

Wage Spillovers and Internal Migration in India

Maggie Liu¹, Çağlar Özden², and He Wang²

¹U.S. Department of the Treasury

²The World Bank

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Research questions

- What is the degree of spatial spillovers between (district level) wages in India?
- What is the role of internal labor mobility in transmitting these wage spillovers between districts?
- How do changes in migration costs impact wage spillovers?

Stylized fact 1: vast spatial variation in income levels

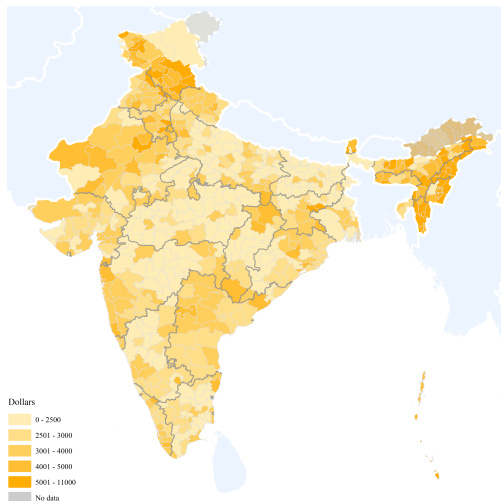


Figure: District average wages of the employed individuals, 2004-05

Stylized fact 2: very low internal mobility

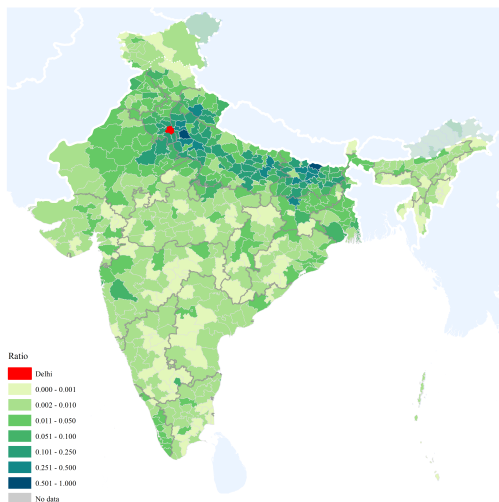


Figure: Immigrants to and emigrants from Delhi, normalized by labor, 2001

What we do and find

- Develop an **analytical framework** on the linkages between labor mobility and wage convergence
 - ▶ This leads us to **spatial autoregressive (SAR)** specification
 - ▶ Movement of labor between regions creates positive spatial wage spillovers
 - ▶ Wages of younger or less educated people are more spatially correlated
- Simulate **counterfactual scenarios** with exogenous productivity shocks and lower migration barriers.
 - ▶ Positive productivity shocks spillover to other markets that have stronger migration linkages
 - ▶ Temperature rise hurts labor markets with linkages

Contributions to the literature

- We add new evidence of spatial spillovers at the sub-national level to the growth literature (*Klenow and Rodriguez-Clare 2005, Ertur and Koch 2007*)
- We contribute to fast growing literature that explores the linkages between labor mobility and labor productivity within a country
 - ▶ Discussions on the sorting of heterogeneous workers (*Bryan et al. 2014, Bazzi et al. 2016, Kicks et al. 2018, Bryan and Morten 2019, Alvarez 2020*)
 - ▶ Our paper highlights that movement of labor between regions creates spatial spillovers and link labor markets across regions
- Contribute to the literature that focuses on internal migration in India (*Munshi and Rosenzweig 2016, Kone et al. 2018, Asher and Novosad 2020*)
- Related to the spatial econometric studies using bilateral economic variables as spatial weights (*Behrens et al. 2012, Qu et al. 2020*)

Model: migration and wages

- Inverse labor demand** in district j

$$\ln w_j = \ln A_j - \phi \ln L_j,$$

- Migration** from district i to j

$$\ln m_{ij} = \ln \rho_{ij} + \beta \ln w_j - \ln \left(\sum_{k=1}^N \rho_{ik} w_k^\beta \right) + \ln E_i$$

