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Barriers within Borders: Structural Transformation and Climate Change in India

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Abstract

This paper examines how climate change is hindering structural transformation in India and the role of internal trade barriers in it. I combine local temperature effects on productivity, consumption, and labor shares with a static spatial equilibrium model to evaluate the potential for labor reallocation out of agriculture as an adaptation to climate change. Empirical findings show that temperature has a more negative impact on agricultural productivity versus manufacturing (supply-side effect), and household expenditure on food increases as incomes fall, consistent with Engel's law (demand-side effect). In equilibrium, rising temperatures increase the agricultural labor share, hindering structural transformation. Theoretically, districts in India could mitigate against the adverse effects of declining agricultural productivity through inter-district trade with less affected districts. Using a market access variable created by using development of Indian highways, I find that improved market access does not disrupt the positive relationship between temperature and agricultural labor share due to existing barriers in trade within India. These trade barriers reduce spatial competition among agricultural buyers and traps labor in low-productivity agriculture. I then use a spatial equilibrium model with internal trade barriers for counterfactual analysis which reveals that removing state-level trade barriers in Indian agriculture would increase income by 4.65% on average for each household and decrease agricultural labor share by 0.1pp on average for each district (~ 28.9 million people across India).

Keywords: Climate Change; Structural Transformation; Trade barriers; Spatial competition

JEL Classification: O13, O14, Q54, P00, F18, J43

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1 Introduction

Maharashtra, the second-largest agricultural goods-producing state in India[1], has experienced several severe droughts over the past decade. During a particularly devastating drought of 2012-13, 11,801 villages were declared drought-affected, with 3,905 villages suffering over 50% crop loss[2]. The crisis was further aggravated by economic distress among farmers, leading to the tragic suicide of 3,146 farmers in Maharashtra in 2013[3]. Farmers' suicides are largely driven by a combination of factors such as persistent crop failures, rising input costs, and the inability to secure fair prices for their produce. Trapped in agriculture due to these financial constraints, farmers find themselves in a low productivity cycle. Climate change threatens to make this cycle even worse. As extreme weather events like droughts and heatwaves become more frequent, farmers could face more frequent low productivity shocks. There is a need for adaptive policies to cope with the adverse effects of climate change by addressing productivity shocks such that low productivity cycles in agriculture can be broken. Additionally, efficient agricultural markets and well-designed trade policies play a crucial role in farmers receiving fair prices for their produce. This can enable farmers to break out of financial traps.

In this paper, I establish three sets of stylized facts about the effect of climate change on structural transformation and the role of trade in this process. In the first set, I explore the effect of climate change on supply-side and demand-side drivers of structural transformation. The second set of stylized facts tests for the equilibrium impact of climate change on labor reallocation. The final set of facts explores the role of trade barriers in exacerbating the effect of climate change, particularly on agricultural labor dynamics as it relates to structural transformation in India. I then embed these productivity estimates for economic sectors into a spatial equilibrium model with internal trade barriers to quantify the role of trade barriers in exacerbating the adverse effects of climate change.

India presents an interesting setting to study this question. As a developing country, India has been going through rapid structural transformation. The economic growth that India has witnessed has reduced agricultural labor share from 63.5% in 1991 to 41.49% in 2019. India has seen labor reallocation happen towards manufacturing and services. However, despite this reallocation of labor away from agriculture, India still remains a country largely dependent on agriculture. A majority of Indian farmers engage in subsistence farming due to land fragmentation over generations. 89.4% of Indian farmers own less than 2 acres of land

[1]See report by Ministry of Agriculture & Farmers Welfare (2022)
[2]See Hindustan Times (2013)
[3]See P.Sainath (2014)

as of 2019. India is also the seventh-largest country in land area, covering 3.28 million square kilometers. The vast size translates into diverse geography. The diverse geography implies that the effects of climate change could vary widely across different regions in India. Figure 3 shows that over the twenty-five year period covered in the study, some regions of India have experienced intense warming while others have cooled down. India is currently the most populous country in the world with 1.44 billion people. This makes the economic and social consequences of climate change significant, particularly in terms of food security, and labor reallocation.

I compile a panel dataset of Indian districts spanning twenty-five years, drawing from various sources. This dataset includes detailed information about sectoral labor shares, expenditure shares on goods, agricultural and manufacturing output, and travel times between districts, reflecting the construction of highways across India. Additionally, the dataset incorporates geolocations of agricultural markets. To analyze the impact of climate on economic dynamics, I integrate this district-level data with climate variables, such as temperature and precipitation, over the same time period.

Using this dataset, I first test the effect of increasing temperature on the productivity of the agriculture and manufacturing sector. Supply-side theories of structural transformation emphasize that labor reallocation is driven by differences in sectoral productivity. As climate change differentially affects economic sectors, these relative productivity changes could drive labor reallocation. I find that rising temperatures have a more detrimental effect on agricultural productivity compared to manufacturing productivity. Therefore, if food security is maintained, labor should ideally shift from agriculture to manufacturing. This movement would also be an adaptation to climate change at an individual level as rising temperatures are related to reduced labor productivity, and increased risks of heat-related illness, exhaustion, and mortality.

I then explore demand-side drivers of structural transformation. These drivers focus on the relative income elasticities of goods. The hierarchy of consumption needs of food over manufacturing goods and services, combined with engel curves drives the movement of labor from agriculture to manufacturing and services as incomes increase. I find that rising temperatures are altering consumption patterns such that income decreases and food share of expenditure increases. This relative increase in demand for food should move labor from manufacturing and services to agriculture, reversing the structural transformation process.

Next, I turn to estimate the equilibrium effect of climate change on structural transformation. I find that as temperatures increase, agricultural labor share increases by 12.45% and manufacturing and service sector labor share declines by 2.56% and 2.46%, respectively. This suggests two key implications. First, demand-side drivers of structural transformation have a more prominent effect than supply-side. The second implication of the above result is that India is struggling to maintain food security as temperatures rise, exacerbating the "food problem". In macroeconomic literature, the "food problem" refers to a situation where poorer countries specialize in low productivity agriculture sector to ensure food security. As maintaining subsistence consumption becomes critical, labor shifts into agriculture, reinforcing the economy's dependence on this vulnerable sector under climate stress.

Trade is often considered an adaptive tool in both the "food problem" and climate change literature. As climate change alters the relative productivity of different sectors, regions may experience shifts in their comparative advantages. Regions with comparative advantage in agriculture could trade with those struggling due to climate impacts, ensuring food security. I first test for comparative advantage among districts and then examine whether districts with higher market access are able to break the positive relationship between rising temperatures and agricultural labor share, as trade should ideally mitigate the effects of climate change on labor reallocation. I find that despite the emergence of comparative advantages in agriculture across districts in India, trade is unable to break this relationship. This suggests that either trade costs are not sufficiently low or trade barriers exist in Indian agricultural markets.

Agriculture in India faces internal trade barriers due to the Agricultural Produce Marketing Committee (APMC) Acts, which were introduced in the 1960s across states in India. These Acts effectively limit cross-state trade in agriculture. I utilize spatial variation in market placement by districts in states to show that increased spatial competition among buyers results in higher prices for farmers and reduced agricultural labor share as temperatures rise. This finding suggests that trade policy reforms could help mitigate the adverse effects of climate change on labor reallocation.

Finally, I develop a spatial equilibium model in which I embed productivity impacts of climate change with internal trade barriers in agriculture to quantify the role of internal trade barriers in exacerbating the adverse effects of climate change on labor reallocation. I run counterfactual simulations using a calibrated model. These counterfactuals simulate scenarios where internal trade barriers in agriculture are removed. This exercise reveals that even under the adverse effects of climate change, removing internal trade barriers helps agricultural labor share to decline by 0.1 percentage points on average for each district. Across the country, it allows about 28.9 million people to shift their labor away from agriculture and therefore advance structural transformation.

To the best of my knowledge, this is the first paper to examine the role of internal trade policies in creating barriers in adaptation to climate change. In this paper I contribute to mulitple strands of literature. The most relevant is the nascent body of literature at the frontier of climate change economics that combines empirical estimates of climate change impacts into a general equilibrium model to provide a comprehensive understanding of policy implications (Balboni (2019), Rudik et al. (2021), Nath (2022), Conte (2022), Cruz (2021)). My work is closely related to Nath (2022) as both address the "food problem" under climate change. However my focus is specifically on internal trade barriers within India and domestic political policies that hinder climate change adaptation - an area that has been largely overlooked in the climate change literature thus far.

Next, I contribute to the literature on the role of trade in structural transformation (Alvarez-Cuadrado and Poschke (2011), Uy, Yi, and Zhang (2013), Święcki (2017), Tombe (2015)). I combine insights from this literature with findings from literature on internal trade barriers and market inefficiencies (Atkin and Donaldson (2015), Fajgelbaum and Redding (2022)). This paper also makes a contribution to the literature on trade and agriculture. This literature is large and varied. Most closely related papers are articles on trade and adaptation in agriculture (Costinot, Donaldson, and Smith (2016), Reilly and Hohmann (1993), Sotelo (2020), Pellegrina (2022), Farrokhi and Pellegrina (2023), Gouel and Laborde (2018), Allen and Atkin (2022)).

Finally, this paper also contributes to the ongoing debate in the literature on climate-induced labor reallocation in India. Liu, Shamdasani, and Taraz (2023) and Emerick (2018) find that as climate shocks intensify agricultural labor share increases in India due to local demand shocks, while Colmer (2021) shows that rising temperatures push labor out of agriculture. This signals the possibility of complex interaction between environmental factors and economic behavior. I build on this empirical literature by comprehensively examining both demand-side and supply-side drivers of structural transformation. Furthermore, I explore the underlying mechanisms behind the movement of labor into agriculture and analyze the role of internal policies in influencing labor responses to climate change. These policies not only exacerbate the "food problem", where labor becomes trapped in low-productivity agriculture to maintain food security, but also hinder the adaptation processes necessary to cope with climate change.

The rest of the paper is organized as follows. Section 2 describes the context of the study with details about structural transformation theories, the Indian economy, and internal trade barriers within India. Section 3 details the sources of data and explains the data I have assembled to conduct this study. Section 4 presents five stylized facts about Climate Change, Structural Transformation, and Trade in India. This section contains reduced form results describing the effect of climate change on structural transformation and the role of internal trade barriers in exacerbating the adverse impacts of climate change and limiting adaptation. In

Section 5, I lay out a static spatial equilibrium model with modeled internal trade barriers to quantify the role of internal trade barriers in exacerbating the effect of climate change on structural transformation. Section 6 details the parameters and methods used to calibrate the model. Section 7 contains counterfactuals about trade policy. Section 8 concludes the paper.

2 Background

2.1 Theories of Structural Transformation

Economic growth in a country is often characterized by significant reallocation of resources, including labor, from agriculture to the manufacturing and services sector (Kuznets (1973), Herrendorf, Rogerson, and Valentinyi (2014)). This reallocation of labor across sectors has been widely studied in both developing and developed economies. Leading theories of structural transformation emphasize the supply and demand drivers that propel this broad economic transition.

On the one hand, supply-side theories of structural transformation place emphasis on differences across sectors in the rates of technological growth. These theories suggest that increases in manufacturing productivity increase wages and attract low-paid agricultural labor to move from agriculture to manufacturing (Harris and Todaro (1970), Ngai and Pissarides (2007)).

On the other hand, demand-side theories emphasize the role of heterogeneity in income elasticities of demand across goods from agriculture, manufacturing, and service sectors (Alvarez-Cuadrado and Poschke (2011)). These income elasticities create a hierarchy of consumption needs and lend themselves to non-homothetic preferences in consumption which drives the reallocation of labor across sectors (Egger and Nigai (2018)). According to Engel's law, as incomes increase food's share of expenditure decreases because the income elasticity of food is relatively inelastic.

The shapes of sectoral Engel curves are key in understanding the relative influence of supply and demand side drivers on structural transformation. If the slopes of Engel curves differ significantly and persist over time, demand-side drivers can effectively account for the reallocation of resources toward sectors with high income elasticities (Comin, Lashkari, and Mestieri (2021)).

2.2 Structural transformation in India

India is the fastest-growing major economy in the world and has seen sustained strong economic growth in recent years. Real GDP growth in India has averaged about 6% since 2000. Economic activity in India has transformed in recent years. Figure 2 shows that the Service sector value-added share has increased rapidly from 37.79% in 1991 to 50.08% in 2019. In that same time period, the agriculture sector value-added in the economy declined from 27.66% to 16.76% over this time. The manufacturing sector follows a hump-shaped curve where initially resources move from agriculture to manufacturing and then the reallocation of resources happens from manufacturing to services (Lin et al. (2019)). Therefore, the manufacturing sector initially sees an increase in resources and then a decline, creating an inverted U-shaped curve.

The economic growth has been accompanied by massive reallocation of labor from agriculture to manufacturing and services. Figure 1 shows that agricultural labor share has steadily declined, which is something one would expect from a fast-developing country. Labor share in agriculture has decreased from 63.5% in 1991 to 41.39% in 2019. The manufacturing sector and services sector have observed a steady increase in labor share over the same time period.

However, despite this rapid economic growth and decline in agricultural labor share, a large portion of labor remains employed in the low-productivity agricultural sector. Developing countries often witness this phenomenon where the low-productivity agricultural sector absorbs a high level of employment. This phenomenon is called the "Food problem" (Schultz (1953)). To maintain food security, a large amount of labor is employed in agriculture. Indian agricultural sector is marred with multiple problems. As of 2019, 89.4% of farmers in India have less than 2 hectares of land (Ministry of Statistics and Programme Implementation (MoSPI) (2023)). These small land holdings in India employ a large amount of labor force and are unable to adopt model agricultural practices (Food and Agriculture Organization of the United Nations (FAO) (2006)).

2.3 Internal Trade Barriers in India

Apart from the above issues with agriculture in India, Indian agriculture also suffers from internal trade barriers at the state level. State governments adopted the Agricultural Produce Marketing Committee (APMC) Acts in the 1960s which established marketing boards in each state. These marketing boards were set up to safeguard farmers from exploitation at the hands of large retailers. The APMC acts require that the initial sale and purchase of agricultural commodities produced within a state must take place at government-designated marketplaces. These laws, in effect, limit the trade of agricultural commodities across state borders (Chand (2012)). Therefore, these laws limit the number of available buyers for farmers' produce, depending on the location of each farmer. I exploit this spatial variation in the amount of competition among buyers, to estimate the role of trade barriers in the effect of climate change on structural transformation. Figure 7 shows the implementation of the APMC acts across states of India.

The origins of the APMC Act date back to the British Raj. The crown's anxiety about the price of cotton faced by the textile mills of Manchester drew their attention to the suppliers of raw cotton. Berar Cotton and Grain Market Act, of 1887 empowered the British resident at the Hyderabad Residency to declare any place in the district as a market for sale and purchase of agricultural produce.

