Spatial Implications of Industrial Policy

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Industrial policies, such as sector-specific production subsidies, can have an uneven effect across regions within a country. We use a multi-sector, multi-region quantitative trade model with input-output linkages calibrated to Indian manufacturing data to analyze the spatial impact of such policies. Our counterfactual 1 percent subsidy reveals highly uneven real-wage effects with different regions affected by different sectoral policies. We show that Pareto improving gains are possible through budget-neutral sectoral subsidies in the presence of trade costs and immobile labor. The magnitude of gains and losses is shaped by the geography of the targeted sectors.

Keywords: industrial policies, spatial economic analysis, input-output models
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1 — Introduction

Industrial Policies - incentives given by governments to target specific sectors or regions - are being widely used across developed and developing countries. Most of the existing research on industrial policy is reduced form in nature, and do not shed light on the general equilibrium effects that occur due to trade links. Given the complex nature of modern supply chains, which span over many regions where sectors are connected vertically and horizontally through input-output networks, it becomes essential to understand the spatial implications of industrial policies. In this paper, we take a step in that direction.

We begin by showing that in the presence of an immobile labor, the competitive market equilibrium is not Pareto optimal and identify the first-best policies that a planner could implement to overcome this market failure. Using a quantitative spatial general equilibrium model calibrated to Indian data, we compute these first-best lump-sum transfers. Next, we examine how far second-best policies, in the form of subsidies given to certain industries, can bring the decentralized equilibrium close to the planner's solution. We find that although subsidies to different industries have different effects on aggregate welfare, a substantial gap still remains between the equilibrium and the optimum. Finally, we argue that subsidies targeted towards specific regions and industries can bring the equilibrium close to the first-best.

Following Caliendo et al. (2018), we build a quantitative trade model with heterogeneous regions, multiple sectors with cross-sectoral links, and costly trade. The cross-sector links capture the interconnectedness of different sectors in the production network, and the heterogeneous regions that differ in their productivity and labor supply, populate the geography upon which production and trade occur. We calibrate our model using Indian manufacturing data and solve for the equilibrium before proceeding to compute optimal policies and perform counterfactual analysis for various policy scenarios. Solving the equilibrium is essential to our paper, as India and many other developing countries lack the necessary internal trade data to populate trade share matrices used in quantitative trade analysis[1].

With the calibrated model, we compute optimal subsidies and counterfactually compare these

1. For example, the United States has the Commodity Flow Survey, and the ROHMLO database provides multiregion input-output tables for the European Union

optimal subsidies with different policy scenarios, such as (1) place blind industrial subsidies, (2) industry blind place based subsidies. We show counterfactual analysis in which each sector is provided with a 1% subsidy and compute the changes in real wages across different regions, which is our primary variable of interest. While a subsidy to certain industries raises aggregate welfare, the effect on real wages is highly non-uniform across space. The change in real wages across different regions shows that the gains are not uniform, and the scale of these changes also varies by the targeted sectors. These differential gains highlight the potential inequality stemming from place-blind industrial subsidies, further illustrating the limitations of place-blind industrial policies in generating aggregate gains without exacerbating spatial inequality.

We show that simple place-blind industrial subsidies and industry-blind place-based subsidies create an equity-efficiency tradeoff and, therefore, the planner with the objective of increasing aggregate welfare is unable to overcome the Pareto frontier using these simple policy tools. Finally, we show that place-based industrial policy targeted towards certain region-industry pairs with low real wages and high specialization (measured by the Location Quotient) yields Pareto gains, overcoming the equity-efficiency trade-off. Within the literature, the rationale for using Place-Based Industrial Policies (PBIP) is that agglomeration elasticities are non-uniform across space; hence, the optimal policy varies across space. We show that even in the absence of increasing returns to scale, which generate the heterogeneous agglomeration elasticities, there is a need for PBIP due to immobile labor, and the underlying industry productivities being independent of labor distribution across space.

This paper is related to two distinct strands of literature. Firstly, this study contributes to the recent and growing literature analyzing the ex-post effects of industrial policies and their mechanisms in various contexts as surveyed by Juhász, Lane, and Rodrik (2024). Bartelme et al. (2025) empirically tests the textbook case of industrial policies, which is increasing returns to scale, and finds that industrial policies do not yield transformative results at a country level, but calls for analysis using granular settings, which we do in this paper. Within the context of international trade, Lashkaripour and Lugovskyy (2023) show that deep trade agreements and related industrial policy tools can be used to correct for within-country misallocation. At a country level, Lane (2025) and Barwick, Kalouptsidi, and Zahur (2025) analyze the historical episodes of industrial policies in South Korea and China, respectively, and show the long-term effects of industrial policy interventions. Incorporating production networks and related distortions, Liu (2019) developed a distortion centrality measure that can be used to rank industries that could be targeted with subsidies to increase an economy's overall efficiency. We contribute to this literature on industrial policies by considering the rich spatial heterogeneity of production within the country (India) and thereby characterizing the optimal policy by taking into account all the general equilibrium effects.

Finally, our modeling approach is closely associated with the spatial economics literature made possible by the theoretical contributions of Eaton and Kortum (2002), Allen and Arkolakis (2014), and Allen, Arkolakis, and Li (2024). The model presented here closely aligns with Caliendo et al. (2018), which studies the spatial equilibrium effect of productivity shocks for the US economy. Atalay et al. (2023) is closely related to our paper as it evaluates both short-term and long-term effects of place-based industrial policies in Turkey, using a model similar to ours (Caliendo, Dvorkin, and Parro 2019). Magerman and Palazzolo (2024) is closest to our work, which computes the gains across EU regions for different policy instruments: trade, industrial, and public policy. Within the spatial economics literature, we contribute to the discussion on optimal spatial policies that yield optimal welfare outcomes, as surveyed by Fajgelbaum and Gaubert (2025). Our contribution lies in further modeling the input-output linkages within a spatial economic model with immobile labor and trade links and numerically computing optimal policies. Further within the spatial & trade analysis context, we add to the growing literature that employs quantitative trade models to study issues related to Indian internal trade (Donaldson 2018; Asturias, García-Santana, and Ramos 2019; Van Leemput 2021; Allen and Atkin 2022).

The remainder of this essay is structured as follows: Section 2 briefly highlights the relevance of geography for Indian manufacturing, followed by Section 3, which describes the quantitative model and presents the equilibrium. Section 4 describes the data and the calibration strategy used to populate different structural parameters of the model. Section 5 describes the counterfactual scenarios and the results of these scenarios. Section 6 concludes with a brief discussion and talks about future work.

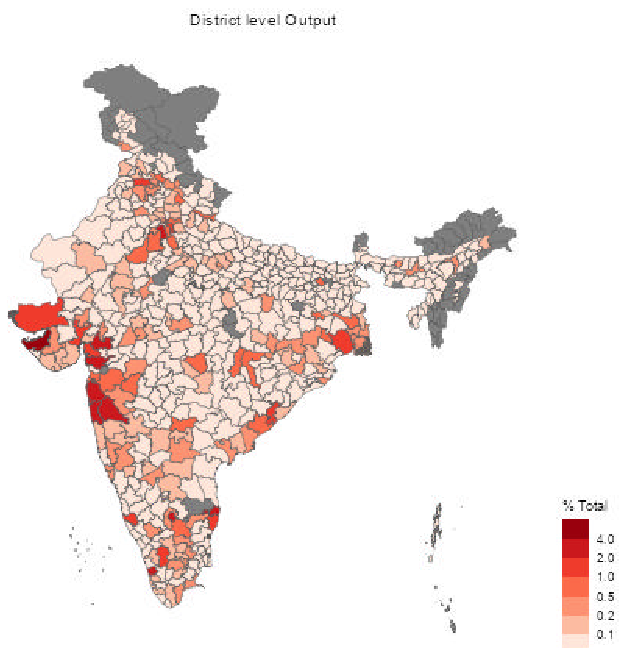


Figure 1 — Share of output by district

Notes. Using Annual Survey of Industries 2006-2010, each district's total output share is shown here. The grey districts are excluded from the analysis.

2 — Geography of Indian Manufacturing

The role of geography is highly relevant in the Indian scenario, as it is characterized by highly uneven spatial patterns. As shown in fig-1, most of the output is concentrated in a select few districts, which are not uniformly distributed across the country. Further, the output of the metal sector (upstream) is heavily concentrated in the eastern region; in contrast, the automobile sector(downstream), which relies heavily on metals, is located elsewhere (see fig-2). There could be numerous reasons that could have caused this heterogeneity, which we do not delve into. We take these distributions of economic activity as given, characterise the optimal policies given these distributions, and conduct counterfactual analysis.

