LFP between 2001 and 2011 would have been mitigated if gendered commuting frictions were relaxed? To answer this question, I set $\lambda = 1$ while keeping the remaining parameter values fixed at their levels in 2011. I then let wages adjust to their new equilibrium level. This simulates the effect of relaxing gendered commuting frictions in general equilibrium. Figure B5 compares the observed change with the counterfactual change implied by the model.

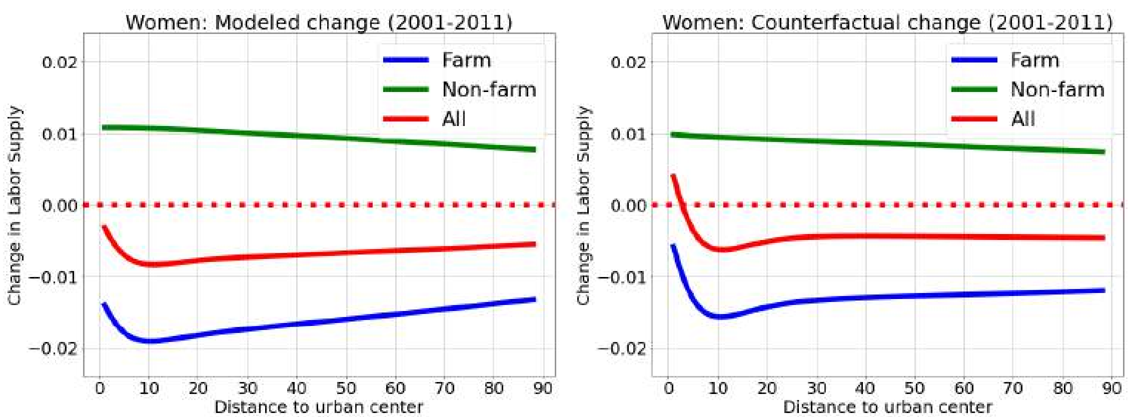
Next, I simulate the impact of a secular reduction in commuting costs, stemming from, for example road upgradation. In the model, this takes the form of an increase in c_j across all villages. Figure B6 presents results. I find muted impacts on women's employment in high-productivity non-farm sectors in this case. This result is in line with empirical evidence on the impact on rural road

Figure B5: Impact of removing gendered commuting frictions



building from India and Uganda (Asher and Novosad, 2020; Herzog et al., 2024). Intuitively, in the absence of complementary interventions that target gendered commuting frictions in particular, a secular decline in commuting costs mostly benefits men.

Figure B6: Impact of reducing secular commuting costs by 10%



Finally, I simulate the impact of a reduction in the value households place in women staying at home (modeled as a reduction in k), or a reduction in stigma against women working non-farm occupations (modeled as an increase in mu). Figures B7 and Figure B8 present these results. These policies turn out to be significantly more effective in increasing female LFP relative to earlier experiments, suggesting that these barriers are the dominant constraints to women's employment in India.