- Labor supply** in district j

$$L_j = \sum_{i=1}^N m_{ij}$$

where $\pi_{ij}^* = \frac{\rho_{ij} w_j^\beta}{\sum_{k=1}^N \rho_{ik} w_k^\beta}$. We should note, as a reminder, π_{ij}^* is approximately the share of workers from district i who move to district j .⁴

When we substitute the terms in equations (8), (9) and (10) into the Taylor expansion expression (7), we obtain

$$\ln w_j \approx \ln A_j - \phi \ln L_j^* + (\beta - \beta^*) \left(-\phi \ln w_j + \phi \sum_{k=1}^N \sum_{i=1}^N \frac{\pi_{ij}^* \pi_{ik}^* E_i}{L_j^*} \ln w_k \right). \quad (11)$$

We can further simplify this expression by introducing the following assumptions on the term $\pi_{ij}^* \pi_{ik}^*$. First, as we discuss in the data section, the number of workers who move from district i to a specific district j as a share of the population of i (π_{ij} , $i \neq j$) is actually quite small. In our data sample, the mean value of π_{ij} is 0.0008 and the median value is zero indicating, that in majority of cases, bilateral migration between any random pair of districts is zero.⁵ Thus, when two such small numbers are multiplied, we assume that the product is equal to zero:

$$\pi_{ij}^* \pi_{ik}^* \approx 0, \quad \forall i, j \text{ or } k, k, j \neq k.$$

Furthermore, majority of the people from a district are non-migrants and the mean value of π_{jj} is 0.95. As a result, we make the following approximation:

$$\pi_{ij}^* \pi_{jk}^* \approx \pi_{jk}^*, \quad \forall k, k, j \neq j.$$

With these assumptions, equation (11) simplifies to

$$\ln w_j \approx \ln A_j - \phi \ln L_j^* + \phi(\beta - \beta^*) \sum_{ij} \frac{m_{ij} + m_{jk}^*}{L_j^*} \ln w_i, \quad (12)$$

where $m_{ij}^* = \pi_{ij}^* E_i$ is the approximate migration flow from district i to district j .⁶

Equation (12) shows how the wage level in any given district is linked to the wages in all of the other districts. Bilateral migration flows, as expressed in the last term, provide

⁴The first order derivative of $f(\beta)$ is given by: $f'(\beta) = -\phi \frac{1}{\sum_{i=1}^N \sum_{j=1}^N \pi_{ij}^* \pi_{ik}^*} \frac{\partial}{\partial \beta} \left(\sum_{i=1}^N \sum_{j=1}^N \frac{\rho_{ij} w_j^\beta E_i}{\sum_{k=1}^N \rho_{ik} w_k^\beta} \right) = -\phi \frac{1}{\sum_{i=1}^N \sum_{j=1}^N \pi_{ij}^* \pi_{ik}^*} \left[\sum_{i=1}^N \sum_{j=1}^N \frac{\rho_{ij} w_j^\beta E_i}{\sum_{k=1}^N \rho_{ik} w_k^\beta} \ln w_j - \frac{\rho_{ij} w_j^\beta E_i}{\sum_{k=1}^N \rho_{ik} w_k^\beta} \sum_{k=1}^N \rho_{ik} w_k^\beta \ln w_k \right]$

⁵This is based on the 2000 and the 2010 Censuses. Migration sample is constrained to males aged 20-65 who ever migrated in the past 10 years for any reason.

⁶Another approximation we apply in Equation (12) is $\pi_{ij}^* E_i / L_j^* \ln w_j \approx \ln w_j$.

Empirical strategy

Estimate wage spillover effects

- With linear approximation, we can derive an **empirical wage function** in the spatial autoregressive (SAR) form:

$$W = \lambda \cdot \Omega W + X\gamma + u$$

- ▶ W indicates the vector of $\ln w_j$
- ▶ Ω is the spatial weight matrix constructed by **bilateral migration flows** normalized by the labor in destination

$$\Omega_{ji} = \frac{m_{ij} + m_{ji}}{L_j}.$$

- ▶ X is a vector including exogenous *weather factors* affecting wages
- **Control function approach** by Qu et al. (2020) solves the *endogenous weights problem*.