To further highlight the high heterogeneity of industrial locations, we use the Location Quotient (LQ) used in regional science literature. The LQ analysis strengthens our argument by showing high levels of specialization and clustering of industries in specific regions. The location quotient of the district-sector pair (i, s) is defined as

$$LQ_i^s = \frac{Y_i^s / \sum_s Y_i^s}{\sum_i Y_i^s / \sum_{i,s} Y_i^s},$$

Where Y_i^s represents the output of a sector-s in district-i. A high LQ (>1) indicates greater specialization of a particular region in a sector relative to the country as a whole. From fig-3, it can be seen that the eastern regions specialize in metal manufacturing, whereas a few districts in the north, south, and west specialize in the manufacturing of automotive goods. Further, Lall and Chakravorty (2005) argue that the spatial inequality of industry location is the leading cause of spatial inequality of wage and competitiveness. The highly uneven spatial distribution of economic activity, coupled with clusters of high specialization, makes it important to study the spatial impacts of industrial policies within the Indian context.

Another distinct feature of the Indian economy is the lack of labor mobility. Although developing countries in general have low labor mobility, India stands out with exceptionally low labor mobility due to the presence of informal insurance and caste-based networks (Munshi and Rosenzweig 2016). As shown by Kone et al. (2018), the cross-district[2] migration rate in India

2. Districts are the lowest administrative structure in India

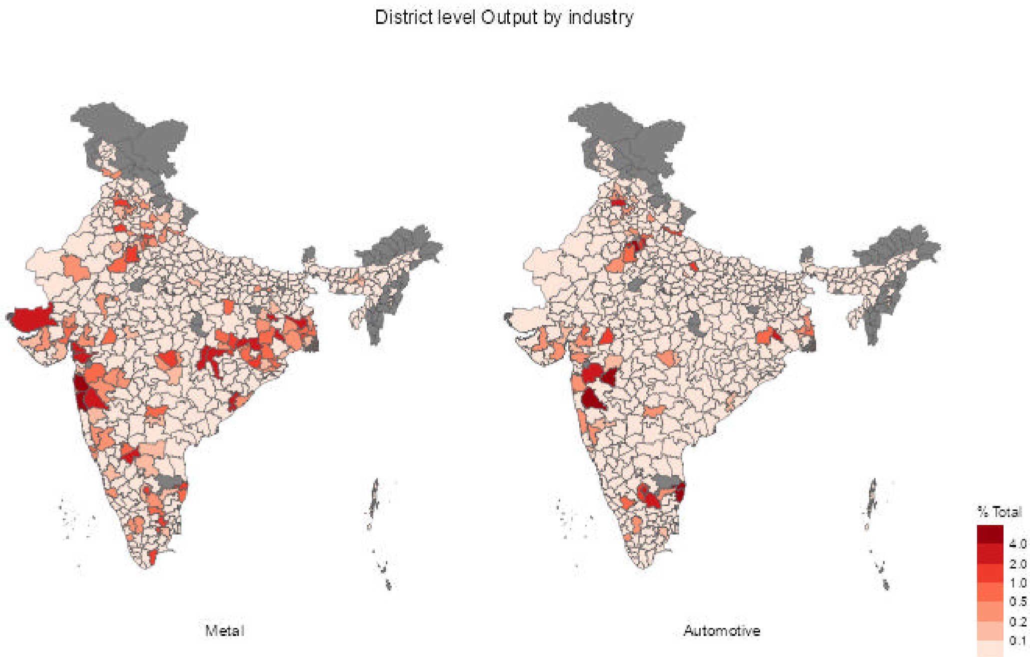


Figure 2 — Share of output by district by sector

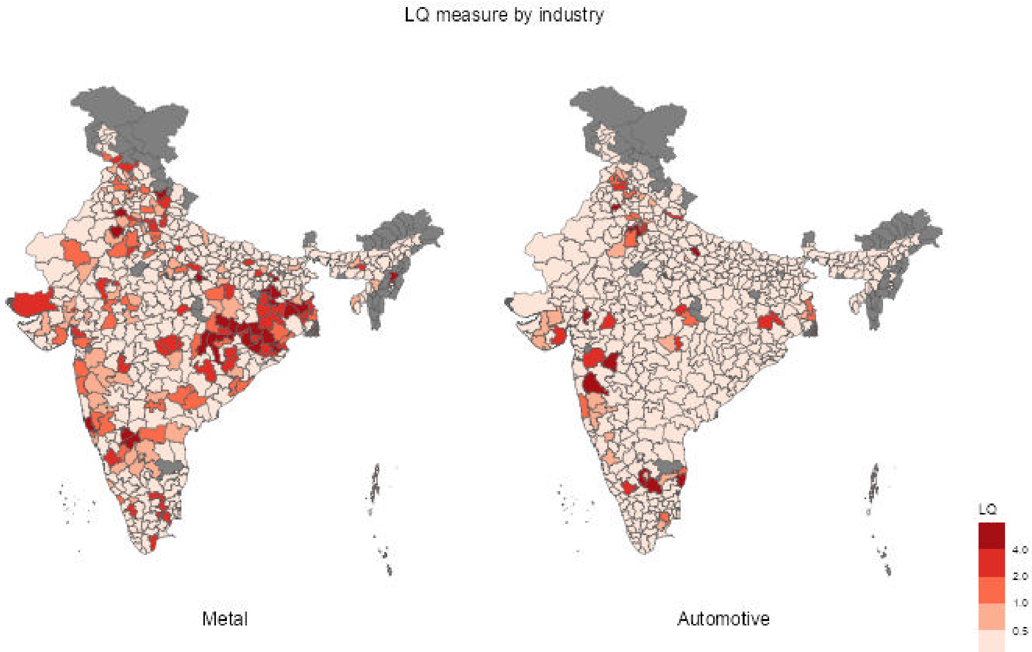
Notes. Using Annual Survey of Industries 2006-2010, each district's total output share is shown here. The right panel is for the automotive manufacturing sector, and the left is for the metal manufacturing sector. The grey districts are excluded from the analysis.

is approximately 2.8%, while similar statistics for Brazil, China, and the USA are 9%, 9.9%, and 20.3%, respectively. This low labor mobility further hinders spatial convergence, exacerbating the inequality produced by the uneven industry location.

3 — Model

Our goal is to develop a quantitative model of the Indian economy, disaggregated by region (district) and sector. For this purpose, we develop a static one-factor model with labor as the only factor, and the economy consists of N regions and S sectors. We index region by $i \in \{1, 2, \ldots, N\}$ and sectors by $s \in \{1, \ldots, S\}$. Labor is immobile across regions; hence, each region's labor supply is inelastic. Within each region, labor is freely mobile across sectors.

Figure 3 — Location Quotients



3.1. Consumers

Consumers in each region $i \in \{1, \ldots, N\}$ maximize their utility from consumption of final goods with a Cobb-Douglas utility structure, given by

$$U_i = \prod_{s=1}^{S} (c_i^s)^{\alpha_s} \quad \text{where} \sum_{s=1}^{S} \alpha_s = 1 \tag{1}$$

α_s denotes the share of consumption for the final domestic good of sector-s. P_i^s denotes the price of the final domestic good of sector-s in region-i. The budget constraint for a representative consumer in region-i is given by

$$\sum_{s=1}^{S} P_i^s \, c_i^s = w_i$$

where c_i^s is the per-capita consumption of the final good from sector-s in region-i.

Wage[3] is the only source of income for consumers and is equalized across the sectors in a

3. The planner may choose to tax the wage income to fund the subsidies to manufacturing or other transfers

region. As the labor is immobile across regions, the real wage ω_i is not equal across regions and is given by

$$\omega_i = \mathcal{C} w_i \left(\prod_{s=1}^{S} (P_i^s)^{-\alpha_s} \right), \quad \text{where } \mathcal{C} = \prod_{s=1}^{S} {\alpha_s}^{\alpha_s} \tag{2}$$

3.2. Technology

Our model comprises a continuum of intermediate goods producers and a final good producer within each region-sector pair. Final goods are used for domestic consumption and the production of other intermediate goods in a roundabout fashion[4]. Final goods of a sector are formed by aggregating the intermediate good varieties sourced from the least-cost producer.