Famines of the 1960s devastated India. U.S. food aid helped the country cope with food insecurity, but it brought India into a precarious "ship-to-mouth" existence. Under these circumstances, India introduced multiple reforms, including new food grains that spurred the Green Revolution, minimum support prices for agricultural goods, power and water subsidies, along with the APMC acts.[4]

The trade limitations across state borders due to the APMC Act create a hierarchical trading structure in the agricultural market in India[5]. After harvest, farmers in India either consume their produce (subsistence farming) or sell the leftovers to local traders in their villages. The local traders transport the goods to the district *mandis* (designated marketplaces), where they sell them to larger regional traders. The regional traders then move the produce to terminal markets, where the produce is processed and prepared for retail consumption. Another important feature of these markets is that individual farmers receive market prices, while intermediaries (*arhatiyas*) earn profits from taking advantage of arbitrage opportunity presented by state-level disparities (Chatterjee (2023)). In this paper, I first test the role of trade barriers in the effect of climate change on structural transformation, using the variation in spatial competition. I then incorporate these agricultural trade barriers into a spatial equilibrium model to quantify the effect of removing these trade barriers in smoothing structural transformation even under climate change.

3 Data

The primary geographic unit of analysis are districts, which are India's secondary administrative units. Conducting the analysis at such fine geographical level enables me to capture localized regional disparities.

[4]For more details about the history and evolution of the APMC markets see: Chand (2012), Union Budget, Ministry of Finance, India (2016), Sharma (2020), Chatterjee (2023)

[5]See Figure 1, Allen and Atkin (2022)

This approach mitigates potential issues inherent in multi-regional spatial models that assume population and economic activity within each unit are concentrated at a single point (Balboni 2019) . I assemble following dataset on agricultural production, manufacturing production, consumption patterns, employment shares, trade costs and agricultural market data covering a 25 year period from 1987-2012 for India.

Agricultural Production: Data on district-level crop yields and cropping patterns, farm-gate prices for 22 crops[6] comes from International Crops Research Institute for the Semi-Arid Tropics (ICRISAT) meso-level data. The dataset covers 311 districts of 19 states of the country for every year of my period of study. I map these districts to Indian districts in 1971 for comparability across data. The 19 states[7] studied in the dataset cover 87.2% of total areaa and 96% of total population of India. I calculate agricultural GDP

Manufacturing Production: Data on labor input in manufacturing and gross sale value is sourced from Annual Survey of Industries (ASI). ASI is the principal source of industrial statistics in India. ASI surveys all manufacturing units with 100 or more workers, every year. I use ASI data from 1999-2010 due to limitation of district identifiers in ASI data outside of those years. One criticism of ASI is that it only includes formal manufacturing sector in India and does not survey informal manufacturing sector which contributes 25% to gross value-added and is 75% of manufacturing employment (Goldar 2023)

Consumption Patterns: I obtain data on consumption patterns of workers in each sector-district from National Sample Survey (NSS) - consumption surveys. NSS surveys are conducted by National Sample Survey Organization (NSSO) which falls under the jurisdiction of Ministry of Statistics and Programme Implementation (MoSPI). The sample surveys are at household level which I aggregate up to district level to form a panel dataset spanning 1987-2012.[8] From the survey, I gather information on the total monthly expenditure per household for those working in agriculture, manufacturing, and services. This includes detailed information on the share of expenditure allocated to food, manufacturing goods, and services for workers in each sector.

Labor Shares: Data for labor share by district-sector-year triplet is sourced from NSS - Employment and Unemployment surveys[9]. The survey asks every individual about their primary industry of work. I use

[6] Rice, Wheat, Sorghum, Pearl millet, Maize, Finger millet, Barley, Cereals, Chickpea, Pigeonpea, Groundnut, Sesamum, Rapeseed and Mustard, Safflower, Castor, Linseed, Sunflower, Soybean, Sugarcane, Cotton, Fruits, Vegetables

[7] Andhra Pradesh, Assam, Bihar, Chattisgarh, Gujarat, Haryana, Himachal Pradesh, Jharkhand, Karnataka, Kerala, Madhya Pradesh, Maharashtra, Odisha, Punjab, Rajasthan, Tamil Nadu, Uttarakhand, Uttar Pradesh, West Bengal.

[8] I use data from four rounds of NSS - consumption surveys: 43rd round (July 1987-June 1988), 55th round (July 1999-June 2000), 66th round (July 2009-June 2010), and 68th round (July 2011-June 2012).

[9] I use data from seven rounds of NSS - Employment Unemployment surveys: 43rd round (July 1987-June 1988), 55th round (July 1999-June 2000); 61st round (July 2004-June 2005), 62nd round (July 2005-June 2006), 64th round (July 2007-June 2008), 66th round (July 2009-June 2010), and 68th round (July 2011-June 2012).

this information to calculate labor shares for each sector, defined as the ratio of total number of individuals employed in a sector to the total number of employed individuals in the district.

District crosswalk & Industry concordance: India is a developing country that has experienced significant economic and political changes over the time period covered in this study. The administrative boundaries of districts in India have undergone numerous changes during this time, necessitating the creation of a district crosswalk to ensure consistency in the dataset. I map all changes in districts of India back to the 1971 districts. During this period, national industry codes have also undergone changes. To ensure concordance between national industry codes and classification of sectors into agriculture, manufacturing, and services, I use national industry codes from 1970 to 2008 (Das et al. 2015). Additionally I utilize the international KLEMS codes to categorize industries into these three sectors. Details on KLEMS codes corresponding to each sector are in Table A1. Notably, the sectors of Construction, Electricity, Gas, and Water Supply, and Mining and Quarrying are classified outside of agriculture, manufacturing, and services.

Trade cost: I obtain trade cost data from Allen and Atkin (2022). They utilize seven editions of Road maps of India published between 1962 and 2011, to create a "speed image" of India. This allows the authors to calculate travel times between districts.

Agricultural Markets: Data for geolocations of government designated marketplaces (*"mandi"*) is sourced from Chatterjee (2023)

Bank access: Data on bank access of each district comes from Fulford (2013)

Climate Variables: I create decadal average temperature and precipitation variables using global monthly average data from Kenji and Atmospheric Research Staff (Eds.) (2023). The data is available at a higher spatial resolution of 0.5° x 0.5° latitude-longitude, which I map to districts of India and take an average over the past decade to create the main explanatory variables used in the paper.

4 Stylized Facts about Climate Change, Structural Transformation, and Trade

4.1 Supply-side and Demand-side theories of structural transformation

Stylized Fact I: *Climate change is diminishing the productivity of the agricultural sector relative to manufacturing.*

To estimate the effect of climate change on agricultural and manufacturing productivity. I estimate the following fixed effect panel regression:

$$log(y_{cnt}) = \beta_1 f(T_{nt}) + X^{'}\beta_2 + \alpha_{cn} + \alpha_{ct} + \alpha_s t + \epsilon_{cnt}$$

where y_{cnt} is the agricultural output of crop c in district n, in year t and is equivalent to manufacturing productivity defined as the fraction of gross value of the product and labor input for each industry c in district n and year t. $f(T_{nt})$ is a function of decadal average temperature. β_1 is our main parameter of interest. $X^{'}$ is a vector of decadal average precipitation as control. α_{cn} is crop-district or industry-district fixed effect, this controls for time-invariant factors that would influence the propagation of a particular crop or industry in a district. α_{ct} is a vector of crop-time or industry-time fixed effect that absorbs all unobserved time-varying differences across crops/industries such as policy changes, and global market fluctuations. Finally, $\alpha_s t$ is state-level time trend that controls for unobserved factors that may be correlated with climate (such as economic growth over time). The last term ϵ_{cnt} is the stochastic error term. Following Liu, Shamdasani, and Taraz (2023) and Colmer (2021), I report Conley standard errors that allow spatial correlation up to 1500 kilometers (Conley (1999)).

Table 1 and Table 2 report the results of panel estimates using the above estimating equation for the agricultural and manufacturing sectors, respectively. Table 1 shows that a 1°C increase in decadal average temperature leads to a 15.97% decline in agricultural output for all crops (column 1), a 16.36% decline in output for crops that are covered under minimum support price (MSP) (column 2), a decline of 10.53% in output of main crop (column 3) - which is the crop that occupies the most area in the district. Rice and Wheat which make up the staple diet of the country, also face a decline of 11.02% for every 1°C increase in decadal average temperature. These estimates are similar to the elasticity of agricultural yield to temperature estimates from Liu, Shamdasani, and Taraz (2023) and Colmer (2021).

Table 2 shows that a 1°C increase in decadal average temperature leads to a 1.50% decline in manufacturing productivity as defined as the ratio of gross sale value to labor input of each industry (column 1), male-dominated manufacturing industries face a decrease of 1.29% in productivity (column 2). There is no significant effect of an increase in temperature on the productivity of the sugar and oils industry, which are the most common manufacturing industries in each district, and female-dominated manufacturing industries. Estimates of the elasticity of manufacturing productivity to temperature are similar to the estimates from Somanathan et al. (2021).

Taken together the estimates from both Table 1 and Table 2 show that agricultural yields are worse affected by an increase in decadal average temperature than manufacturing productivity. This is possibly because the agricultural sector is doubly affected by a decline in land and labor productivity, and is directly dependent on climate-sensitive factors like water availability, temperature, and soil quality. However, the manufacturing sector is affected by labor productivity and increased input costs but is less sensitive to direct environmental variables.

Supply-side theories of structural transformation would hypothesize that if food security is maintained and climate change impacts the manufacturing sector less than agriculture, then labor reallocation should happen from agriculture to manufacturing.

Stylized Fact II: *Climate change is decreasing incomes and increasing food share of expenditure.*

I estimate the effect of an increase in temperature on the total expenditure of households and on the share of expenditure on food, manufacturing goods, and services. I estimate the following fixed effect panel regression:

$$log(y^{\tilde{k}}_{nkt}) = \beta_1 f(T)_{nt} + X^{'}\beta_2 + \alpha_n + \alpha_t + \alpha_r t + \epsilon^{\tilde{k}}_{nkt}$$

where $y^{\tilde{k}}_{nkt}$ is either the total expenditure or the share of expenditure on food, manufacturing, and services denoted by $\tilde{k}$ by people living in region n and working in sector k at time t. $f(T_{nt})$ is a function of decadal average temperature. β_1 is our main parameter of interest. $X^{'}$ is a vector of decadal average precipitation as control. α_n is the district fixed effect that controls for district-specific tastes for goods, α_t is the time fixed effect that controls for time-varying differences such as economic policy shocks and global macroeconomic trends. $\alpha_r t$ is a linear region time trend that accounts for different regions in India trending differently over time. Finally, $\epsilon^{\tilde{k}}_{nkt}$ is a stochastic error term. I report Conley standard errors that allow spatial correlation up to 1500 kilometers.

Table 3 reports the result of estimating the above equation. Panel A shows the estimates for the effect of temperature on total expenditure and share of expenditure on goods for households engaged in the agricultural sector. Similarly, panel B reports the results for households working in the manufacturing sector, and panel C for service sector workers. I find that an increase of 1°C in decadal average temperature results in a decrease of 0.2% in total expenditure for households that work in the agricultural sector (Panel A, column 1). Further analysis shows that an increase of 1°C in decadal average temperature increases food share of expenditure for agricultural households by 6.05% (Panel A, column 2), and decreases the share of expenditure on manufacturing goods by 11.20% (Panel A, column 3). The effect of temperature on the share of expenditure on services is insignificant (Panel A, column 4).

Results for households engaged in the manufacturing sector (Panel B) show that an increase of 1°C in decadal average temperature decreases the total expenditure by 0.43% (Panel B, column 1), increases food share of expenditure by 6.62% (Panel B, column 2). The effect of temperature on the share of expenditure on manufacturing goods, and services is insignificant for manufacturing sector workers (Panel B, columns 3 and 4).

The only sector workers that see an increase in total expenditure when temperature increases is the service sector, which sees an increase of 4.15% for every 1°C increase in temperature (Panel C, column 1). Service sector workers also increase food share of expenditure by 1.64% (Panel C, column 2) and share of expenditure on services by 8.60% (Panel C, column 4). The service sector is the least affected by rising temperatures in terms of productivity because its activities do not directly rely on environmental factors. Unlike agriculture and manufacturing, the service sector primarily operates in urban areas. This inherent difference helps shield the service sector from the direct impacts of environmental changes. Labor supply decline in the service sector could also increase wages and therefore expenditure.

According to Engel's law, as the incomes of households working in the agriculture and manufacturing sectors decrease, the food share of expenditure for these households increases. The results from Table 3 discussed above demonstrate that climate change is the driving force behind these changing consumption patterns. Demand-side theory of structural transformation would predict that as income decreases and households switch their consumption to prioritize necessities like food, rather than manufacturing goods and services, this increase in the relative demand for food should move labor reallocation toward the agricultural sector. Therefore, Fact I & II are making opposing predictions about the reallocation of labor, therefore further analysis of the effect of climate change on labor reallocation is required.

4.2 Climate Change and Structural Transformation

Stylized Fact III: *Climate Change is inhibiting structural transformation in India.*

Now we turn to estimate the effect of increasing temperature on labor reallocation across economic sectors in India. I estimate the following fixed effect panel regression:

$$log(y_{nkt}) = \beta_1 f(T)_{nt} + X^{'}\beta_2 + \alpha_n + \alpha_t + \alpha_r t + \epsilon_{nkt}$$

where $log(y_{nkt})$ is the logarithm value of the share of labor working in sector k to all employed people in region n at time t. $f(T_{nt})$ is a function of decadal average temperature. β_1 is our main parameter of interest. $X^{'}$ is a vector of decadal average precipitation as control. α_n is the district fixed effect that controls for district-specific tastes for goods, α_t is the time fixed effect that controls for time-varying differences such as economic policy shocks and global macroeconomic trends. $\alpha_r t$ is a linear region time trend that accounts for different regions in India trending differently over time. Finally, ϵ_{nkt} is a stochastic error term. I report Conley standard errors that allow spatial correlation up to 1500 kilometers.

Table 4 reports the results of estimating the above equation. The results show that an increase of 1°C in decadal average temperature increases agricultural labor share by 12.45$\%$, decreases manufacturing labor share by 2.56$\%$, and service sector labor share by 2.46$\%$ for each district. These results show that climate change is inhibiting structural transformation in India by pulling labor back into agriculture. At the Conference of the Parties meetings organized by the United Nations Framework Convention on Climate Change, India has argued that since the developed world has already used its "fair share" of the global carbon budget for their own development, developing countries like India should be granted the same opportunity (Ministry of Environment, Forest and Climate Change, India (2023)). The process of economic development is characterized by the reallocation of resources - including labor, out of agriculture. The results in this section suggest that climate change could pose a significant internal challenge for India in achieving its economic growth objectives.