- Migration data
 - ▶ Source: 2001 and 2011 waves of the National Census of India
 - ▶ Aggregated district-to-district migrant counts by gender, age, education, reason for migration, and duration of migration
- Wage data
 - ▶ Source: 2004-05 and 2011-12 waves of the National Sample Survey (NSS)
 - ▶ District average wages of the employed individuals

Results: wage spillovers via migration

Table: Results of SAR model estimation

Weight matrix Dependent var.	2004		2011	
	For work ln(wage) (1)	All mig. ln(wage) (2)	For work ln(wage) (3)	All mig. ln(wage) (4)
W·Y	0.157*** (0.047)	0.199*** (0.042)	0.162** (0.065)	0.106*** (0.028)
Δt	-0.274*** (0.082)	-0.239*** (0.082)	-0.389*** (0.059)	-0.397*** (0.059)
Δp	-0.003** (0.001)	-0.002** (0.001)	-0.002*** (0.000)	-0.002*** (0.000)
Origin FE from gravity	-0.084*** (0.013)	-0.074*** (0.014)	-0.085*** (0.012)	-0.087*** (0.013)
Destination FE from gravity	0.031*** (0.011)	0.026** (0.012)	-0.016* (0.009)	-0.022** (0.010)
Constant	7.930*** (0.033)	7.815*** (0.034)	8.272*** (0.035)	8.242*** (0.034)
Observations	577	577	612	612

Robust standard errors in parentheses. Sample: males aged 20-59.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Results: wage spillovers by subgroups

Table: SAR results by young/old and low/high educated, 2011

Weight matrix Dependent var.	Young		Old		Low edu.		High edu.	
	For work ln(wage) (1)	All mig. ln(wage) (2)	For work ln(wage) (3)	All mig. ln(wage) (4)	For work ln(wage) (5)	All mig. ln(wage) (6)	For work ln(wage) (7)	All mig. ln(wage) (8)
W-Y	0.178*** (0.068)	0.122*** (0.031)	0.124** (0.060)	0.063** (0.028)	0.115** (0.055)	0.088*** (0.026)	0.104** (0.049)	0.054** (0.022)
Δt	-0.469*** (0.065)	-0.476*** (0.065)	-0.311*** (0.067)	-0.320*** (0.067)	-0.385*** (0.063)	-0.392*** (0.063)	-0.328*** (0.058)	-0.334*** (0.058)
$\Delta \rho$	-0.002*** (0.000)	-0.002*** (0.000)	-0.002*** (0.001)	-0.002*** (0.001)	-0.001** (0.000)	-0.001* (0.000)	-0.003*** (0.000)	-0.003*** (0.000)
Constant	8.109*** (0.036)	8.068*** (0.036)	8.551*** (0.035)	8.550*** (0.036)	7.773*** (0.029)	7.739*** (0.029)	8.671*** (0.028)	8.670*** (0.028)
FEs from gravity	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	612	612	612	612	612	612	612	612

Robust standard errors in parentheses. Dependent variables are the district average wages for the corresponding subgroups.

Young: age 20-44; Old: age 45-64; Low edu.: primary and below; High edu.: secondary and above. Males only.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

- ▶ Wages of **younger** and **less educated** people are more correlated across districts