3.2.1. Intermediate Goods

Each sector-s has a continuum of intermediate good varieties-z, and each region receives idiosyncratic productivity corresponding to these varieties. For any intermediate good of variety z^s belonging to sector-s, the vector of productivity draws in all regions is given as $z^s = (z_1^s, z_2^s, \ldots, z_N^s)$. The distribution of these productivity draws will be explained later below. The production function corresponding to variety-z^s in region-i is given by

$$q_i^s(z_i^s) = z_i^s \; [l_i^s(z_i^s)]^{\gamma^s} \prod_{k=1}^{S} \left[M_i^{sk}(z_i^s) \right]^{\gamma^{sk}} \tag{3}$$

where z_i^s denotes the productivity of producing variety-z^s in region-i; $l_i^s(.)$ and $M_i^{sk}(.)$ denote the labor demand and material demand from sector-k respectively. $\gamma_i^{sk} \geq 0$ is the cost share spent on materials from sector-k, and $\gamma^s \geq 0$ is the labor share. We assume constant returns to scale, i.e $\sum_{k=1}^{S} \gamma^{sk} = 1 - \gamma^s$.

Let ς_i^s be the unit cost of the input bundle needed to produce intermediate good varieties in

across space.

4. Following Caliendo et al. (2018), we refer to final goods used in producing intermediate goods as 'materials' and the intermediate goods used in producing final goods as 'intermediates'.

region-sector pair (i, s),

$$\varsigma_i^s = (1 + t_i^s)\, \lambda_i^s\, [w_i]^{\gamma^s} \prod_{k=1}^{S} \left[P_i^k\right]^{\gamma^{sk}} \tag{4}$$

where $\lambda_i^s = [\gamma_i^s]^{-\gamma^s} \prod_{k=1}^{S} \left[\gamma_i^{sk}\right]^{-\gamma^{sk}}$. $t_i^s < 0$ ($t_i^s > 0$) denotes the subsidy given (tax levied) by the government for every unit of intermediate good produced in region-i and sector-s. The unit cost of producing intermediate goods with idiosyncratic productivity draw z_i^s in (i, s) will be given by

$$\frac{\varsigma_i^s}{z_i^s}.$$

Intermediate good firms operating in (i, s) with idiosyncratic productivity draw z_i^s will produce the variety only when its equilibrium prices match or exceed this cost. This means that the intermediate good producers of a variety exist in a region-sector pair if and only if they are the least-cost producer for some final good producer. The equilibrium price will be determined competitively as the least-cost supplier of any particular variety in a given region.

3.2.2. Final Goods

Final goods producers in sector-s are CES aggregators of intermediate goods sourced from the least-cost producer. The final goods are not tradable and are used as materials by the intermediate goods producers or consumed by the consumers. The production of final goods is given by

$$Q_i^s = \left[\int \tilde{q}^s(z^s)^{\frac{\eta-1}{\eta}}\, dz^s\right]^{\frac{\eta}{\eta-1}} \tag{5}$$

where $\tilde{q}^j(z^j)$ denotes the quantity demanded of an intermediate good of a given variety, and the price of this final good in region-n is given by

$$P_i^s = \left[\int \min_n \left\{\frac{\tau_{in}\, \varsigma_n^s}{z_n^s}\right\}^{1-\eta} dz^s\right]^{\frac{1}{1-\eta}} \tag{6}$$

The final goods aggregators of each sector in every region source each variety from the least cost producer, considering the trade costs associated with shipping. τ_{in} represents the trade costs[5]

5. We assume trade costs to be symmetric i.e $\tau_{in} = \tau_{ni}$

of shipping intermediate goods from region-n to i. η is the elasticity of substitution between varieties, and the aggregation is done over the measure of varieties (z^s) within each sector. Given that the productivity draws are stochastic, the distribution of prices could be computed from the relevant order statistics.

3.2.3. Derivation of Prices

The prices in equilibrium are determined by the distribution of productivity across regions. For a variety z_i^s belonging to a region-sector pair (i, s), the productivity is drawn from a Frechet distribution with the following CDF.

$$P(Z_i^s \leq z) = exp(-A_i^s \; z^{-\theta^s})$$

A_i^s denotes the scale parameter of the productivity distribution, directly relating it to the mean productivity in the region-sector pair (i, s). The parameter θ^s controls the dispersion of productivity draws and differs by sector-s. Departing from the standard independence assumptions regarding productivity draws made in the literature, we follow Lind and Ramondo (2023) to allow for correlated productivity draws while maintaining the max-stability property of the Frechet distribution. The vector of productivity draws for an intermediate good variety in sector-s across regions follows

$$\mathbf{P}\left(Z_1^s \leq z_1, Z_2^s \leq z_2, \ldots, Z_N^s \leq z_N\right) = exp\left[-\sum_{i=1}^{N}\left(A_i^s \, z_i^{-\theta^s}\right)^{\frac{1}{1-\rho}}\right]^{1-\rho} \tag{7}$$

Here, ρ denotes the degree of correlation across regions. Given the productivity distribution and the final good sector being the least cost aggregator, the price of the final good of sector-s in region-i is given as

$$P_i^s = \Gamma\Big(\frac{\theta^s + 1 - \eta}{\theta^s}\Big)^{\frac{1}{1-\eta}} \; \left[\sum_{n=1}^{N}\left[A_n^s \left(\tau_{in} \, \varsigma_n^s\right)^{-\theta^s}\right]^{\frac{1}{1-\rho}}\right]^{\frac{\rho-1}{\theta^s}} \tag{8}$$

The expenditure share on goods from region-n in region-i within sector-s is given by

$$\pi_{in}^{s} = \frac{\left[A_{n}^{s}\ \left(\tau_{in}\varsigma_{n}^{s}\right)^{-\theta^{s}}\right]^{\frac{1}{1-\rho}}}{\sum_{n=1}^{N}\left[A_{n}^{s}\left(\tau_{in}\ \varsigma_{n}^{s}\right)^{-\theta^{s}}\right]^{\frac{1}{1-\rho}}} \tag{9}$$

Using these trade shares, we can populate a multi-region input-output model by solving for equilibrium given the model parameters. This is particularly important given the lack of intra-country trade data for India.

3.2.4. *Balanced Government Budget*

The government budget condition is satisfied by taxing the workers' labor income to subsidise the manufacturing. The budget condition is as follows.

$$\sum_{k=1}^{S}\sum_{n=1}^{N}\frac{-t_{n}^{k}}{1+t_{n}^{k}}X_{n}^{k} = (\sum_{n=1}^{n} w_{n}l_{n})t_{w}$$

When the government provides manufacturing subsidies ($t_{n}^{k} < 0$), the total cost of the subsidy is given by the left-hand side of the above equation, and it is funded by taxing the workers, given by the right-hand side of the above equation. Given this budget constraint, a worker's disposable income is obtained by adjusting the wage income by a factor of $(1 - t_{w})$.

$$t_{w} = \frac{\sum_{k=1}^{S}\sum_{n=1}^{N}\frac{-t_{n}^{k}}{1+t_{n}^{k}}X_{n}^{k}}{\sum_{n=1}^{n} w_{n}l_{n}} \tag{10}$$

3.2.5. *Market Clearing*

Let X_{i}^{s} denote the expenditure on the final good of sector-s in region-i. This expenditure is the sum of final consumption by the consumers and the materials used by the intermediate good producers in the region.

$$X_{i}^{s} = \alpha^{s}w_{i}l_{i}(1-t_{w}) + \sum_{k=1}^{S}\mathcal{M}_{i}^{ks}$$

$\mathcal{M}_{i}^{ks}$ denotes the total value of materials used by intermediate producers of sector-k in region-i.

Given the Cobb-Douglas production function of the intermediate good producers, the value of materials can be written in terms of wage expenditure as follows

$$\mathcal{M}_i^{ks} = \gamma^{ks} \sum_{n=1}^{N} \pi_{ni}^{k} \frac{X_n^k}{1+t_n^k}$$

Therefore, the expenditure defined above can be written as

$$X_i^s = w_i(1-t_w)\sum_{k=1}^{S} l_i^k + \sum_{k=1}^{S} \gamma^{ks} \sum_{n=1}^{N} \pi_{ni}^{k} \frac{X_n^k}{1+t_n^k} \tag{11}$$

Finally, the wage income of each sector in a region is given by

$$w_i l_i^s = \gamma^s \sum_{n=1}^{N} \pi_{ni}^{s} \frac{X_n^s}{1+t_n^s} \tag{12}$$

The wage income is determined by the factor share of the total revenue of sector-s in region-i, which is the sum of global expenditure sourced from this sector-region pair. Labor allocations across sectors within each region are constrained by the inelastic labor supply in a region, given by

$$\sum_{k=1}^{S} l_i^k = l_i$$

Trade is always balanced at the aggregate level. At the regional level, trade is not balanced in the presence of non-zero taxes/subsidies. At the regional level, sectors within a region can run deficits or surpluses such that regional trade is balanced when there are no taxes/subsidies.