Fact I & II help us understand more about the effect of Climate Change on Structural Transformation. As discussed in Fact I, the observed differential impact of temperature on the agriculture and manufacturing sectors would push labor from the agriculture sector if food security is maintained. However, the discussion of Fact II infers that the effect of temperature on consumption patterns should pull labor into the agricultural sector. The results in this section show that labor is being pulled back into the agricultural sector. This could be due to two reasons - demand-side drivers of structural transformation might be dominating over supply-side drivers and India is struggling to maintain food security under high temperatures with current physical and market structures.

The hypothesis that demand-side drivers dominate supply-side drivers in forming the patterns of structural transformation is supported in the literature (Comin, Lashkari, and Mestieri (2021), Alvarez-Cuadrado and Poschke (2011)). Subsistence farming limits a farmer's ability to sustain shocks. The productivity shocks due to climate change keep subsistence farming households in agriculture by creating monetary barriers that prevent them from being able to switch to other sectors. Land fragmentation is known to have multifaceted detrimental effects - it increases the expense due to duplication of fixed equipment, hinders mechanization, and requires a larger labor force to maintain (Shaw (1963), Knippenberg, Jolliffe, and Hoddinott (2018)). Subsistence farmers are unable to make capital investments and rely on labor inputs (including family labor) (Miracle (1968)), climate change is increasing this reliance on labor by subsistence farmers (Aragón, Oteiza, and Rud (2021)). These subsistence needs combined with high labor shares give rise to "food problem" as termed by Gollin, Parente, and Rogerson (2007).

Ideally trade can solve "food problem" (Tombe (2015)). India is a large country with multilple climate zones across its regions. If agricultural productivity of regions within India is differently affected by heat, then potentially comparative advantage of these regions could shift. Regions with newly gained comparative advantage in agriculture could potentially export their surplus produce to areas within India more severely affected by heat. This could result in a scenario where living standards are unperturbed by productivity or income losses due to climate change (Costinot, Donaldson, and Smith (2016)). I discuss adaptation abilities of trade in India in next section.

4.3 Structural Transformation, Climate Change, and Trade

In this section, I lay out my final set of stylized facts. These facts capture the adaptive capability of trade in mitigating the negative effect of climate change on structural transformation in India.

Stylized Fact IV: *If different regions of India are differently affected by Climate Change, then internal trade within India should help alleviate the "food problem".*

First, I estimate the heterogenous effect of temperature on agricultural and manufacturing productivity. I estimate this heterogenous effect to identify if agricultural and manufacturing productivity in different regions of India is differently affected by heat, such that comparative advantages could arise with the country. I allow the effect of $f(T)$ on the productivity of sectors to vary across a temperature step function $g(T)$ by interacting the two functions. Therefore, I estimate the following equation:

$$log(y_{cnt}) = \beta_1 f(T_{nt}) + \sum_{b \in B \neq [20,25)} \beta_b tempbin_{nt}^b + \gamma_b(tempbin_{nt}^b \cdot f(T_{nt})) + X^{'}\beta_2 + \alpha_{cn} + \alpha_{ct} + \alpha_s t + \epsilon_{cnt}$$

where $tempbin_{nt}^b$ are indicators for the temperature bin that includes temperature T_{nt} for $b \in B = \{<15, 15-20, 20-25, 25-30\}$. I estimate the total effect of temperature on agricultural/manufacturing productivity conditional on being in a temperature bin b, these effects have been plotted in Figure 5. The trend of the productivity estimates across temperature bins matters more than the estimates themselves. Panel A shows the declining productivity of the agricultural sector as we move across temperature bins. This indicates that a 1°C temperature increase in a higher temperature bin [25,30) has a worse impact on agricultural productivity than the same temperature increase at a lower temperature bin, (- ∞,15). While Panel B shows that the effect of a 1°C increase in temperature is about the same across temperature bins for manufacturing productivity.

Now that we have established that temperature impacts on agricultural productivity vary across temperature bins. This variation drives comparative advantages between regions. These differences in agricultural productivity should lead to regional specialization. In an ideal world, if trade functioned efficiently, it should be able to mitigate the positive relationship between temperature and agricultural labor share. I test this hypothesis by creating two agricultural market access measure for each district in India - in-state and out-state, following Donaldson and Hornbeck (2016), which are defined as:

$$MA_{nt}^{in-state} = \sum_{i \neq n} (\text{travel-time}_{nit}^{-\phi} Y_{it}) \mathbb{1}_{\text{state of } n \text{ = state of } i}$$

$$MA_{nt}^{out-state} = \sum_{i \neq n} (\text{travel-time}_{nit}^{-\phi} Y_{it})$$

where Y_{it} is district i's total agricultural income, travel-time$_{nit}$ is the time it takes to reach district i from district n in year t. $\phi > 0$ and it measures how quickly market access declines with travel time. The gravity literature measures $\phi = 1.5$ for developing countries, which is the value used in this paper. Using this measure of market access, I estimate the interactive effect of market access and temperature on agricultural labor share, in other words, I explore how the elasticity of agricultural labor share to temperature changes with reductions in cost of trading agricultural goods:

$$log(y_{nt}^{ag}) = \beta_1 f(T)_{nt} + \beta_2 MA_{nt}^{ag} + \gamma(f(T)_{nt} \cdot MA_{nt}^{ag}) + X^{'}\beta_2 + \alpha_n + \alpha_t + \alpha_r t + \epsilon_{nkt}$$

where dependent variable is agricultural labor share and MA_{nt}^{ag} is in-state or out-state agricultural market access. γ reveals the interactive effect of market access and temperature on agricultural labor share. I also control for bank access in this estimation. One might be concerned about possible endogeneity in highway construction, as it could be more likely to occur in areas with a higher concentration of agricultural production, and therefore more agricultural labor. These endogeneity concerns are alleviated by the fact that most of the highway concentration was part of central government-planned national programs aimed at connecting different regions of the country, rather than being specifically targeted by the state government towards agricultural areas since agriculture in India is a state subject.

Columns 1 and 2 of Table 5 report the results for out-state market access, with column 2 reporting results with controls for bank access. As one would expect, increased market access to other districts (decreased trade costs) enables agricultural labor share to decrease ($\beta_2 < 0$), the coefficient is more negative when I control for access to bank. Asher and Novosad (2020) found a similar result, showing that when villages gain access to roads, agricultural labor tends to exit the sector in India. More central to the hypothesis presented above, I find that decreased trade costs (increased market access) do not mitigate the positive relationship between temperature and agricultural labor share ($\gamma > 0$). The results show that initially, access to the market does allow labor to exit agricultural sector. However, when the temperature rises above 25.7°C (22.8°C when I estimate controls for access to bank)lower trade costs become ineffective as labor shifts back into agriculture, driven by the need to maintain food security in response to declining agricultural productivity due to rising temperatures. This result implies that either trade costs are not sufficiently low or certain barriers in the trade of agricultural goods persist, which prevents labor from leaving the agricultural sector.

Columns 3 and 4 of Table 5 report the results for in-state market access, with column 4 reporting results with controls for bank access. Since agriculture is a state subject in India, therefore agricultural policies and regulations vary at the state level. The results show that increased market access to districts within the state certainly helps more labor leave the agricultural sector, than market access to out-state districts. However, as the temperature rises above 23.8°C (25.6°C when controlled for bank access), market access within the state becomes ineffective. This is likely because temperature shocks have a uniformly negative impact on agricultural productivity across districts within the same state, limiting the ability of one district to trade surplus goods with another. The comparative advantages within the state do not arise with temperature shifts and therefore do not help labor reallocate out of agriculture.

As discussed earlier, these findings suggest that either trade costs are still too high for trade to effectively help adapt to impacts of climate change or possibly barriers to trade of agricultural goods exist within India, limiting trade. Internal trade barriers within India in agricultural sector, as discussed in Section 2.3, could possibly be limiting the ability of trade to be a meaningful adaptation tool.

Stylized Fact V: *Internal trade barriers in agricultural markets in India are limiting the adaptation capabilities of agricultural workers through labor reallocation.*

The internal state-level trade barriers created by the APMC Act in India reduce competition among buyers of agricultural goods, which in turn lowers the prices that farmers receive for their goods(Chatterjee (2023)). Figure 6 shows that all states in India have adopted some form of the APMC act. Therefore to analyze the role of trade barriers in exacerbating the effect of climate change on agricultural labor share, I use the location of government-designated marketplaces in each district. Farmers are mandated to sell their produce at these markets (Figure 7). This allows me to create a district-level measure of spatial competition which farmers observe:

$$comp_n = \frac{1}{N} \sum_{markets} \sum_{q \neq r} \left[\frac{1}{distance_{rq}} \right] \mathbb{1}_{\{\text{state of } q = \text{state of } r\}}$$

This measure is constructed by taking a weighted sum of the average of distances between all the markets in a district. r and q are markets within the same state, N is the total number of markets in a district. I only have a cross-section of geolocations of APMC markets across India. As a result, this measure of spatial competition is also cross-sectional. This measure of spatial competition is similar to the one created by Chatterjee (2023), but their measure was at each marketplace level. In contrast, I aggregate it to the district level to align with the rest of my dataset. This allows for consistency in the analysis across the study.

In this section, I test how the elasticity of agricultural labor share to temperature varies with increasing spatial competition. I hypothesize that the internal trade barriers imposed by the APMC Act reduce competition, keeping labor in agriculture. The lack of competition results in lower prices received by subsistence farmers, and this decreases their ability to exit agriculture.

$$log(y_{nt}^{ag}) = \beta_1 f(T)_{nt} + \gamma(f(T)_{nt} \cdot comp_n^{ag}) + X^{'}\beta_2 + \alpha_n + \alpha_t + \alpha_r t + \epsilon_{nkt}$$

where $comp_n^{ag}$ is the spatial competition measure for each district as calculated above. I also control for access to bank in each district. This is to absorb the variation due to liquidity constraints faced by farmers. Table 6 presents results of this analysis. The results show that even though temperature increases agricultural labor share, However as spatial competition increases in a district agricultural labor share decreases at every temperature realization. This result is even more salient when I control for bank access. Figure 9 plots the demaned estimates of above estimation. The figure highlights the same results, that as spatial competition increases in a district, labor is able to exit agriculture.

I also estimate the causal effect of spatial competition on the prices received by farmers and the agricultural labor share in each district. To do this, I apply a border discontinuity design within district pairs. I match all districts that share a border but belong to different states. I then regress the differences in prices and agricultural labor share between these district pairs on the difference in their spatial competition. Between the district pairs, other determinants of agricultural markets like demand, taste, soil quality, education[10], rainfall, and temperature do not vary. Therefore, any differences in prices and agricultural labor shares stem directly from the discontinuity across state borders, driven by internal trade barriers.

$$\Delta log(y_{nt}^{ag}) = \beta_1 \Delta comp_n^{ag} + \alpha_{ss'} + \epsilon_{nt}^{\tilde{a}g}$$

Table 7 presents the results of above estimation. Column 1 reports the causal effect of internal trade barriers on price received by the farmers. I find that the marginal effect of spatial competition on prices is an increase of 4.14%, this result implies that bordering districts with one unit higher spatial competition can yield 4.14% higher prices for crops for farmers. This result is similar to Chatterjee (2023) who find 3.5% higher prices in markets with higher competition.

I then estimate the causal effect of spatial competition on agricultural labor shares and find that a one-unit increase in competition in neighboring district reduces agricultural labor share by 19.37% (column 2). The results intensifies when I control for access to banks, and shows a reduction in agricultural labor by 24.57% (column 4). These findings underscore the role of trade barriers in trapping labor in the agricultural sector. They also reveal that the underlying mechanism is the lower prices received by subsistence farmers, whose precarious financial situations prevent them from breaking free from agriculture, as even a small increase in income could alleviate their economic constraints and improve their quality of life.

As discussed above, temperature changes smoothly across bordering districts. I test for differences in the adaptation capacity of districts under heatwave. The results are presented in column 4 of Table 7, I find a weaker relationship suggesting that under a heatwave the districts with higher spatial competition are able to adapt better by allowing labor to exit agriculture. The estimates show a 3.37% further decline in agricultural labor share under heatwave in districts with higher spatial competition than the ones with less competition.

[10]Education was a state subject in the Constitution of India until 1976. 42nd amendment to the constitution shifted education to the concurrent list - governed by both the center and the state.

To summarize, I have shown that climate change is altering the relative productivity of sectors with agricultural productivity being more negatively affected than manufacturing sector productivity. Supply-side theory of structural transformation theorizes that this alteration in relative productivity should induce labor to exit the agricultural sector. I then show that climate change is also modifying consumption patterns due to a decrease in income for workers. I show a decline in income and an increase in food expenditure due to increasing temperatures. Demand-side theory of structural transformation theorizes that since food is a necessity, such changes in consumption would increase agricultural labor share. I then show thattemperature increases are indeed increasing agricultural labor share in India. Therefore reversing the structural transformation and economic growth of the country.

Having established that climate change is worsening India's "food problem", I test whether trade can serve as an adaptation tool. However, I find that increased market access (lower trade costs) does not mitigate the positive relationship between temperature and agricultural labor share. This suggests that either trade costs are not sufficiently low or there exists a barrier in ability to trade in agriculture across India. I then show that internal trade barriers present in the agricultural market exacerbate the effect of climate change on agricultural labor by trapping labor in the sector. I now present a model that incorporates key features of the Indian economy pertaining to structural transformation, trade, and climate change.