Simulations: wage spillovers from Delhi

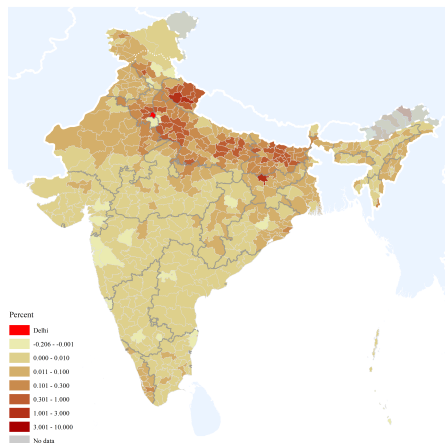


Figure: Wage spillover of the 10% productivity increase in Delhi

Simulations: wage spillovers from other big cities

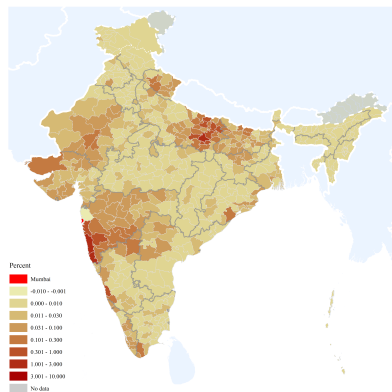


Figure: 10% increase in Mumbai

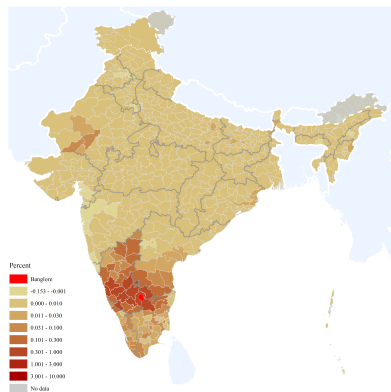


Figure: 10% increase in Bangalore

Simulations: wage change due to temperature rise

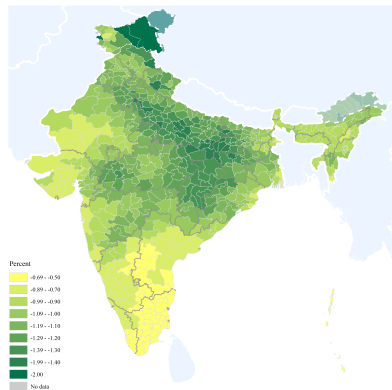


Figure: Wage change due to temperature rise

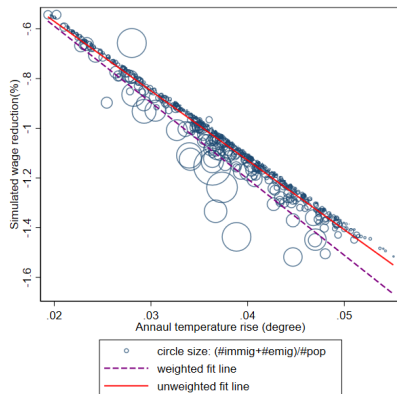


Figure: Wage change and temperature rise

Simulations: the impact of Golden Quadrilateral

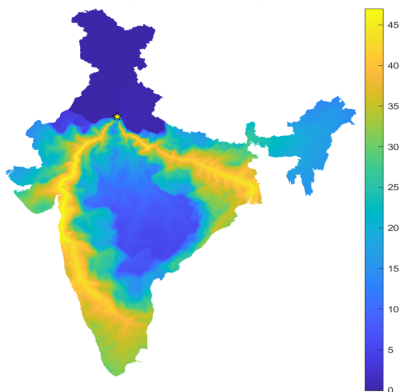


Figure: Percentage change of travel time to Delhi with GQ

Conclusion

- Linkages between local markets are critical for development. Labor mobility provides the most potent linkage.
- This paper models and quantifies the how labor flows transmit wage spillovers.
 - ▶ A spatial equilibrium model of labor mobility and wages determination in local labor markets lead to a SAR specification - with endogenous weights.
 - ▶ Estimation of the SAR model (with bilateral migration and wage data) shows the strength of the wage spillovers.
 - ▶ Simulations show how the effects of productivity shocks, climate change or infrastructure investments spillover to other regions via migration linkages.

THANK YOU!

Maggie Liu* yuanyuan.liu@treasury.gov

Çağlar Özden cozden@worldbank.org

He Wang hwang21@worldbank.org

*This research was conducted prior to when Maggie Liu was an employee at the U.S. Department of the Treasury. The findings, interpretations, and conclusions expressed in this paper are entirely those of the author and do not necessarily reflect the views or the official positions of the U.S. Department of the Treasury.