3.3. Competitive market equilibrium

Given labor supply and productivity parameters $(\{l_i\}_{i=1}^{N}, \{A_i^s\}_{i=1,s=1}^{N,S})$, the competitive market equilibrium $(\{t_i^s\}_{i=1,s=1}^{N,S} = 0, t_w = 0)$ consists a set of input cost prices, final good prices, expenditures, labor allocations, $\{x_i^s, P_i^s, X_i^s, l_i^s\}_{i=1,s=1}^{N,S}$, a set of wages in each region, $\{w_i\}_{i=1}^{N}$, a set of pair-wise trade shares for each sector, $\{\pi_{in}^s\}_{i=1,n=1,s=1}^{N,N,S}$ such that optimality conditions for the consumers, intermediate producers and final good producers hold, equations - (4), (8), (9),(11), (12) hold and aggregate trade is balanced at the individual regional level.

Proposition 1 (Existence of Unique Spatial Equilibrium)**.** Given the structural parameters of the model $\{\alpha, \gamma, \theta^s, \eta, \rho\}$, productivity parameters $\{A_i^s\}$, trade costs $\{\tau\}$, vector of labor supply $\{l_i\}$ and a vector of government subsidies (taxes) $\{t_i^s\}$, there exists an unique equilibrium that determines the input-prices $\{x_i^s\}$, final good prices $\{P_i^s\}$, trade shares $\{\pi_{in}^s\}$, wages $\{w_i\}$ and labor allocations $\{l_i^s\}$.

Proof: It follows from Allen, Arkolakis, and Li (2024)

Proposition 2 (Efficiency of Market Equilibrium)**.** With no taxes/subsidies, the spatial equilibrium is not Pareto optimal but rather constrained optimal. Immobile labor restricts the set of possible equilibria, and the resultant equilibrium depends on the initial spatial distribution of productivity and labor. In knife-edge cases where the initial productivity and labor are jointly optimal, the market equilibrium is Pareto optimal.

Proof: It is straightforward to see that a real wage differential exists between regions, and the market equilibrium is constrained to allocate labor optimally across space. Furthermore, there is a missing market for labor mobility, which deviates from the First Welfare Theorem and results in inefficiency.

3.4. The social planner

This section derives the optimality conditions for the market equilibrium defined above using a social planner. The social planner respects the individual optimality conditions of both consumers and producers, and only uses lump-sum transfers across space. This strategy of lump sum transfers across space does not cause any distortions between the price indices and only reallocates purchasing power using a per capita transfer of δ_i to a consumer in region-i, which is revenue-neutral. The planner's problem is defined[6] as

$$\max_{\{C\}} \quad \sum_{i=1}^{N} L_i \, log\left(\prod_{s=1}^{S}\left(\frac{C_i^s}{L_i}\right)^{\alpha^s}\right)$$

s.t

$$\sum_{i=1}^{N}\sum_{s=1}^{S}[P_i^s Q_i^s] = \sum_{i=1}^{N}\sum_{s=1}^{S}\left[P_i^s C_i^s + \sum_{k=1}^{S}\sum_{n=1}^{N}\pi_{ni}^k \gamma^{ks} P_n^k Q_n^k\right]$$

$$w_i l_i^s = \gamma^s \sum_{n=1}^{N} \pi_{ni}^s P_n^s Q_n^s \qquad \forall i, s$$

$$\sum_{k=1}^{S} l_i^k = L_i \qquad \forall i$$

Notice that the only meaningful difference[7] in the planner's problem is that the resource constraints hold in aggregate, and individual regions can run deficits or surpluses. Using FOC of the above, in addition to the optimality conditions of the individual consumption problem, yields the condition

$$w_i + \delta_i = w_n + \delta_n.$$

This shows that the planner acts as an insurer against bad draws of luck (Mongey and Waugh 2024) as ex-ante identical individuals receive different realizations of real wages due to birth. As the transfers are revenue neutral, the individual transfer to region-i is given as

$$\delta_i = \sum_{n=1}^{N} \frac{L_n}{\sum_{n=1}^{N} L_n}(w_n - w_i).$$

The planner essentially taxes the consumption in high-wage regions to fund the low-wage regions. This strategy of lump-sum transfers is not feasible due to political economy constraints; hence, the planner can use second-best policies, such as subsidizing intermediate producers in low-wage regions by taxing consumers in high-wage regions.

6. With minor modifications where Q_i^s is the quantity equivalent of final good expenditure X_i^s

7. The other difference one might observe is that the previous equations are modified to write the resource constraint where C_i^s represents the total final good consumption of sector-s in region-i. The same is reflected in the objective of the planner, which weights each individual equally.

3.5. Second-best policies

The second-best policies provide subsidies to intermediate good manufacturers by funding these subsidies through a tax on wage income, as shown in (10). These optimal subsidies will result in surpluses/deficits adhering to the principle of transferring resources from high-income regions to low-income regions, as shown earlier. We compute the optimal policies using numerical methods, as an analytical characterization of optimal policies is cumbersome given the sectoral and trade links across multiple regions and sectors. The numerical computation of optimal subsidies follows the maximization of the aggregate welfare subject to constraints given by (4), (8), (9),(11), (12). We write the problem below.

$$\max_{\{t_i^s\}_{i=1,s=1}^{N,S}} \sum_{i=1}^{N} L_i \frac{w_i(1-t_w)}{\prod_{s=1}^{S} P_i^s}$$

s.t

$$\varsigma_i^s = (1+t_i^s)\,\lambda_i^s\,[w_i]^{\gamma^s} \prod_{k=1}^{S} \left[P_i^k\right]^{\gamma^{sk}} \qquad \forall i, s$$

$$P_i^s = \Gamma\left(\frac{\theta^s+1-\eta}{\theta^s}\right)^{\frac{1}{1-\eta}} \left[\sum_{n=1}^{N} \left[A_n^s\,(\tau_{in}\,\varsigma_n^s)^{-\theta^s}\right]^{\frac{1}{1-\rho}}\right]^{\frac{\rho-1}{\theta^s}} \qquad \forall i, s$$

$$\pi_{in}^s = \frac{\left[A_n^s\,\left(\tau_{in}\varsigma_n^s\right)^{-\theta^s}\right]^{\frac{1}{1-\rho}}}{\sum_{n=1}^{N}\left[A_n^s\,(\tau_{in}\,\varsigma_n^s)^{-\theta^s}\right]^{\frac{1}{1-\rho}}} \qquad \forall i, n \in [1,\ldots,N], s$$

$$X_i^s = w_i(1-t_w)\sum_{k=1}^{S} l_i^k + \sum_{k=1}^{S}\gamma^{ks}\sum_{n=1}^{N}\pi_{ni}^k \frac{X_n^k}{1+t_n^k} \qquad \forall i, s$$

$$w_i l_i^s = \gamma^s \sum_{n=1}^{N} \pi_{ni}^s \frac{X_n^s}{1+t_n^s} \qquad \forall i, s$$

$$t_w = \frac{\sum_{k=1}^{S}\sum_{n=1}^{N}\frac{-t_n^k}{1+t_n^k}X_n^k}{\sum_{n=1}^{n} w_n l_n}$$

The strategy we follow to compute the optimal subsidies involves simulating the surface of the planner's objective for different scenarios, leveraging faster computational tools to find a global optimum. The implementation of this optimization problem is in progress and will be updated in future versions of this paper.

4 — Data & Calibration

In this section, we describe the data and the strategy used to calibrate the model described previously. One of the primary datasets for our calibration is the Annual Survey of Industries (ASI) data. This dataset covers the universe of large manufacturing units and a sample of smaller manufacturing units registered in India. This dataset is aggregated to form 8246 district-sector observations curated from 589 districts and 14 sectors[8] with the necessary data on output, inputs, and wages paid. Nearly 50% of the observations are zeros, as not all sectors operate in every district. The manufacturing data calibrates the productivity scale parameters (A_i^s) by estimating the mean revenue productivity at the region-sector level. With the aggregated panel data (2006-2010) at the region-sector level, the revenue productivity is calculated using the non-parametric approach proposed by Gandhi, Navarro, and Rivers (2020). The productivity Ω_i^s is identified by estimating the production function and is related to the structural parameters of the model as

$$\Omega_i^s = [A_i^s]^{\frac{1}{\theta^s}}\ \Gamma(1 - \frac{1}{\theta^s}).$$

θ_s, also known as trade elasticity, controls the dispersion of the productivity draws within each sector, and is taken from Caliendo et al. (2018). The productivity parameters are identified using the trade elasticity of each sector as reported in the literature and estimates of revenue productivity obtained from the production data[9]. Tab-A1 shows the list of sectors and the associated trade elasticities.