5 The Model

5.1 Consumption

Workers in each region n and sector k minimize their expenditure subject to certain utility level. Workers decide their allocation of consumption of final goods from all sectors through a CES non-homothetic aggregator as defined in Comin, Lashkari, and Mestieri (2021).

$$w_{nk}L_{nk} = min \sum_{\tilde{k}}^{K} p_{n\tilde{k}} C_{nk}^{\tilde{k}}$$

$$\text{subject to utility constraint} \sum_{\tilde{k}} (\gamma^{\tilde{k}})^{1/\sigma} C_{nk}^{\eta_{\tilde{k}}/\sigma} (C_{nk}^{\tilde{k}})^{\frac{\sigma-1}{\sigma}} = 1$$

The parameter $\gamma^{\tilde{k}}$ is the fixed sectoral taste of a good, σ is the elasticity of substitution between goods of each sector, and $\eta_{\tilde{k}}$ is the sector specific income elasticity. $C_{nk}^{\tilde{k}}$ is the consumption level of good $\tilde{k}$ by a household working in sector k and living in region n. C_{nk} is the utility level, represented by real consumption of a household. Solving the expenditure minimization problem results in optimal consumption of a household. Using that optimal consumption, I find $s_{nk}^{\tilde{k}}$ which denotes expenditure share on good $\tilde{k}$ by a household working in sector k and residing in region n, relative to the household's total expenditure.

$$s_{nk}^{\tilde{k}} = \gamma^{\tilde{k}} C_{nk}^{\eta_{\tilde{k}}} \left(\frac{p_{n\tilde{k}}}{w_{nk} L_{nk}} \right)^{1-\sigma}$$

Household's expenditure function for achieving certain utility:

$$E_{nk} = w_{nk} L_{nk} = \sum_{\tilde{k}=1}^{K} \left(\gamma^{\tilde{k}} C_{nk}^{\eta_{\tilde{k}}} p_{nk}^{1-\sigma} \right)^{\frac{1}{1-\sigma}}$$

5.2 Production

The production section of the model follows the multi-sector model of Caliendo and Parro (2015). Each sector produces a continuum of intermediate goods $\omega_k \in [0, 1]$. The final good in sector k in district n is a CES composite of intermediate varieties indexed by ω_k from the lowest cost suppliers across districts of India. The production technology of Q_{nk} is a CES aggregator given as:

$$Q_{nk} = \left[\int_0^1 r_{nk}(\omega_k)^{\frac{\psi-1}{\psi}} \right]^{\frac{\psi}{\psi-1}} \tag{1}$$

where ψ is the elasticity of substitution between intermediate goods, $\psi > 0$ and $r_{nk}(\omega_k)$ is the demand of intermediate goods ω_k from the lowest cost supplier. The production function for each intermediate good is linear in labor.

$$q_{nk}(\omega_k) = z_{nk}(\omega_k) \cdot l_{nk}(\omega_k)$$

Since, labor is the only input firms in district n domestic price of goods in district n is $\frac{w_n}{z_{nk}(\omega_k)}$. All intermediate goods in sector k ω_k in each district n receive the productivity draw of z_{nk} which is a random variable drawn from Fréchet distribution, $F_{nk}(z) = e^{-\lambda_{nk} z^{-\theta_k}}$ with shape parameter θ_k and sector-district specific scale parameter λ_{nk}. Since temperature increase due to climate change affects productivity of each sector-region pair. Here, I model sector-region specific scale parameter λ_{nk} as modeled in Nath (2022) :

$$\lambda_{nk} = f(\mu_{nk}, T_{nk}, E(T_{nk}))$$

where μ_{nk} is baseline productivity of sector-region pair, T_{nk} is temperature realization in region n while $E(T_{nk})$ is the expectation of temperature realization.

5.3 Trade

Trade section of the model follows Eaton and Kortum (2002). Intermediate goods producer face an iceberg trade cost, τ_{njk} that varies by sector k, exporting district n, and importing district j. Trade costs are modeled utilizing stylized fact #5 which states that agriculture faces trade barriers across state borders. Trade costs in agriculture sector are defined as:

$$\tau_{nja} = \begin{cases} d_{nja} & \text{if } n \text{ and } j \text{ are in same state} \\ \infty & \text{otherwise} \end{cases} \tag{2}$$

While, trade costs in manufacturing sector are d_{njm} which is just the distance between districts. Service sector produces non-tradable goods. After taking into account trade costs, the price of an intermediate good produced in district n and consumed in district j is:

$$p_{njk} = \frac{w_n \tau_{njk}}{z_{nk(\omega_k)}}$$

Since, z_{nk} is a random variable drawn from Fréchet distribution, therefore p_{njk} also follows fréchet distribution.

$$Pr[p_{njk} \leq p] = 1 - e^{-T_{njk} p^{\theta_k}} \tag{3}$$

where $T_{njk} = \lambda_{nk}(w_n \tau_{njk})^{-\theta_k}$. The lowest price of an intermediate good ω_k in district j produced in district n is denoted as $p_{jk}(\omega_k)$

$$p_{jk} = \min_{n \neq j} \{ \frac{w_n \tau_{njk}}{z_{nk(\omega_k)}} \}$$

$p_{jk}(\omega_k)$ also has fréchet distribution.

$$Pr[p_{jk} \leq p] = 1 - \prod_{n=1}^{N} Pr[p_{njk} \geq p] \tag{4}$$

and using Equation 3, we get

$$Pr[p_{jk} \leq p] = 1 - e^{-\Phi_{jk} p^{\theta_k}}$$

where $\Phi_{jk} = \sum_{n=1}^{N} T_{njk} = \sum_{n=1}^{N} T_{njk} = \lambda_{nk}(w_n \tau_{njk})^{-\theta_k}$. For agricultural sector trade across state borders and service sector where $\tau_{njk} = \infty$, $\Phi_{jk} = \lambda_{nk}(w_n)^{-\theta_k}$. $p_{nk}(\omega_k)$ has fréchet distribution, therefore $p_{nk}(\omega_k)^{\theta_k}$ has exponential distribution. Assume, $y = p_{nk}(\omega_k)^{\theta_k}$, therefore $Pr[p_{nk}(\omega_k)^{\theta_k} \leq y] = 1 - e^{-\Phi_{nk} y}$. The density of exponential function is $f_y(y) = \Phi_{nk} e^{-\Phi_{nk} y}$.

The price index, P_{nk} for sector k and district n is an aggregate measure of the prices of all goods in that sector. Using the CES aggregator framework, the price index is:

$$(P_{nk})^{1-\psi} = \int p^{1-\psi} f(p)\, dp$$

$\psi > 0$ is the elasticity of substitution among varieties. Substituting, $p = y^{1/\theta_k}$ and $f(p)$

$$(P_{nk})^{1-\psi} = \int (y^{1/\theta_k})^{1-\psi} \Phi_{nk} e^{-\Phi_{nk}} y \, dy$$

Solving for price index,

$$P_{nk} = (\Phi_{nk})^{-1/\theta_k} \left[\Gamma \left(1 + \frac{1-\psi}{\theta_k} \right) \right]^{\frac{1}{1-\psi}}$$

Assuming, $\left[\Gamma \left(1 + \frac{1-\psi}{\theta_k} \right) \right]^{\frac{1}{1-\psi}}$ to be A_j, price index can be written as

$$P_{nk} = A_j (\Phi_{nk})^{-1/\theta_k} \tag{5}$$

where $\Phi_{nk} = \sum_{n=1}^{N} \lambda_{nk}(w_n \tau_{njk})^{-\theta_k}$

The demand function for final goods for variety ω_k is the solution to the cost minimization problem for final goods producer:

$$r_{nk}(\omega_k) = \left(\frac{p_{nk}(\omega_k)}{P_{nk}}\right)^{-\psi} Q_{nk}$$

5.4 Expenditure Shares

Expenditure shares are expressed as π_{njk}, it represents the share of total expenditure from district n on goods from sector k that are sourced from district j. $\pi_{njk} = X_{njk}/X_{nk}$,

$$X_{njk} = Pr\left[\frac{w_n \tau_{njk}}{z_{nk}(\omega_k)} \leq min_{h \neq j} \frac{w_h \tau_{nhk}}{z_{hk}(\omega_k)}\right] X_{nk}$$

Using the properties of fréchet distribution, expenditure share can be derived as:

$$\pi_{njk} = \frac{\lambda_{jk}(w_j \tau_{njk})^{-\theta_k}}{\sum_{h=1}^{N} \lambda_{hk}(w_h \tau_{nhk})^{-\theta_k}} \tag{6}$$

5.5 Market Clearing

The model has two market clearing conditions, First is labor market clearing condition which states that total labor in a location will be distributed across the three sectors $\in (a, m, s)$:

$$L_n = L_{na} + L_{nm} + L_{ns} \tag{7}$$

Second market clearing conditions is goods market clearing which states that total income in each district n sector k pair is the sum of all domestic sales and sales to other districts in all goods produced by sector k.

$$w_n L_{nk} = \sum_{\tilde{k}} \left(\pi_{nn}^{\tilde{k}} P_{nk} C_{nk}^{\tilde{k}} + \sum_{n \neq j} \pi_{nj}^{\tilde{k}} P_{jk} C_{jk}^{\tilde{k}}\right) \tag{8}$$

In a situation where autarky exists in districts of India, income should equal expenditure in each sector such that, $P_{nk}C_{nk} = w_n L_{nk}$. This implies that employment share, $l_{nk} = \frac{L_{nk}}{L_n}$ equals expenditure share, $s_{nk} = \sum_{\tilde{k}} s_{nk}^{\tilde{k}}$.

In case of presence of trade, employment share in each sector can be calculated using Equation 8.

$$l_{nk} = \sum_{\tilde{k}} \left(\pi^{\tilde{k}}_{nn} s^{\tilde{k}}_{nk} + \sum_{n \neq j} \pi^{\tilde{k}}_{nj} s^{\tilde{k}}_{jk} \frac{w_n L_n}{w_j L_j} \right) \tag{9}$$

Above equation[11] illustrates that in the presence of trade, labor shares in each sector are dependent on domestic consumer preferences as well as trade between districts in India. Labor share of agricultural sector in a district n is defined by the share of expenditure from residents of district n on goods from their location $\pi^{\tilde{k}}_{nn}$, the share of expenditure of their income that they make on food $s^{\tilde{k}}_{nk}$ and the total exports the region n makes to all other regions j (second half of the equation). As discussed in stylized fact II in Section 4.1, climate change increases food share of expenditure. Therefore, if we consider a scenario where agricultural productivity is declining (evidenced in stylized fact I in Section 4.1), then the reduction in comparative advantage of location n in agriculture will increase food imports, reducing the amount of money locals spends on food from their own region $\pi^{\tilde{k}}_{nn}$. While, food share of expenditure increases $s^{\tilde{k}}_{nk}$ and food exports from region n fall as well reducing $\pi^{\tilde{k}}_{nj}$. Therefore, the above equation reflects the horserace between the "food problem" and trade that drives the labor reallocation across sectors (structural transformation).

5.6 Equilibrium

Given L_n, Z_{nk}, τ_{njk} an equilibrium under increased temperature T_n due to climate change is a wage vector w_n and prices P_{nk} that satisfies following equilibrium conditions holds in each sector-region pair market:

(1) $P_{nk} = (\Phi_{nk})^{-1/\theta_k} \left[\Gamma \left(1 + \frac{1-\psi}{\theta_k}\right) \right]^{\frac{1}{1-\psi}}$

(2) $\Phi_{nk} = \sum_{n=1}^{N} \lambda_{nk} (w_n \tau_{njk})^{-\theta_k}$

(3) $\pi_{njk} = \frac{\lambda_{jk}(w_j \tau_{njk})^{-\theta_k}}{\sum_{h=1}^{N} \lambda_{hk}(w_h \tau_{nhk})^{-\theta_k}}$

(4) $w_n L_{nk} = \sum_{\tilde{k}} \left(\pi^{\tilde{k}}_{nn} P_{nk} C^{\tilde{k}}_{nk} + \sum_{n \neq j} \pi^{\tilde{k}}_{nj} P_{jk} C^{\tilde{k}}_{jk} \right)$

(5) $s^{\tilde{k}}_{nk} = \gamma^{\tilde{k}} C^{\eta_{\tilde{k}}}_{nk} \left(\frac{p_{n\tilde{k}}}{w_{nk} L_{nk}} \right)^{1-\sigma}$

(6) $l_{nk} = \sum_{\tilde{k}} \left(\pi^{\tilde{k}}_{nn} s^{\tilde{k}}_{nk} + \sum_{n \neq j} \pi^{\tilde{k}}_{nj} s^{\tilde{k}}_{jk} \frac{w_n L_n}{w_j L_j} \right)$

[11] Above equation also appears in Nath (2022) and Uy, Yi, and Zhang (2013)

6 Model Calibration

I use a mix of quantification methods to solve the model. Table 8 documents the sources of parameters that validate the calibrated model.

6.1 Parameter Estimates

The baseline period for model estimation is set to 1999-2000. I use the estimated sectoral productivity measures, λ_{nk} from the estimates presented in Table 1 and Table 2. The bilateral trade costs τ_{njk} are calculated using travel times between districts in India using Allen and Atkin (2022). Sector-specific trade barriers are modeled as discussed in Section 5.3.

The non-homotheticity utility elasticities. η_a, η_m are taken from Comin, Lashkari, and Mestieri (2021). The sectoral trade parameters γ_a, γ_m are calculated as the average level of sectoral consumption shares for each district. The parameter value for cross-sector elasticity of substitution, σ is taken from Nath (2022). I use Tombe (2015) estimates for trade elasticities: $\theta_a = 4.06$, and $\theta_m = 4.63$. I estimate a relative value of γ_a/γ_m of 1.76 is about three times higher than estimates from Conte (2022) for Sub-Saharan Africa. These estimates show that people in India spend less on agricultural goods than people in Sub-Saharan Africa. Given that India is more developed than Sub-Saharan Africa, it follows that India has a lower relative expenditure on agriculture to manufacturing than Sub-Saharan Africa.

6.2 Model Fit

Before using the quantified model to estimate counterfactuals, I first assess the plausibility of the quantified fundamentals. To check how well the model fits the observed data within the sample, I regress observed wages to model-generated wages. A linear regression results in a coefficient of 0.821 with a R^2 value of 0.66. Figure 10 shows that the model-estimated wages closely match the wages found in observed data. Figure 11 shows that the distribution of model generated wages closely follows the distribution of observed wages in the sample.

7 Counterfactual analysis

This section uses the calibrated model to quantify the impact of internal trade barriers. I estimate a counterfactual scenario where there are no internal trade barriers in agriculture such that internal trade costs are no longer set at ∞ but instead match the trade costs of manufacturing ($\tau_{nja} = \tau_{njm}$). This hypothetical scenario is relatively easily achievable through policy reforms. In this counterfactual, the effects of climate change on sectoral productivity remain unchanged. The analysis shows that removing these trade barriers, even under the adverse effects of climate change, reduces agricultural labor share across India. On average, each district experiences a 0.1 percentage point decrease in agricultural labor share. Overall, the estimates show that 28.9 million people across India should be able to leave agriculture and adapt to climate change by reallocating their labor to less affected sectors, thus advancing structural transformation. Figure 12 shows the differential effect of removing trade barriers across the country. The model predicts an increase in agricultural labor share in districts with major cities that currently have a low baseline agricultural labor share but are well-suited for agricultural productivity.

8 Conclusion

This paper shows that agricultural productivity is more severely affected by climate change than manufacturing, indicating that workers could adapt by shifting labor out of agriculture, while also advancing structural transformation in a developing country like India. The story on the consumption side is somewhat different. In this paper, I show that climate change is shifting consumption patterns such that food share of expenditure is increasing as incomes decrease. This shift indicates that labor should move in to agricultural sector to maintain food security. Ultimately, I find that these two competing forces lead to a reallocation of labor back into agriculture as temperatures rise, largely due to India's reliance on subsistence farming. Subsistence farmers' inability to cope with productivity shocks due to climate change, their large reliance on labor combined with limited capacity to adopt new technology, give rise to the "food problem", where labor becomes concentrated in low productivity agricultural sector.