Figure B7: Impact of increasing μ by 10%

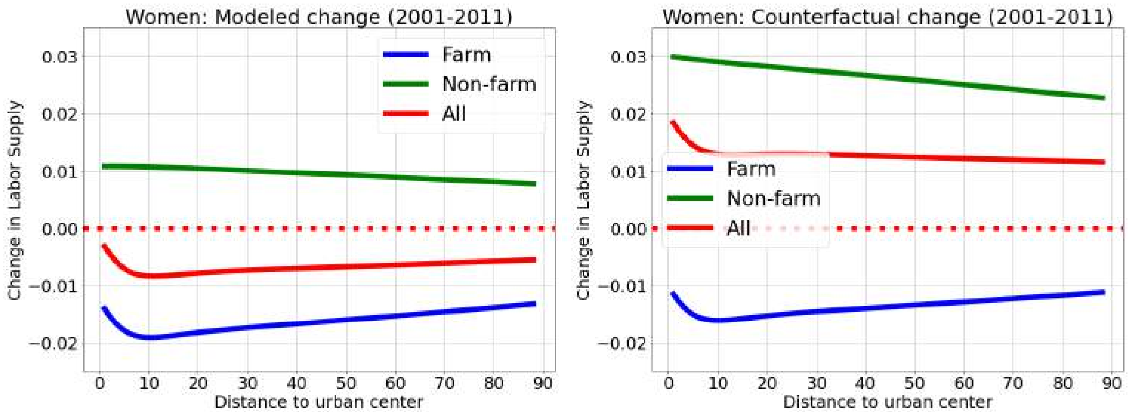
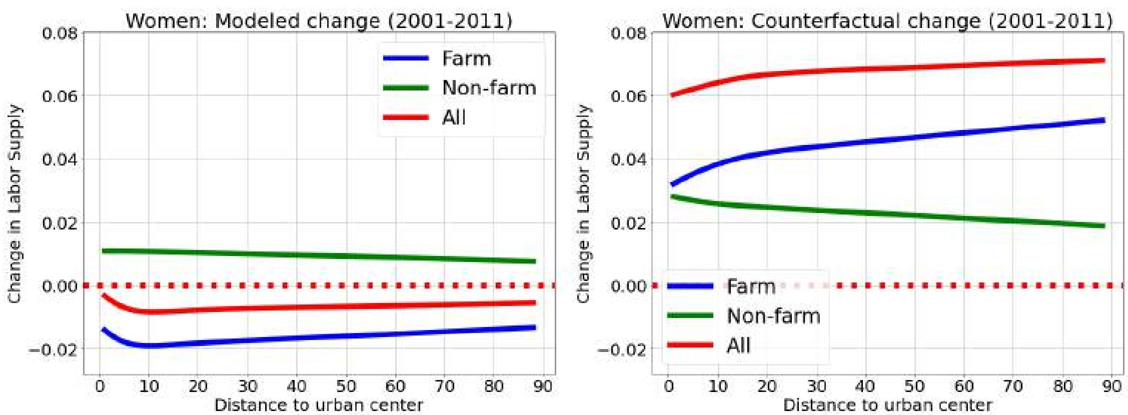


Figure B8: Impact of reducing k by 10%



B.4 Counterfactual Welfare Exercises

In this subsection, I describe how I quantify the impact of relaxing gendered commuting frictions on total production in the economy. This is my main measure of welfare.

Given the production function $Y_s = A_s F(L_s)$, the percent change in production in each sector $s \in$ (farm, non-farm city, non-farm village) can be written as:

$$\Delta \ln Y_s = \frac{\partial \ln Y_s}{\partial \ln L_s} \Delta \ln L_s = \epsilon_s^y \Delta \ln L_s$$

Where ϵ_s^y is the elasticity of output with respect to labor.

Total production in the economy is $Y_{tot} = \sum_j Y_s$. This implies:

$$\Delta Y_{tot} = \sum_s \Delta Y_s$$

dividing both sides by Y_{tot} gives us the percentage change in production:

$$\Delta \ln Y_{tot} = \frac{\sum_s \Delta Y_s}{Y_{tot}}$$

$$\implies \Delta \ln Y_{tot} = \frac{\sum_s \frac{\Delta Y_s}{Y_s} Y_s}{Y_{tot}} = \frac{\sum_s Y_s \Delta \ln Y_s}{Y_{tot}}$$

$$\implies \Delta \ln Y_{tot} = \sum \frac{Y_s}{Y_{tot}} \epsilon_s^y \Delta \ln L_s$$

I use this formula to calculate the percent change in total output in response to setting $\lambda = 1$. Values for the implied change in effective labor in each sector ($\Delta \ln L_s$) come from the model. Following (Aayog, 2017), I fix the output share of agriculture at 0.4, non-farm city at 0.4, and non-farm village at 0.2. The output elasticity with respect to labor for agriculture is assumed to be 0.5 for agriculture and 0.4 for both non-farm city and non-farm village.