Further, we use the Census-2011 data to obtain the distribution of the working population across the districts and the 66^{th} round of NSSO to obtain the mean nominal wage at the district level. As the ASI covers only manufacturing sectors with no output information for agriculture, mining, and service sectors. As these sectors combined account for up to 62% of the total output, we could not restrict our analysis to just manufacturing. To overcome this missing data, we proxy the structural productivity parameter (A_i^s) for the combined agriculture, mining, and service sector by multiplying the nominal wage by the working population at the district level[10].

8. Details of the sectors are mentioned in the appendix
9. For the missing observations, the productivity parameters are assigned a value less than the minimum observed.
10. We plan to further improve upon this in the future iterations by considering other relevant ways to proxy the

The ADB Input-Output table provides the technical coefficient matrix $[\gamma]$, representing the share of materials from other sectors and the labor share. This input-output table also provides the shares of final expenditure $\{\alpha\}$ allocated to each sector by consumers.

To estimate the trade costs $\{\tau\}$, we use GIS data on Indian districts and calculate the straight-line distance between all the possible pairs of district centroids. With this pairwise distance matrix between districts, we follow Asturias, García-Santana, and Ramos (2019) to determine the pairwise trade costs between the districts.

Further, we assume $\eta = 2$, which measures the elasticity of substitution between intermediate varieties [11], and a correlation parameter $\rho = 0.2$. With these model parameters, trade costs, productivity parameters, and labor supply, we solve for the equilibrium to arrive at the equilibrium set of wages, output, expenditures, trade shares, and labor allocations. The algorithm used to compute the equilibrium is detailed in the appendix, which follows Levchenko and Zhang (2016).

Before proceeding to the counterfactual analysis, we establish the credibility of our calibration by benchmarking our model predictions against the observed values of output, wages, and labor allocations for each region-sector pair. Fig-4 shows the model's performance in predicting nominal wages against. The Pearson correlation between the log-transformations of model-implied nominal wages and the nominal wages from data at the district level is about .46[12]. Further multiplying the nominal wages by the working population at the district level yields the total income, and the model's performance in predicting this income is shown in fig-5. For the other relevant variables, such as total output, labor allocations, and wage income at the district sector level, the correlations between the log-transformed model-implied values and data are 0.70, 0.69, and 0.66, respectively [13]. Despite the simplistic assumptions, our model performance is good and can be relied on for counterfactual analysis. Furthermore, we present regression results to support our model's performance, which are included in the appendix.

Lastly, with the calibrated model, it is now possible to identify the real wages across regions, our primary variable of interest. Fig-6 shows the log real wages across the regions. The highest real wages are in highly industrialised and central parts of the country, which benefit from its

productivity parameter of the non-manufacturing sectors.

11. $\theta^s > \eta - 1$ is satisfied
12. Spearman rank correlation is 0.704
13. Spearman correlation values 0.68, 0.67, 0.67 respectively

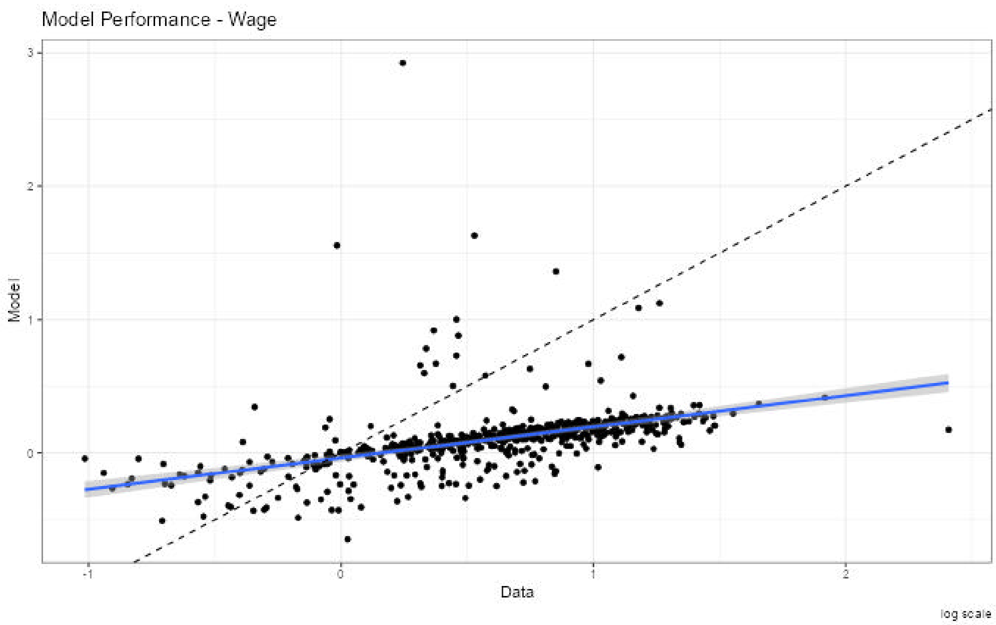


Figure 4 — Model Performance - Nominal Wage

Notes. For each region, the model-implied values of nominal wages in logs are plotted on the y-axis and the log values from the data are plotted on the x-axis. The performance of the model-implied nominal wage values is shown here. The blue solid line is the simple linear fit between the model-implied values and data, while the dashed line is the 45° line.

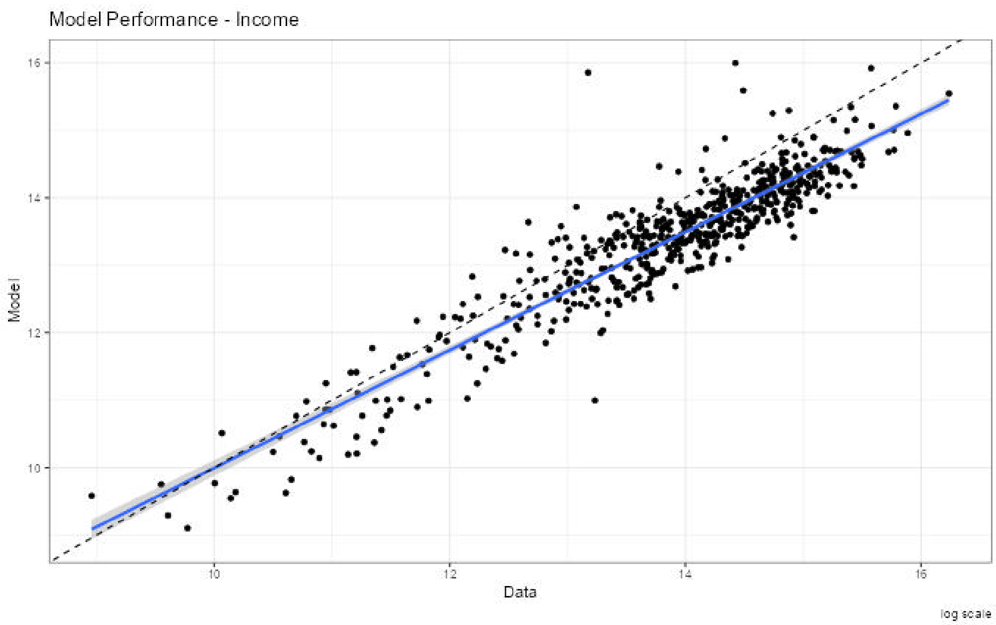


Figure 5 — Model Performance - Nominal Income

Notes. For each region, the model-implied values of nominal total income in logs are plotted on the y-axis and the log values from the data are plotted on the x-axis. The performance of the model-implied nominal wage values is shown here. The blue solid line is the simple linear fit between the model-implied values and data, while the dashed line is the 45° line.

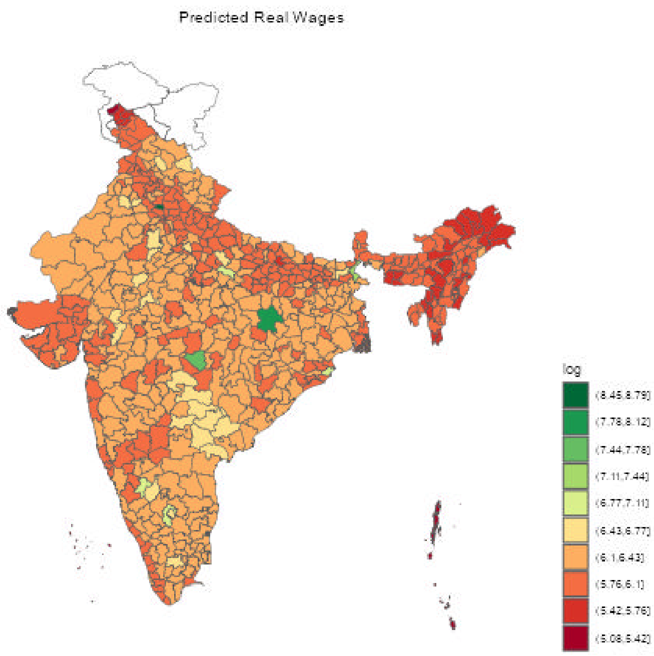


Figure 6 — Predicted log real wage

geography and high productivity, while the lowest real wages are in the frontier regions. The lowest real wage is observed in the district of Nicobar, Andaman & Nicobar Islands ($\omega = 161.69$), while the highest is observed in the district of Panipat, Haryana ($ln(\omega) = 6568.59$). The absolute values of real wages are irrelevant; only the relative levels are necessary for comparison across different regions. Moreover, we are only interested in the changes of these real wages in counterfactual analysis, and the scale of these values is irrelevant. The inequality of real wage across spatial units, measured by the mean log deviation[14], is 0.0456.