I find that trade, which is often acknowledged as an adaptation tool in both climate change and "food problem" literature is ineffective in India in helping labor adapt my reallocating away from agriculture. This is because Indian agricultural market suffers from inefficiencies. Particularily, an agricultural policy adopted in the 1960s limits agricultural trade across state borders. This policy reduces the profits that farmers can receive by reducing the spatial competition among the buyers of farm produce. I find that districts with more spatial competition help labor exit agriculture at every temperature. I utilize a border discontinuity design between pairs of districts that share a border but are in different states. This design estimates a weak causal relationship suggesting that even during a heatwave the neighboring district with higher spatial competition helps labor exit agricultural sector and therefore adapt to climate change.

I then calibrate a spatial equilibrium model with internal trade barriers using the dataset used for reduced form analysis. Counterfactual exercise of removing internal trade barriers shows an increase of 4.65% in income for each household and decrease in agricultural labor share of 0.1 percentage point on average across all districts, holding the adverse effects of climate change constant for all districts. This estimate shows that removing trade barriers can help about 28.9 million people across India to adapt to climate change. This research underscores the importance of internal market reforms to enable smoother structural trans- formation and enhance adaptation in response to climate change. Beyond India, these findings have broader implications for other developing countries facing similar challenges, indicating that internal political economy reforms may be as critical as international trade policy in mitigating the economic impacts of climate change.

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Figures and Tables

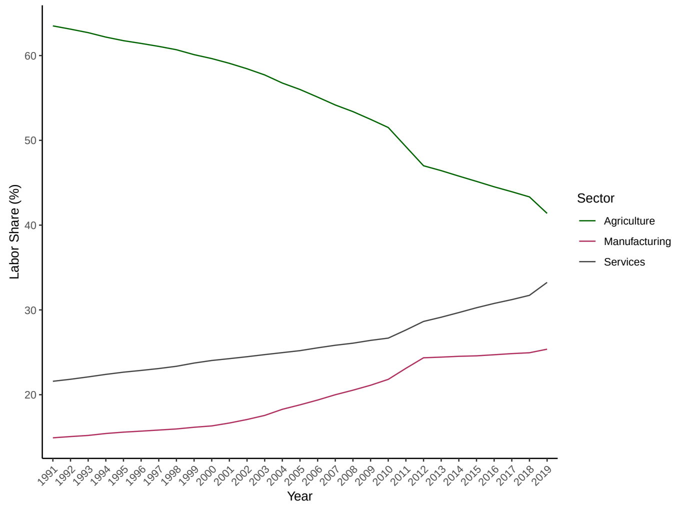

Figure 1: Labor Share

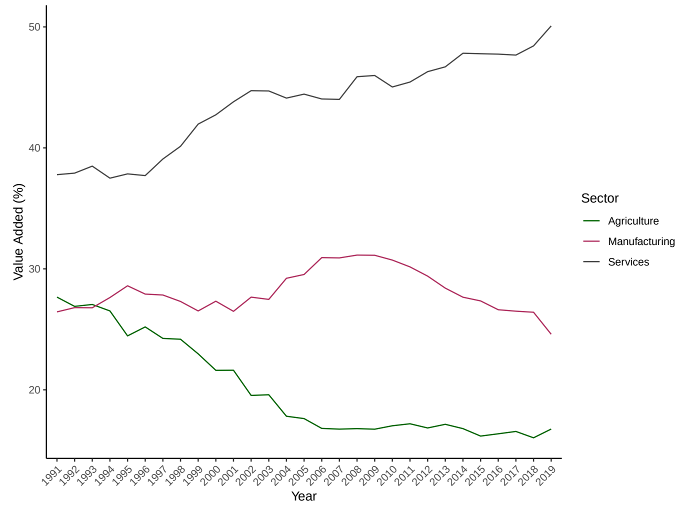

Figure 2: Value Added

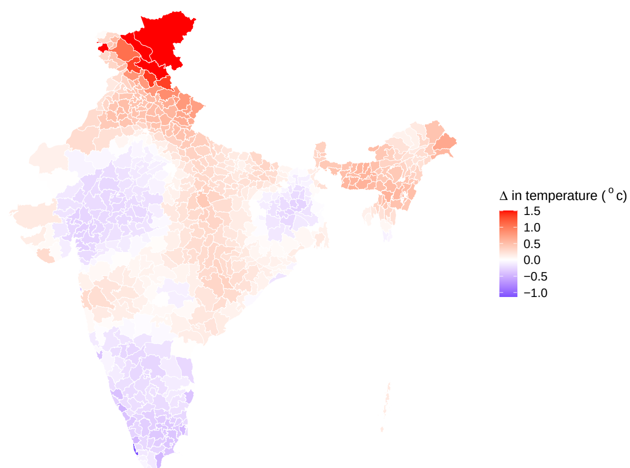

Figure 3: Change in Temperature (1987 - 2012)

Note: *Figure 1 and 2 show structural transformation in India from 1991 to 2019. Figure 1 shows labor share changing over time in 3 broad sectors - Agriculture, Manufacturing, and Services. Figure 2 shows value added by sectors. Data for Figures 1 & 2 is sourced from World Bank Open Data. Figure 3 shows the decadal average temperature change between 2008 and 1987 in districts in India. Data is sourced from Global Meteorological Forcing Dataset for Land Surface Modeling provided by Department of Civil and Environmental Engineering, Princeton University (2006).*

Table 1: Agricultural Productivity

	All crops	MSP crops	Main crop	Rice & Wheat
	(1)	(2)	(3)	(4)
T	-0.1741***	-0.1787***	-0.1113***	-0.1168***
	(0.0121)	(0.0119)	(0.0276)	(0.0234)
P	0.0142**	0.0130*	0.0210*	0.0323***
	(0.0060)	(0.0073)	(0.0111)	(0.0024)
Observations	63593	59153	4610	9080
R^2	0.94	0.94	0.91	0.96
$R^2 Adj.$	0.93	0.93	0.89	0.96
Average Q ('000 tons)	43.16	48.02	403.49	241.57
No. Districts	240	240	240	240
Crop-District FE	x	x	x	x
Crop-Year FE	x	x	x	x
State Year time trend	x	x	x	x

Note: *The table shows the effect of temperature on agricultural yield. Dependent variable is log value of crop yield. Column 1 shows the impact of temperature on all crops produced in a district, Column 2 reports impact of temperature on crops covered under Minimum Support Price (MSP) by Government of India. Column 3 shows the impact on the main crop of the district, determined by the area in a district dedicated to a crop. Column 4 shows the impact of temperature on Rice and Wheat. I report conley Standard errors for spatial correlation upto 1500kms* * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$_

Table 2: Manufacturing Productivity

	All Ind.	Sugar & Oils	Male Dominated	Female Dominated
	(1)	(2)	(3)	(4)
T	-0.0151***	0.0232	-0.0130***	-0.0889
	(0.0023)	(0.0526)	(0.0018)	(0.1675)
P	-0.0121	-0.0058**	-0.0124	0.0071
	(0.0119)	(0.0024)	(0.0118)	(0.0098)
Observations	53623	1840	52162	1461
R^2	0.73	0.66	0.72	0.76
$R^2 Adj.$	0.55	0.53	0.54	0.59
Average Productivity	5198.2	7893.38	5254	3205.32
No. Districts	346	302	346	278
Industry-District FE	x	x	x	x
Industry-Year FE	x	x	x	x
State Year time trend	x	x	x	x

Note: *The table shows the effect of temperature on manufacturing productivity. Dependent variable is log value of industry productivity. Productivity is defined as the ratio of annual gross value and total mandays in the year. Column 1 shows the impact of temperature on all industries. Column 2 reports the impact on Sugar and Oil industry as these are most common industries in India. Column 3 shows the impact of temperature on male dominated industries defined as industries with more male workers than female workers. Similarly, Column 4 reports the effect of temperature on female dominated industries. I report conley Standard errors for spatial correlation upto 1500kms. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$*

Table 3: Consumption

	Expenditure (1)	Food (2)	Manufacturing (3)	Service (4)
Panel A: Agriculture				
T	-0.0020***	0.0588***	-0.1188*	-0.0051
	(0.0001)	(0.0100)	(0.0695)	(0.0177)
P	0.0041	-0.0381***	-0.0119	0.0013
	(0.0040)	(0.0088)	(0.0143)	(0.0011)
Observations	1288	1288	1287	1288
R^2	0.77	0.59	0.53	0.82
Average	INR 5928.28	58.95%	20.59%	23.55%
Panel B: Manufacturing				
T	-0.0043***	0.0641***	0.0241	-0.0634
	(0.0011)	(0.0060)	(0.0612)	(0.0619)
P	-0.0026	-0.0037	0.0049	-0.0077***
	(0.0078)	(0.0063)	(0.0177)	(0.0006)
Observations	1236	1236	1236	1235
R^2	0.59	0.23	0.41	0.71
Average	INR 5881.49	63.80%	20.15%	31.93%
Panel C: Service				
T	0.0407***	0.0163***	0.0478	0.0825***
	(0.0000)	(0.0001)	(0.0584)	(0.0171)
P	0.0047***	-0.0073**	-0.0022	-0.0115***
	(0.0000)	(0.0032)	(0.0024)	(0.0024)
Observations	1288	1288	1288	1288
R^2	0.59	0.42	0.54	0.83
Average	INR 7102.78	58.13%	22.14%	35.54%
District FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Region-Time FE	Y	Y	Y	Y

Note: *The table shows the effect of temperature on log value of total expenditure, log value of share of expenditure on food, manufacturing goods, and services by workers working in agriculture, manufacturing, and the service sector. Panel A shows the impact of temperature on multiple expenditure categories by Agricultural workers. Panel B shows the impact of temperature on expenditure for Manufacturing sector workers, and Panel C shows estimates for service sector workers. I report Conley standard errors that allow for spatial and serial correlation upto 1500kms.* * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Panel estimates of the effect of temperature on labor share of economic sectors

	Agriculture	Manufacturing	Service
	(1)	(2)	(3)
T	0.1173***	-0.0259**	-0.0249**
	(0.0055)	(0.0121)	(0.0118)
P	0.0001	-0.0034	-0.0005
	(0.0185)	(0.0025)	(0.0168)
Observations	2177	2159	2177
R^2	0.70	0.72	0.60
$R^2 Adj.$	0.64	0.67	0.53
Average Labor Share	47.87	11.57	33.16
No. Districts	311	311	311
District FE	x	x	x
Year FE	x	x	x
Region Year time trend	x	x	x

Note: *The table shows the effect of temperature on labor share of different sectors. Dependent variable is log value of labor share in a sector-district. Labor share is defined as number of people employed in a sector in a district divided by number of people employed in a district. Column 1 shows the impact of temperature on Agricultural Labor share, Column 2 for Manufacturing, and Column 3 for Service sector labor share. I report Conley standard errors that allow for spatial and serial correlation upto 1500kms.* * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

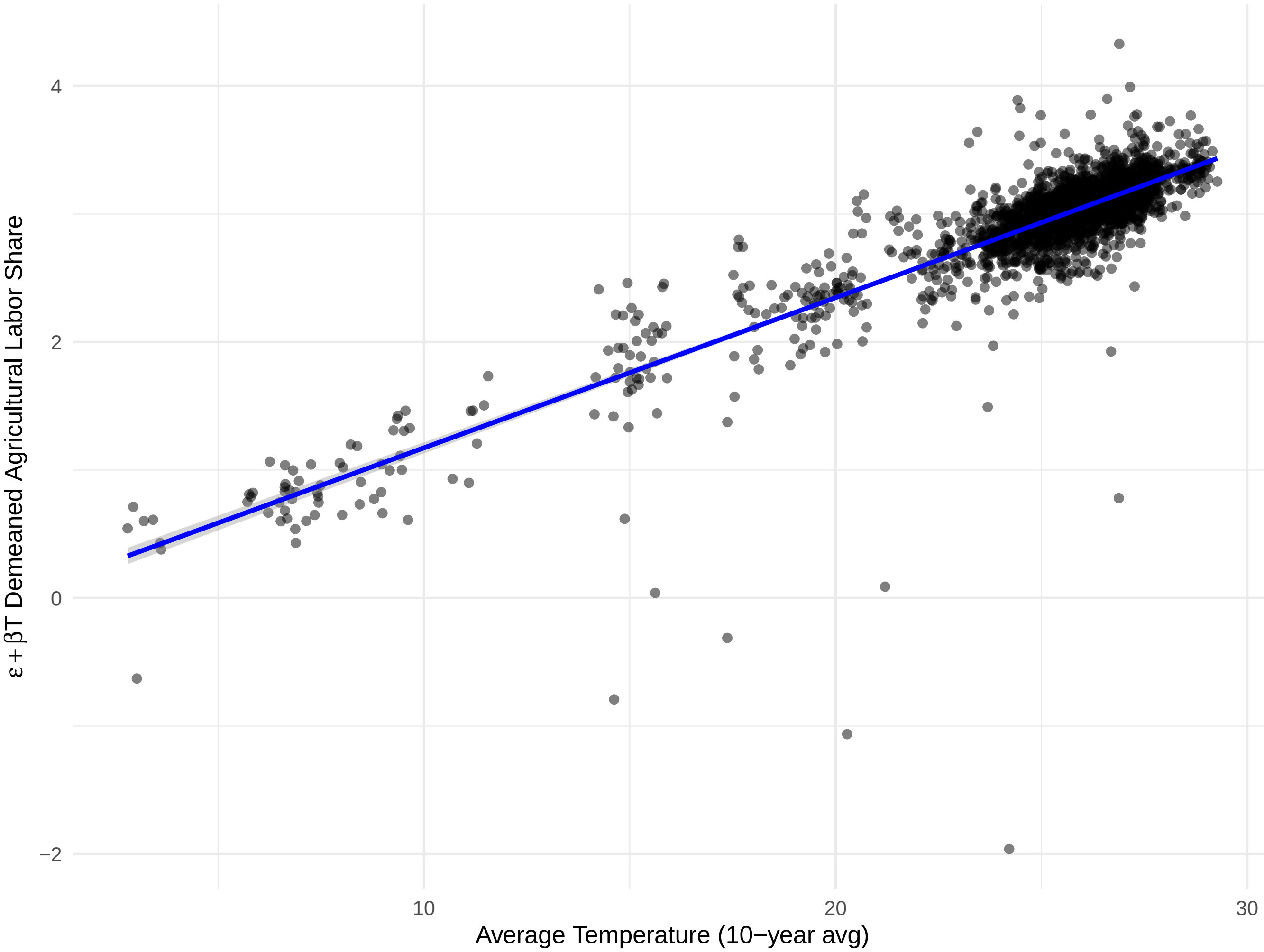

Figure 4: Agricultural Labor Share vs Decadal Average Temperature

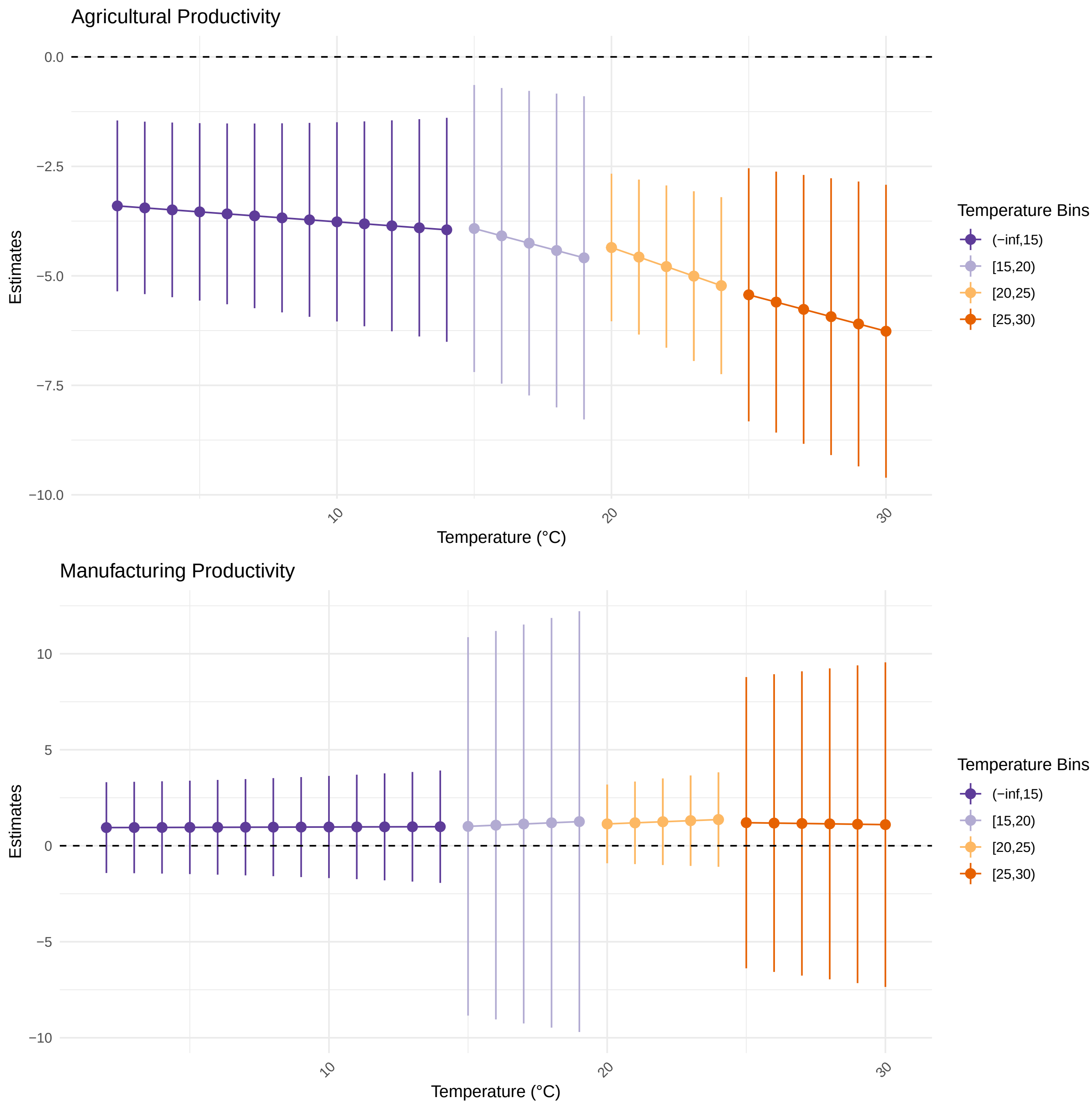

Figure 5: Heterogenous effect of temperature on sector productivity by temperature bins

Table 5: Panel estimates of the impact of market access on relationship between temperature and agricultural labor share

	Ag Labor Share (1)	Ag Labor Share (2)	Ag Labor Share (3)	Ag Labor Share (4)
T	0.0845***	0.0238**	0.0932***	0.0324**
	(0.0002)	(0.0114)	(0.0014)	(0.0143)
P	0.0237***	0.0146	0.0234***	0.0142
	(0.0088)	(0.0105)	(0.0087)	(0.0095)
$MA^{outstate}$	-0.0077***	-0.0114***		
	(0.0011)	(0.0025)		
$MA^{instate}$			-0.0405***	-0.0401***
			(0.0056)	(0.0074)
$T * MA^{outstate}$	0.0003***	0.0005***		
	(0.0000)	(0.0001)		
$T * MA^{instate}$			0.0017***	0.0016***
			(0.0004)	(0.0003)
Bank access		-0.0012		-0.0010
		(0.0008)		(0.0006)
Observations	1116	888	1116	888
R^2	0.71	0.81	0.71	0.81
$R^2 Adj.$	0.61	0.74	0.61	0.74
Average Labor Share (Ag)	51.18	51.18	51.68	51.68
Avg MA Outstate	12.13	12.13	-	-
Avg MA Instate	-	-	4.03	4.03
No. Districts	311	244	311	244
District FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Region Year time trend	Y	Y	Y	Y

Note: *The table shows the effect of temperature on agricultural labor share as mitigated/exacerbated by market access. Dependent variable is log value of labor share in agricultural sector. Column 1 shows the impact of temperature on Agricultural Labor share as altered by out-state market access, Column 2 also includes control for bank access. Column 3 reports estimates for mitigation by in-state market access, column 4 includes control for bank access. I report Conley standard errors that allow for spatial and serial correlation upto 1500kms.** $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

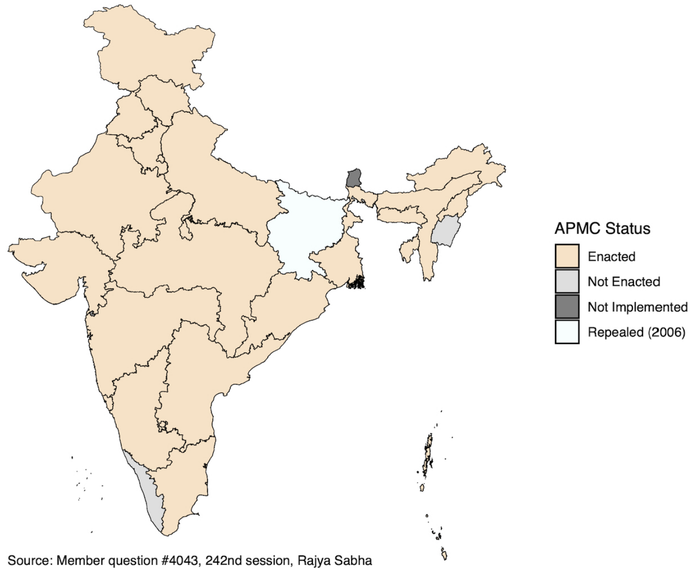

Figure 6: APMC Status

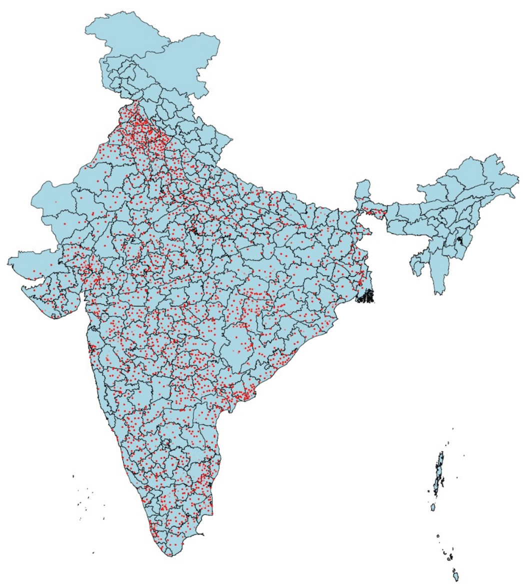

Figure 7: APMC Markets

Table 6: Panel estimates of the interactive effect of temperature and spatial competition on Agricultural Labor Share

	Ag Labor share	Ag Labor share
	(1)	(2)
T	0.1605***	0.1860***
	(0.0420)	(0.0495)
$T * comp$	-0.0118***	-0.0150***
	(0.0037)	(0.0035)
$BankAccess$		-0.0035
		(0.0070)
Observations	1927	1503
R^2	0.73	0.72
Average	48.01	52.12
District FE	Y	Y
Year FE	Y	Y
Regiontime FE	Y	Y

Note: *The table shows the effect of temperature on agricultural labor share as mitigated by spatial competition among buyers of farm produce. Spatial competition measure is created as an average of inverse distance between government designated marketplaces in a district. Column 1 reports the estimates for this estmation, column 2 reports results when bank access has been controlled for. I report Conley standard errors that allow for spatial and serial correlation upto 1500kms.* * *$p < 0.1$, ** $p < 0.05$, *** $p < 0.01$*

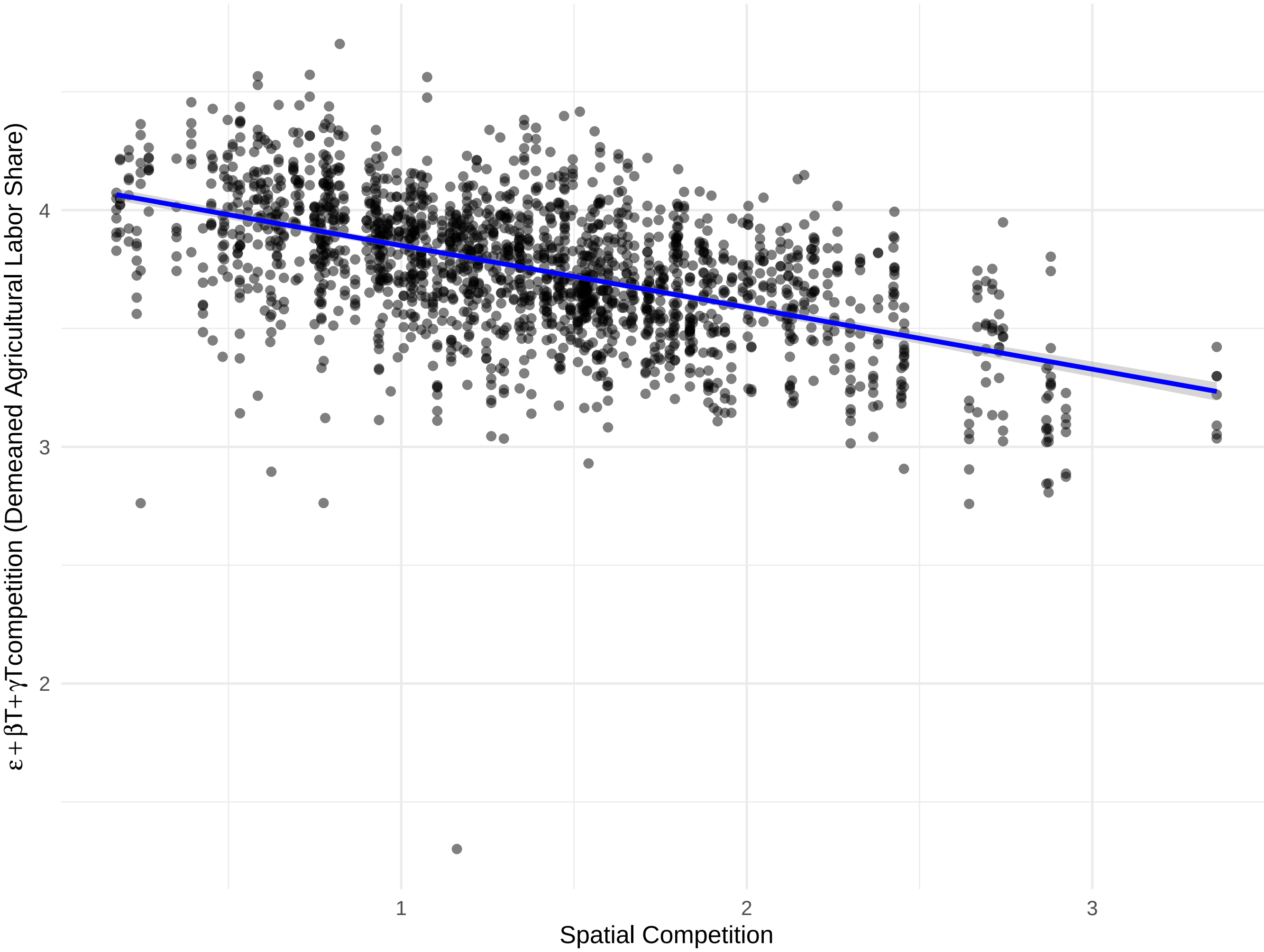

Figure 8: Agricultural Labor Share vs Spatial Competition

Table 7: Border Discontinuity

	$\Delta Price$	$\Delta LaborShare$	$\Delta LaborShare$	$\Delta LaborShare$
	(1)	(2)	(3)	(4)
$\Delta comp$	0.0406	-0.2153	-0.2016	-0.2820
	[0.0133]***	[0.0543]***	[0.0603]***	[0.0610]***
	(0.0062)***	(0.1257)*	(0.1240)	(0.1061)**
	{0.0000}***	{0.1164}*	{0.1158}*	{0.1358}**
$\Delta BankAccess$				-0.0008
				[0.0002]***
				(0.0006)
				{0.0004}**
$Heatwave$			-0.0000	
			[0.0190]	
$\Delta comp * Heatwave$			-0.0337	
			[0.0708]	
			{0.0022}***	
Observations	5117	1274	1274	1252
R^2	0.12	0.28	0.28	0.28
State Pair FE	Y	Y	Y	Y
Crop FE	Y	X	X	X

Note: *Square brackets contain heteroskedasticity robust standard errors. Curly brackets contain Conley standard errors with cutoff at 1100 kms. Round brackets are clustered.* * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