5 — Policy Simulations & Results

For our counterfactual analysis, we simulate the calibrated model with a 1% subsidy to each sector individually. To achieve a balanced budget in the presence of these subsidies, consumers are uniformly taxed with an ad valorem tax on their wage income. The two policy counterfactuals we focus on in the main text are the subsidies given to the metal manufacturing and automotive manufacturing sectors. Fig-7 shows the percentage of real wages for the above subsidy scenarios. The left panel shows the changes due to subsidies given to the metal manufacturing sector, and

14. also known as Theil-L index given by $T_L = \frac{1}{\sum_{i=1}^{N} L_i} \sum_{i=1}^{N} L_i(log(\bar{\omega}) - log(\omega_i))$

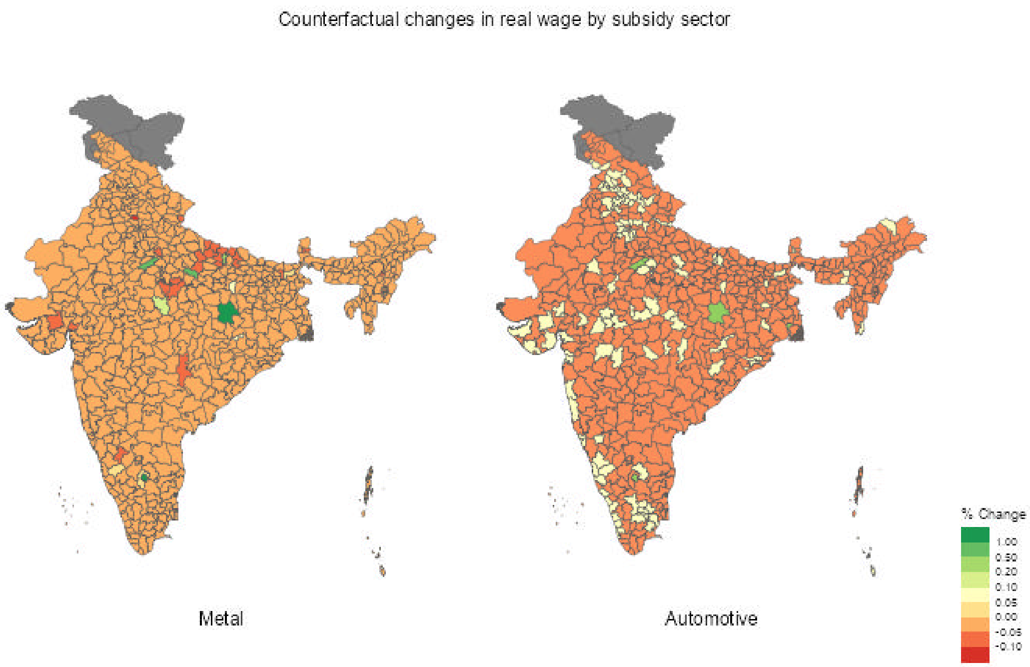


Figure 7 — Counterfactual change in real wages

Notes. Left panel shows changes in real wages due to a 1% subsidy given to the metal manufacturing sector, and the right panel shows changes in real wages due to a 1% subsidy given to the automotive manufacturing sector.

the right panel shows the same due to subsidies given to the automotive manufacturing sector. The results for the remaining sectors are shown in the appendix.

When the subsidy is given to the metals, the highest real wage change of 1.09% is observed in the district of Chennai, Tamil Nadu, and the lowest of -0.12% is observed in the district of Panipat, Haryana. Similarly, when the subsidy is applied to automotive manufacturing, the highest real wage change of 0.07% is observed in Chennai, while the lowest change of -0.03% is observed in Panipat, Haryana. Tab-1 shows the descriptive statistics[15] for the counterfactual change in real wages for a 1% subsidy to each sector individually. Col-3 shows the standard deviation of counterfactual real wage changes, and Col-4 shows the change in inequality compared to the competitive equilibrium measured earlier. The highest standard deviation and also the highest increase in inequality is observed when the metal industry is provided with subsidies. All the scenarios, except when a subsidy is given to the food and leather industries, yield a marginal and

15. These mean values are calculated by weighting the district level changes in real wage with total population.

insignificant decline in the weighted real wage changes. Inequality also decreases or remains the same when subsidy is provided to the food and leather industries. The minimal effect of subsidies on aggregate real wages could be due to the small magnitude of the subsidy. Although there is little deviation in the aggregate real wage, significant heterogeneity emerges when the effects are analyzed at the district level (see appendix). This heterogeneity is in both the scale of effects in each scenario and the specific incidence of these effects. The correlation of real wage changes across districts for different policy scenarios is very low and sometimes negative, as shown in Table A3, which highlights that the effects vary at the district level for each counterfactual scenario. These varied effects further reflect the role of underlying economic geography factors, such as location, productivity, and composition shares, and their interaction with policies to affect spatial inequalities.

Table 1 — Summary of counterfactual changes in real wage

	Min	Max	W.Mean	SD	Inequality Change
Food	-0.07	0.42	0.00	0.02	-0.0023
Textile	-0.03	1.09	-0.01	0.05	0.0141
Leather	-0.00	0.34	0.00	0.01	0
Wood	-0.01	0.60	-0.00	0.03	0.0012
Paper	-0.01	0.79	-0.00	0.04	0.002
Fuel	-0.07	0.42	-0.00	0.04	0.0019
Chemical	-0.05	1.01	-0.01	0.05	0.0125
Rubber	-0.01	0.20	-0.00	0.01	0.0007
Mineral	-0.02	0.70	-0.00	0.03	0.0036
Metal	-0.12	1.09	-0.02	0.09	0.0283
Machinery	-0.03	0.30	-0.00	0.02	0.0012
Electrical	-0.03	0.35	-0.00	0.03	0.0015
Automotive	-0.03	0.07	-0.00	0.01	0.0012
NEC	-0.03	0.50	-0.00	0.02	0.0006

6 — Conclusion

We have shown that the competitive market equilibrium is not Pareto efficient and have highlighted the non-trivial role of the planner. Using our calibrated model, we showed that the subsidies given to sectors can have uneven effects across regions. The magnitude of these subsidies varies significantly across districts, and the mechanisms driving these differences will be studied in future iterations of this paper by extensively incorporating forward and backward linkages. Further, we are in the process of characterising optimal spatial policies within the realm of our model. For these optimal policies, it would be essential to compare the efficiency gains of these policies with those of place-blind industrial subsidies and region-specific subsidies.

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A — Appendix Section

A.1. Trade Elasticities

We use trade elasticities from Caliendo et al. (2018) for all the manufacturing sectors #1-14 in the table-A1. For the manufacturing sector, the elasticity is assumed to be 5, which is the value for the overall trade elasticity used in the literature. Further iterations will try to calibrate this elasticity for the non-manufacturing sector using appropriate data.

Table A1 — Sectors and Trade Elasticities

Sectors	θ^s
Food and Beverages	2.55
Textiles	5.56
Leather	5.56
Wood	9.46
Paper	9.46
Fuels	51.08
Chemicals	4.75
Rubber	1.66
Minerals	2.76
Metals	6.78
Machinery	1.52
Electricals	10.60
Automotive	1.01
NEC*	5
Other Non-manufacturing†	5

* *Includes recycling and other unclassified manufacturing*

† *Combines agriculture, mining and services, parater value by assumption*

A.2. Algorithm for Solving Equilibrium

I compute the equilibrium using the following procedure with the calibrated model parameters.

Step1: Start with a guess of $x_i^s, P_i^s \,\&\, w_i$

Step2: Compute new input prices and final good prices using eq-4 & eq-8.

Step3: Repeat **Step2** until the intermediate and final good prices converge to a fixed point.

Step4: Use the converged prices to calculate the trade shares, updated wages using eq-9 & eq-12 respectively. Repeat from **Step2:** untill convergence is achieved.

A.3. Regression Analysis of Model Performance

In the table-A2, we show the regression results of the data observations of labor allocations, sales, and wages with their model-predicted counterparts. The model-implied values have good predictive performance as seen in their coefficient estimates and R-squared values.