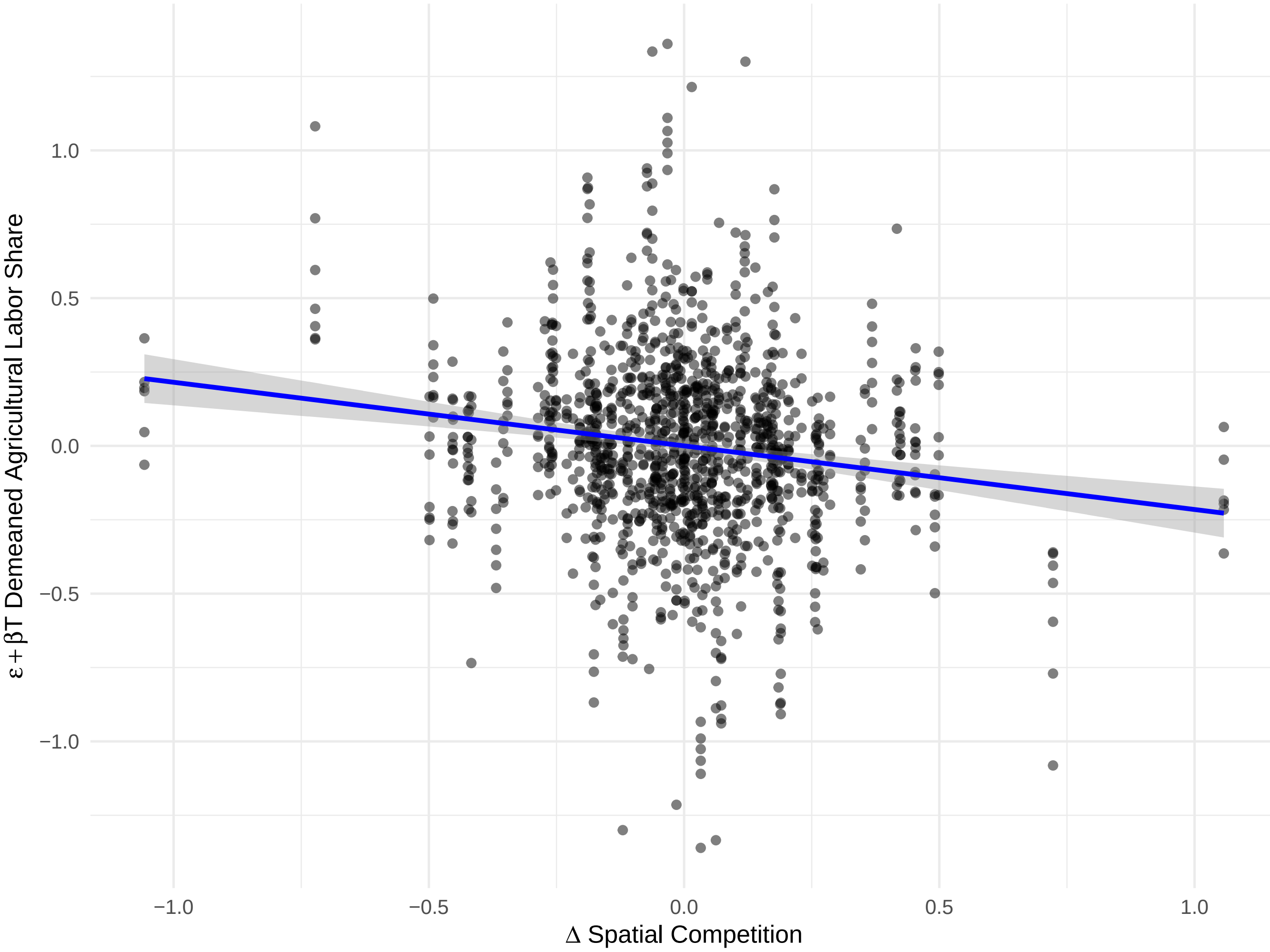

Figure 9: Agricultural Labor Share vs Spatial Competition

Table 8: Model Parameters

Parameter	Description	Value
σ	Cross-sector Elasticity of Substitution	0.27
η_a	Agriculture Utility Elasticity	0.20
η_m	Manufacturing Utility Elasticity	1.00
γ_a	Agriculture Taste Parameter	1.76
γ_m	Manufacturing Taste Parameter	1.00
θ_a	Agriculture Trade Elasticity	4.06
θ_m	Manufacturing Trade Elasticity	4.63

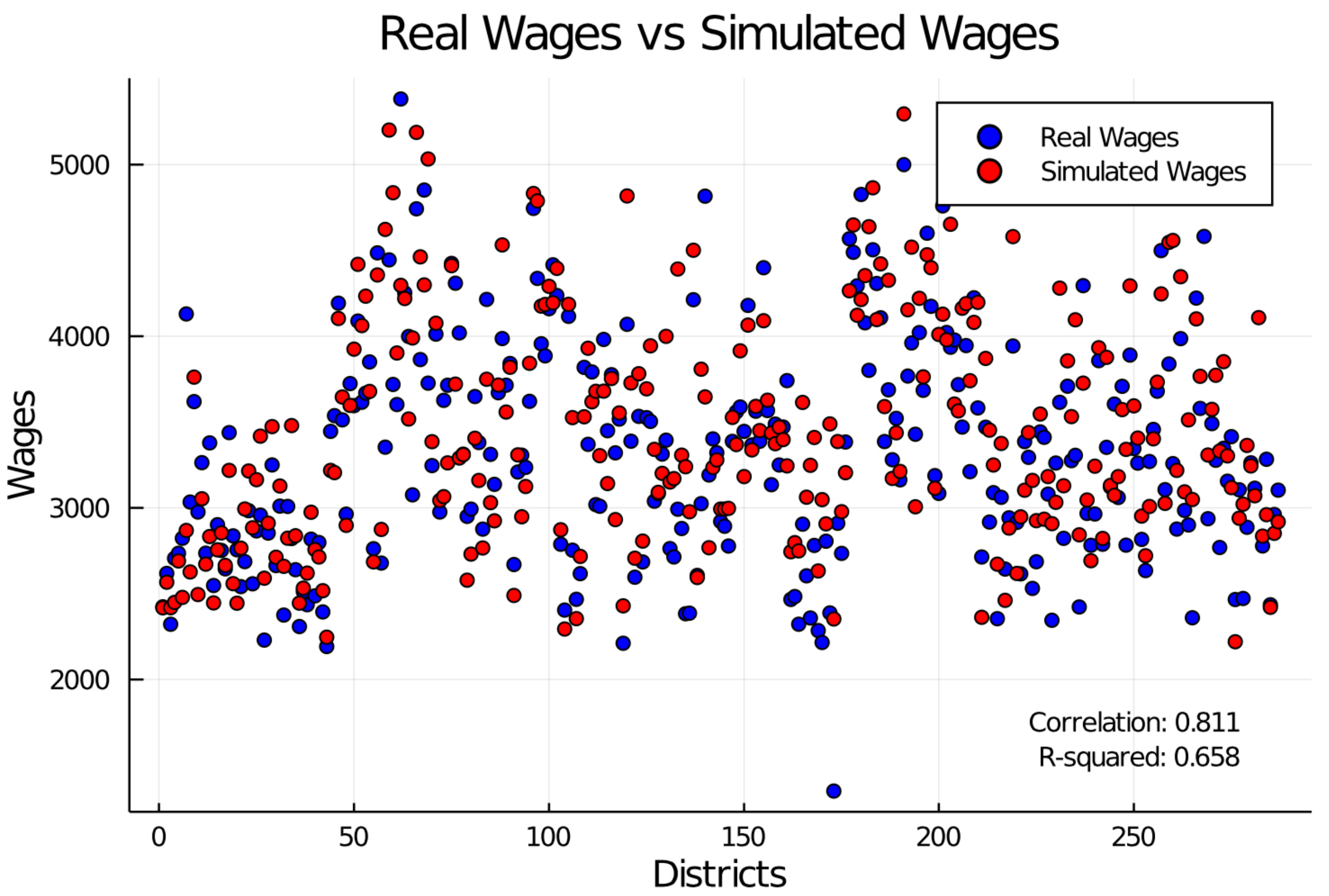

Figure 10: Model Fit

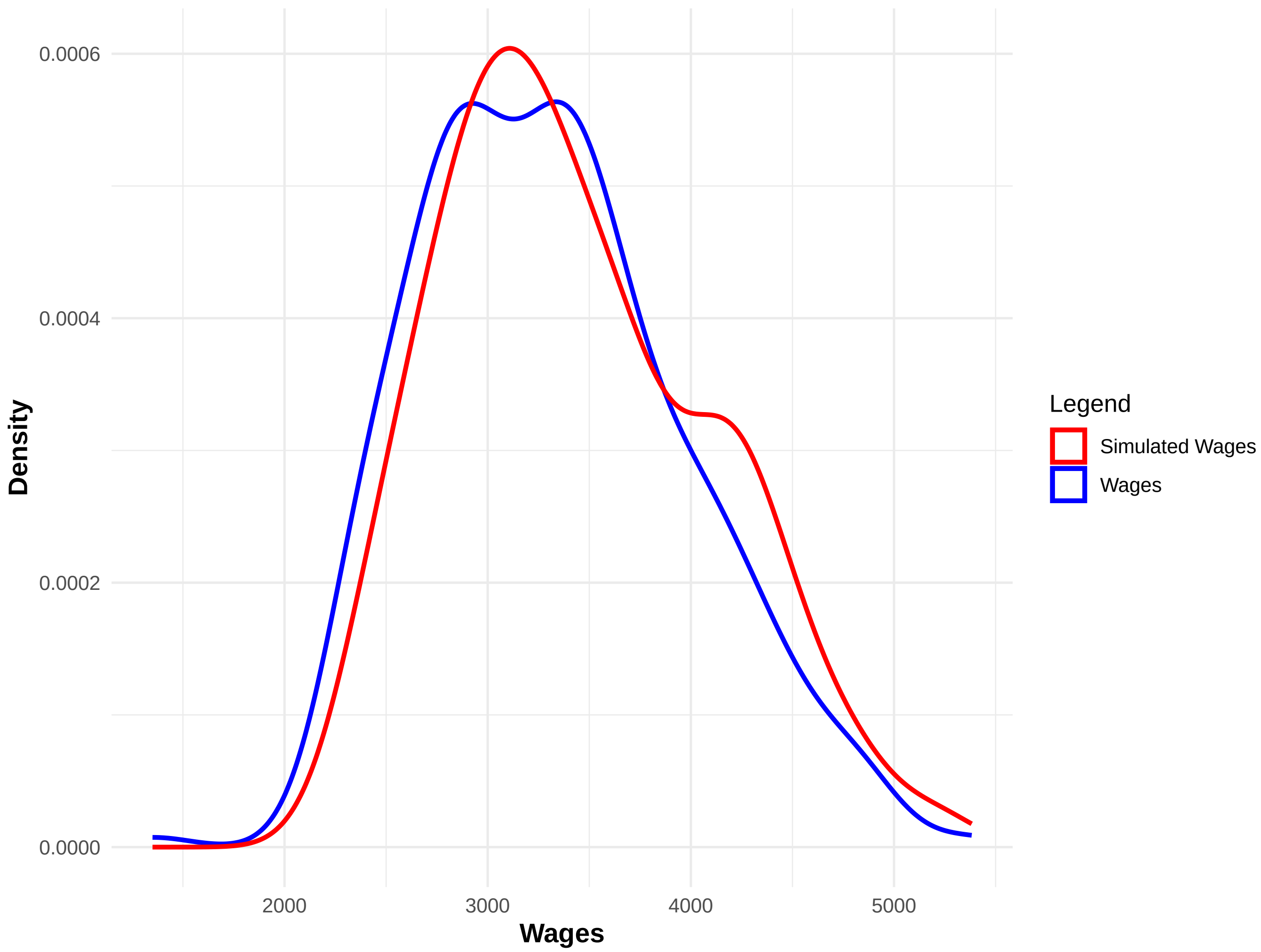

Figure 11: Density Plot

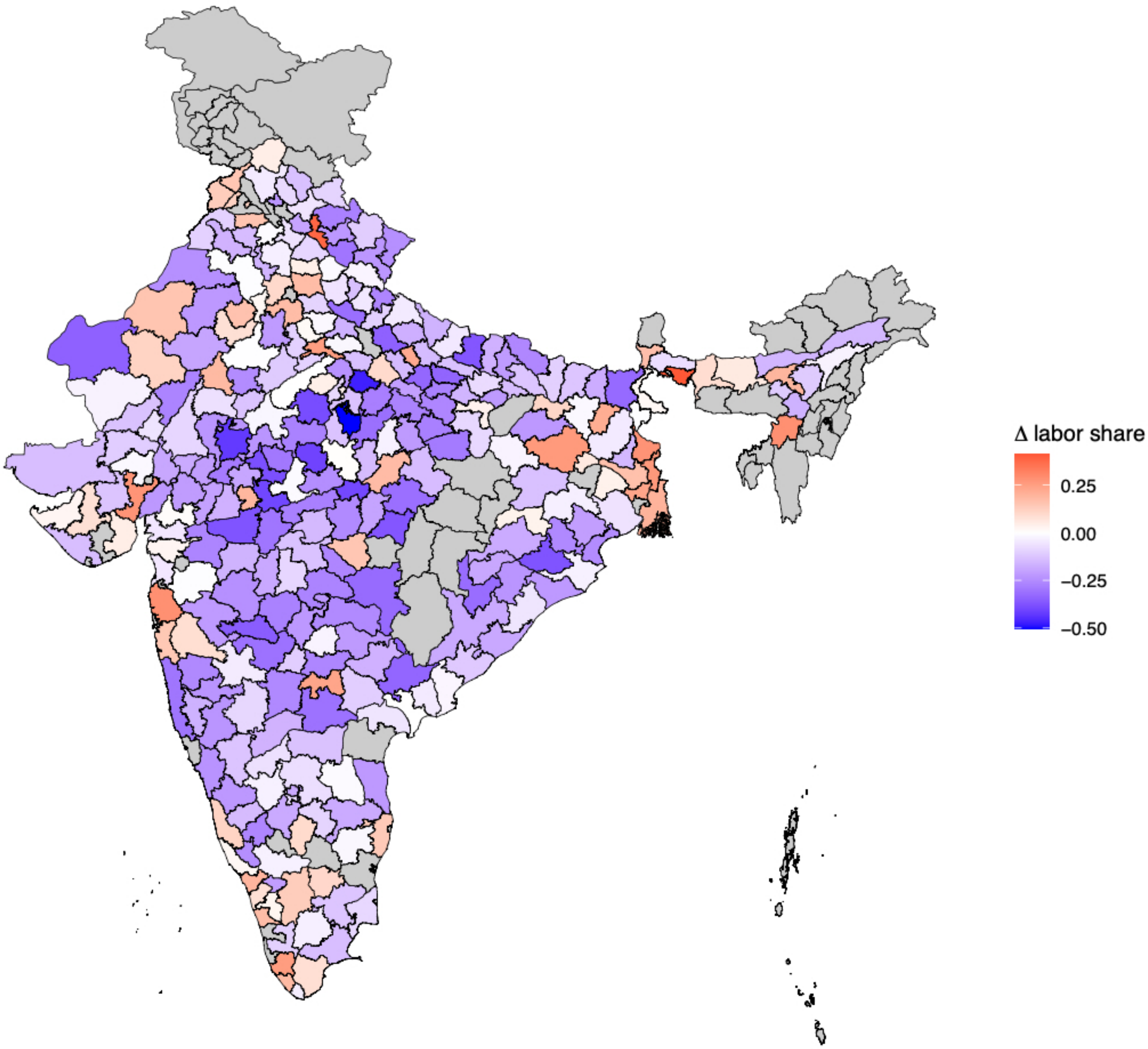

Figure 12: Counterfactual: No internal trade barriers

A Appendix

A.1 Additional Figures and Tables

Table A1: Sector Composition

S.no	KLEMS Code	Description	Sector
1	A+B	Agriculture, Forestry, and Fishing	Agriculture
2	15 to 16	Food, Beverages and Tobacco	Manufacturing
3	17 to 19	Textiles, Textile Products and Leather and Footwear	Manufacturing
4	20	Wood and Cork	Manufacturing
5	21 to 22	Pulp, Paper, Paper Products, Printing and Publishing	Manufacturing
6	23	Coke, Refined Petroleum and Nuclear Fuel	Manufacturing
7	24	Chemicals and Chemical Products	Manufacturing
8	25	Rubber and Plastics	Manufacturing
9	26	Other Non-Metallic Mineral	Manufacturing
10	27 to 28	Basic Metals and Fabricated Metal Products	Manufacturing
11	29	Machinery	Manufacturing
12	30 to 33	Electrical and Optical Equipment	Manufacturing
13	34 to 35	Transport Equipment	Manufacturing
14	36 to 37	Manufacturing and Recycling	Manufacturing
15	G	Trade	Services
16	60 to 63	Transport and Storage	Services
17	H	Hotels and Restaurants	Services
18	64	Post and Telecommunications	Services
19	J	Financial Intermediation	Services
20	L	Public Admin, Defense and Compulsory Social Security	Services
21	M	Education	Services
22	N	Health and Social Work	Services
23	70OP	Other Services	Services
24	71 to 74	Scientific R&D, Architecture, Engineering, Advertising	Services