Table A2 — Regression results of model performance

Data Observations:	log(Sales)		log(Wages)		log(Labor)	
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Model Predictions						
Constant	1.0***		1.8***		0.54***	
	(0.13)		(0.11)		(0.04)	
log(Sales)	1.6***	1.7***				
	(0.02)	(0.14)				
log(Wages)			1.5***	1.5***		
			(0.02)	(0.12)		
log(Labor)					0.55***	0.49***
					(0.007)	(0.05)
Fixed-effects						
State		Yes		Yes		Yes
Industry		Yes		Yes		Yes
District		Yes		Yes		Yes
Fit statistics						
Observations	8,246	8,246	8,246	8,246	8,246	8,246
R^2	0.49	0.82	0.48	0.80	0.43	0.79
Within R^2		0.53		0.48		0.36

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

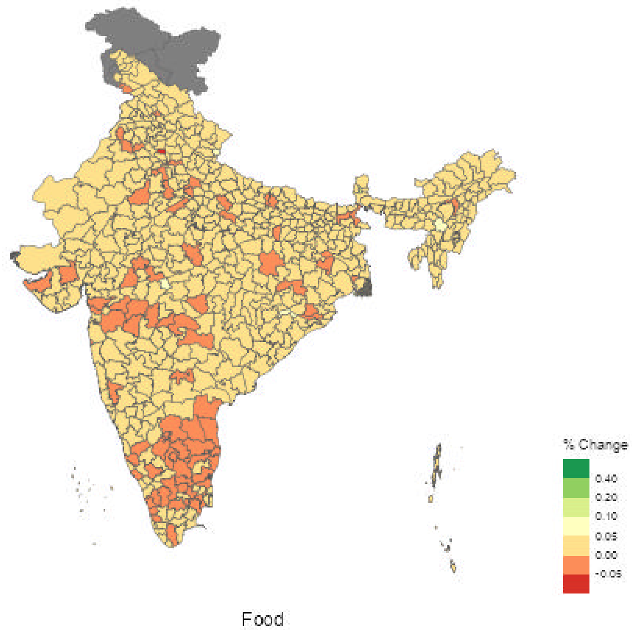
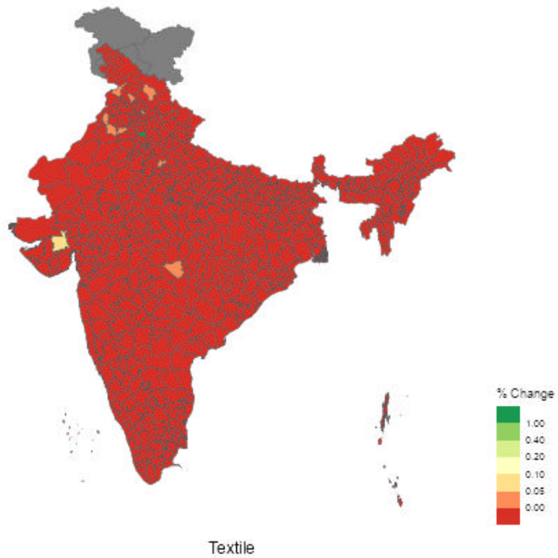


Figure A1

A.4. Counterfactuals by Sectoral Subsidy

We show the counterfactuals where each of the sectors receives a 1% subsidy. In the main text, we have shown the results for the metal manufacturing and automotive manufacturing sectors; here, we present the results for the other 12 sectors. Tab-A3 shows the correlation of real wage changes across each counterfactual scenario.



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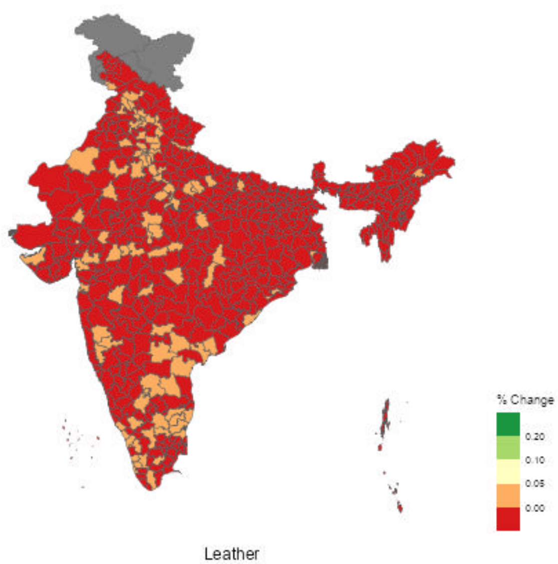

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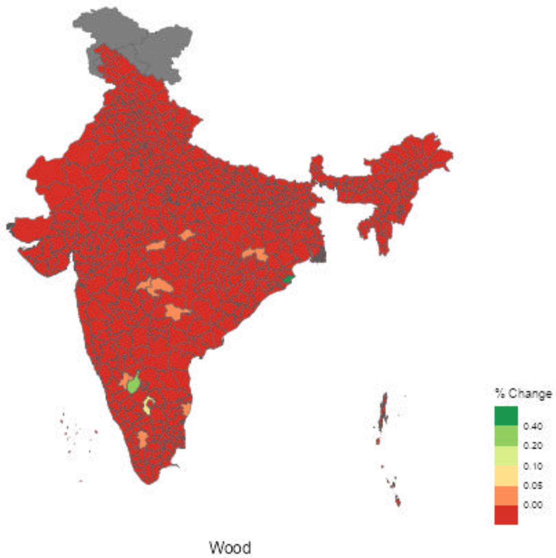

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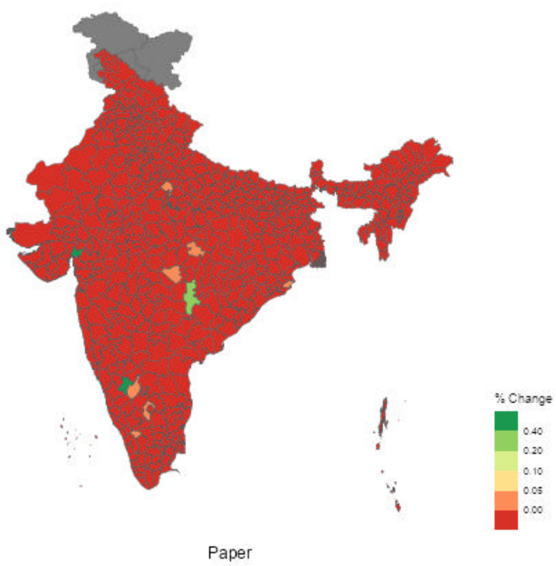

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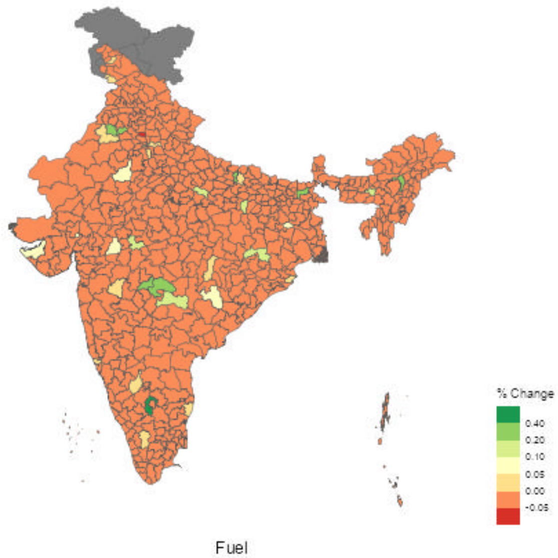

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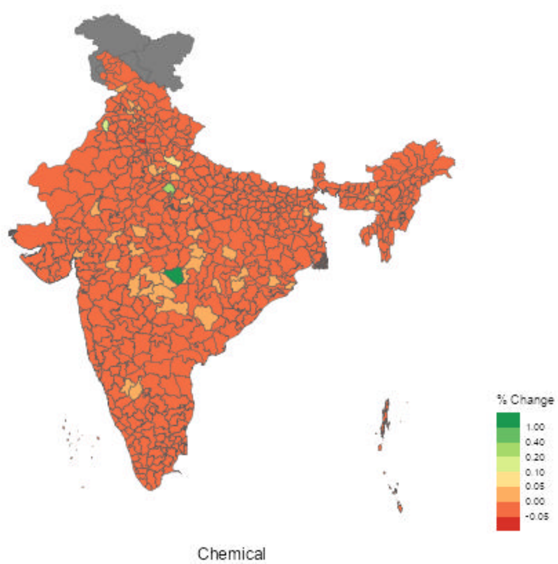