Table A2: Agriculture Output

	All crops	MSP crops	Main crop	Rice & Wheat
	(1)	(2)	(3)	(4)
T	-0.0889***	-0.0878***	-0.1041***	-0.0322***
	(0.0043)	(0.0038)	(0.0368)	(0.0105)
P	0.0104***	0.0105***	0.0162***	0.0169***
	(0.0037)	(0.0040)	(0.0007)	(0.0033)
Observations	58855	54427	4610	9071
R^2	0.82	0.82	0.90	0.86
$R^2 Adj.$	0.81	0.81	0.88	0.85
Average Output (ton/hectare)	1.06	1.11	1.69	1.86
No. Districts	240	240	240	240
Crop-District FE	x	x	x	x
Crop-Year FE	x	x	x	x
State Year time trend	x	x	x	x

Note: *Agricultural output is a fraction of yield and area for each crop-district-year pair * p < 0.1, ** p < 0.05, *** p < 0.01*

Table A3: Manufacturing Wages

	All Ind.	Sugar & Oils	Male Dominated	Female Dominated
	(1)	(2)	(3)	(4)
T	0.0108***	-0.0064	0.0108***	0.0172**
	(0.0017)	(0.0246)	(0.0017)	(0.0086)
P	-0.0149	-0.0261*	-0.0151	-0.0035
	(0.0111)	(0.0137)	(0.0108)	(0.0233)
Observations	53650	1840	52184	1466
R^2	0.74	0.68	0.73	0.79
$R^2 Adj.$	0.57	0.56	0.56	0.64
Average Wages (INR)	220.94	209.07	223.16	141.6
No. Districts	346	302	346	278
Industry-District FE	x	x	x	x
Industry-Year FE	x	x	x	x
State Year time trend	x	x	x	x

Note: *Wages per manday. Conley standard errors up to 1500kms * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$*

Service Sector data: The data used for following estimation is sourced from Zomato, India's largest food delivery service platform. Zomato employs between 700,000 to 1 million food delivery personnel across the country. The dataset is a sample of all food deliveries that occured in major cities of India during March, 2022. The dataset includes detailed information about each delivery, such as the time taken to complete the delivery, the rating received by the driver, the type pf meal ordered (categorized as breakfast, lunch, dinner, or snack), and the delivery personnel's unique ID. Additionally, the dataset captures the delivery person's vehicle type and its condition, whether the delivery occured during a local festival, traffic density at the time, whether multiple deliveries were made simultaneously, and the city where the order took place.

Table A4: Service Productivity

	Time Taken	Rating
	(1)	(2)
T	0.0023*	-0.0002
	(0.0008)	(0.0002)
P	0.0024***	0.0001
	(0.0004)	(0.0002)
Observations	30845	29929
R^2	0.37	0.03
$R^2 Adj.$	0.37	0.03
Average	26.29	4.64
Order Type FE	x	x
Vehicle Condition FE	x	x
Vehicle Type FE	x	x
City FE	x	x
Driver FE	x	x

Note: *The table shows the effect of temperature on service sector productivity. Dependent variable in Column 1 is log of time taken to complete a delivery by a delivery driver. Dependent variable in Column 2 is log of rating received from the customer for that order delivery. Each regression includes controls for precipitation, traffic density on roads, if the day was observed as religious festival in the city, and if the driver was completing multiple deliveries in a ride.* * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

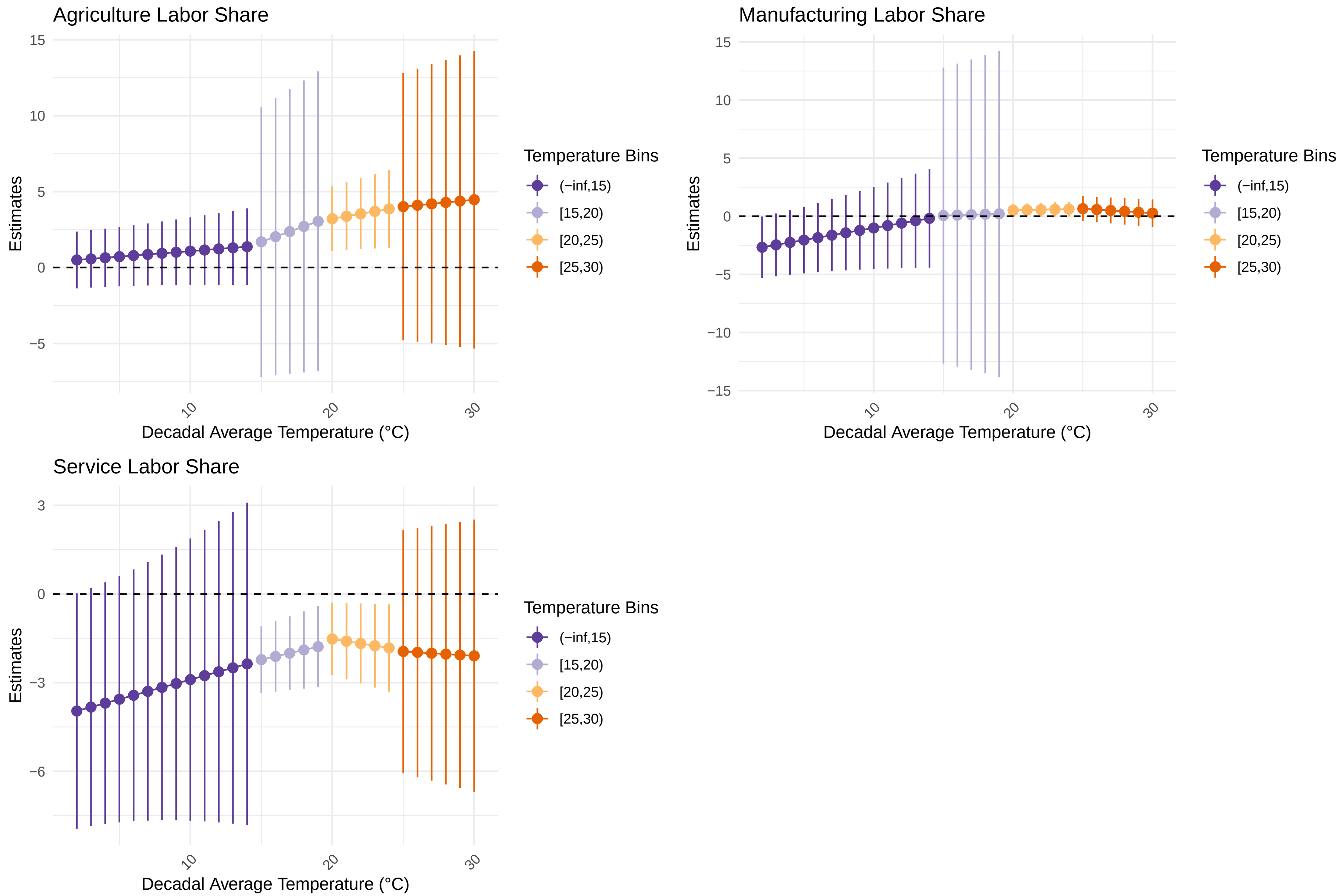

Figure A1: Heterogenous effect of temperature on Labor Share of Economic Sectors by temperature bins

A.2 Model Derivation

A.2.1 Worker cost minimization problem

$$w_{nk}L_{nk} = min \sum_{\tilde{k}}^{K} p_{n\tilde{k}} C_{nk}^{\tilde{k}}$$

subject to utility constraint

$$\sum_{\tilde{k}} (\gamma^{\tilde{k}})^{1/\sigma} C_{nk}^{\eta_{\tilde{k}}/\sigma} (C_{nk}^{\tilde{k}})^{\frac{\sigma-1}{\sigma}} = 1$$

The parameter $\gamma^{\tilde{k}}$ is the fixed sectoral taste of a good, σ is the elasticity of substitution between goods of each sector, and $\eta_{\tilde{k}}$ is the sector specific income elasticity.

$$\mathcal{L} = \sum_{\tilde{k}}^{K} p_{n\tilde{k}} C_{nk}^{\tilde{k}} + \lambda \left[1 - \left(\sum_{\tilde{k}} (\gamma^{\tilde{k}})^{1/\sigma} (C_{nk})^{\eta_{\tilde{k}}/\sigma} (C_{nk}^{\tilde{k}})^{\frac{\sigma-1}{\sigma}} \right) \right]$$

$$\frac{\partial \mathcal{L}}{\partial C_{nk}^{\tilde{k}}} = p_{n\tilde{k}} - \lambda (\gamma^{\tilde{k}})^{1/\sigma} (C_{nk})^{\eta_{\tilde{k}}/\sigma} (C_{nk}^{\tilde{k}})^{-1/\sigma} = 0$$

$$\frac{\partial \mathcal{L}}{\partial \lambda} = 1 - \left(\sum_{\tilde{k}} (\gamma^{\tilde{k}})^{1/\sigma} (C_{nk})^{\eta_{\tilde{k}}/\sigma} (C_{nk}^{\tilde{k}})^{\frac{\sigma-1}{\sigma}} \right) = 0$$

$$p_{n\tilde{k}} = \lambda (\gamma^{\tilde{k}})^{1/\sigma} (C_{nk})^{\eta_{\tilde{k}}/\sigma} (C_{nk}^{\tilde{k}})^{-1/\sigma} \tag{10}$$

$$p_{n\hat{k}} = \lambda (\gamma^{\hat{k}})^{1/\sigma} (C_{nk})^{\eta_{\hat{k}}/\sigma} (C_{nk}^{\hat{k}})^{-1/\sigma} \tag{11}$$

Taking ratio of Equation 10 and Equation 11 results in derivation of optimality condition between consumption $C_{nk}^{\tilde{k}}$ and $C_{nk}^{\hat{k}}$

$$C_{nk}^{\tilde{k}} = \frac{\gamma^{\hat{k}}}{\gamma^{\tilde{k}}} C_{nk}^{\eta_{\hat{k}} - \eta^{\tilde{k}}} \left(\frac{p_{n\hat{k}}}{p_{n\tilde{k}}} \right)^{\sigma} C_{nk}^{\hat{k}}$$

Rewriting Equation 10 gives us optimal $C_{nk}^{\tilde{k}}$

$$C_{nk}^{\tilde{k}} = \left(\frac{\lambda}{p_{n\tilde{k}}}\right)^{\sigma} \gamma^{\tilde{k}} C_{nk}^{\eta_k} \tag{12}$$

I then use the utility function to derive the Hicksian demand,

$$\sum_{\tilde{k}} (\gamma^{\tilde{k}})^{1/\sigma} C_{nk}^{\eta_{\tilde{k}}/\sigma} \left[\left(\frac{\lambda}{p_{n\tilde{k}}}\right)^{\sigma} \gamma^{\tilde{k}} C_{nk}^{\eta_{\tilde{k}}} \right]^{\frac{\sigma-1}{\sigma}} = 1$$

$$\lambda = \left(\sum_{\tilde{k}} \gamma^{\tilde{k}} C_{nk}^{\eta_{\tilde{k}}} p_{n\tilde{k}}^{1-\sigma} \right)^{\frac{\sigma}{1-\sigma}}$$

substituting λ back in to optimal consumption

$$C_{nk}^{\tilde{k}} = \left(\sum_{\tilde{k}} \gamma^{\tilde{k}} C_{nk}^{\eta_{\tilde{k}}} p_{n\tilde{k}}^{1-\sigma} \right)^{\frac{\sigma}{1-\sigma}} \frac{\gamma^{\tilde{k}} C_{nk}^{\eta_{\tilde{k}}}}{p_{nk}^{\sigma}}$$

expenditure function:

$$E_{nk} = \sum_{\tilde{k}=1}^{k} p_{n\tilde{k}} C_{nk}^{\tilde{k}}$$

substituting optimal consumption in above equation gives minimum cost expenditure

$$E_{nk} = w_{nk} L_{nk} = \sum_{\tilde{k}=1}^{K} \left(\gamma^{\tilde{k}} C_{nk}^{\eta_{\tilde{k}}} p_{nk}^{1-\sigma} \right)^{\frac{1}{1-\sigma}}$$

rewriting consumption and consumption shares

$$C_{nk}^{\tilde{k}} = \gamma^{\tilde{k}} C_{nk}^{\eta_{\tilde{k}}} \left(\frac{E_{nk}}{p_{n\tilde{k}}} \right)^{\sigma}$$

$$s_{nk}^{\tilde{k}} = \frac{p_{n\tilde{k}} C_{nk}^{\tilde{k}}}{E_{nk}}$$

$$s_{nk}^{\tilde{k}} = \gamma^{\tilde{k}} C_{nk}^{\eta_{\tilde{k}}} \left(\frac{p_{n\tilde{k}}}{w_{nk} L_{nk}} \right)^{1-\sigma}$$