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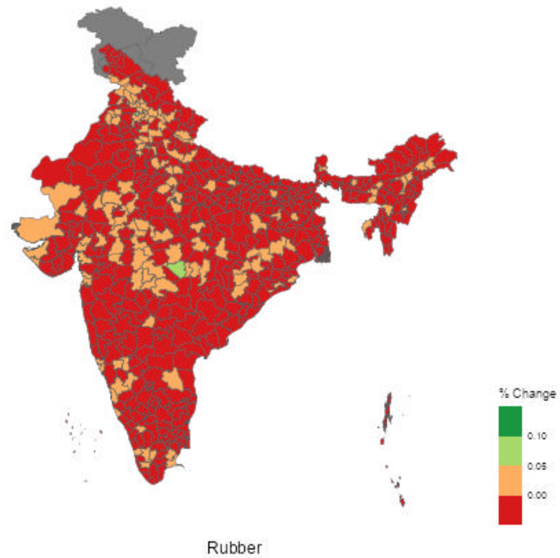

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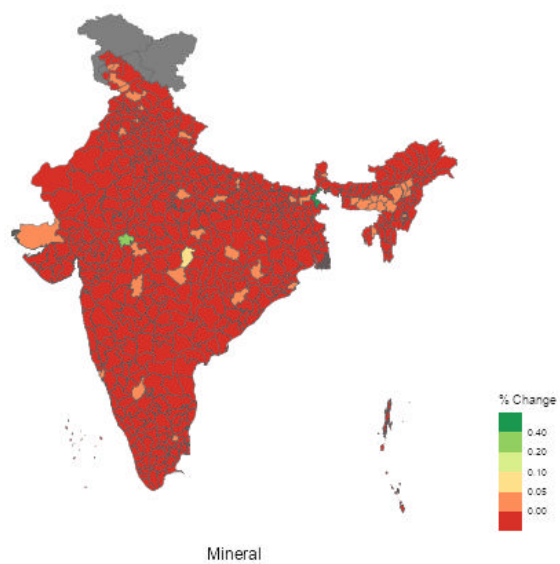

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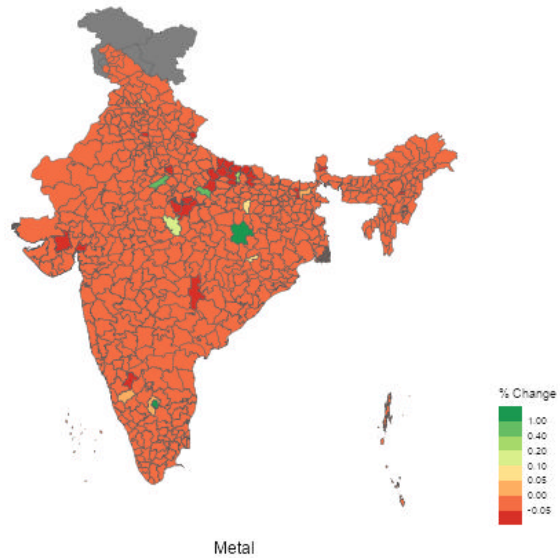


Figure A10

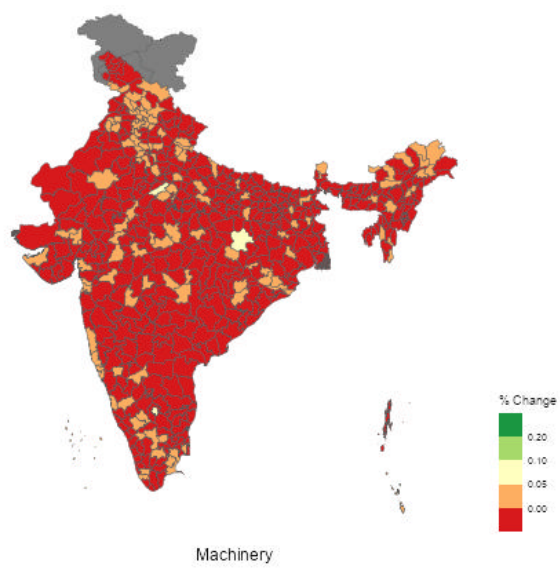
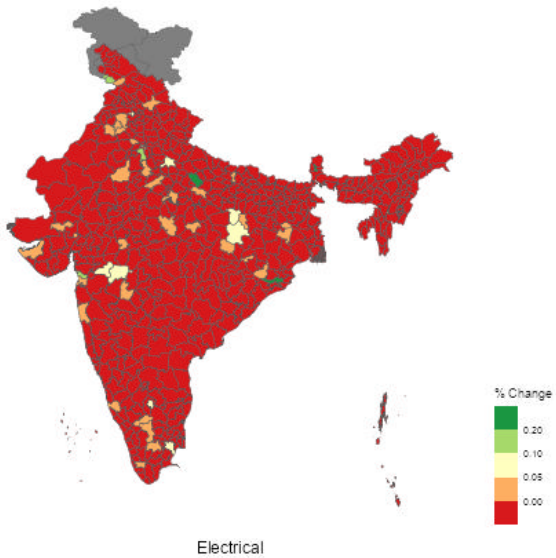


Figure A11



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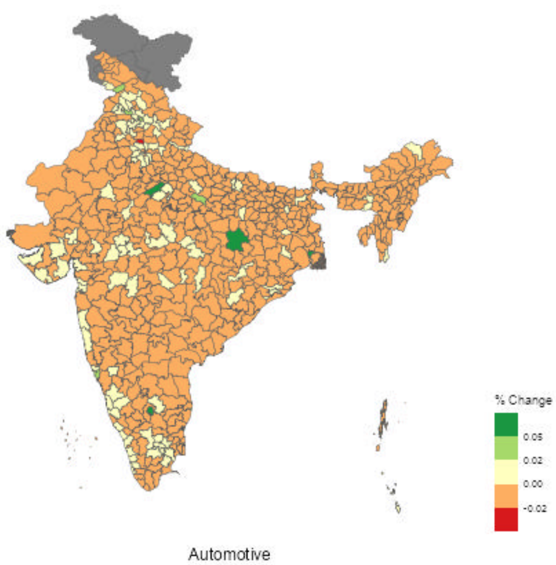

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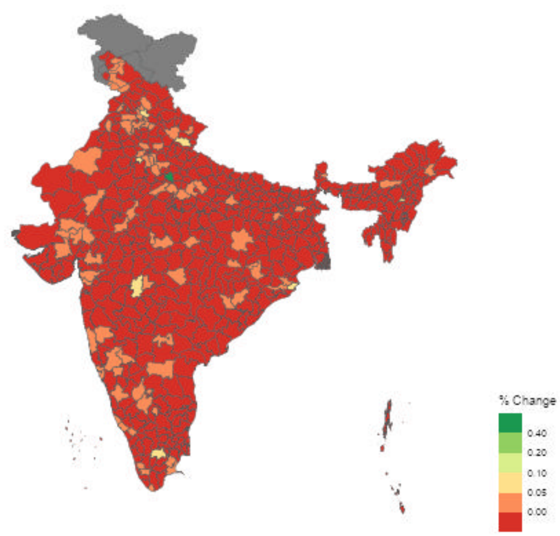

Figure A14

Table A3 — Correlation Matrix of counterfactual changes by each subsidy scenario

	Food	Textile	Leather	Wood	Paper	Fuel	Chemical	Rubber	Mineral	Metal	Machinery	Electrical	Automotive	NEC
Food	1													
Textile	-0.13	1												
Leather	0	-0.01	1											
Wood	-0.01	-0.01	-0.01	1										
Paper	0.03	0	-0.01	0.02	1									
Fuel	-0.13	-0.09	-0.03	0.06	-0.04	1								
Chemical	0	-0.01	0.01	0.03	0.04	0.03	1							
Rubber	0.14	0.09	0.09	-0.01	0.02	-0.03	0.41	1						
Mineral	-0.02	-0.04	-0.01	0.03	-0.01	0.01	0.01	0.06	1					
Metal	-0.18	-0.07	-0.03	-0.02	-0.04	0.1	-0.05	-0.05	-0.03	1				
Machinery	0.57	0.05	0.04	-0.02	-0.03	-0.05	0.01	0.54	0	0.31	1			
Electrical	-0.02	-0.06	0.06	-0.02	-0.02	-0.01	-0.02	0.12	-0.01	0.17	0.12	1		
Automotive	0.07	-0.1	0.23	-0.05	-0.04	0.03	0.02	0.28	-0.03	0.64	0.52	0.35	1	
NEC	-0.08	-0.04	0.01	0.16	0	-0.06	0.04	0.07	-0.01	0.01	0	0.05	0.08	1