ADAPTATION IN MOTION: TEMPORARY MIGRATION UNDER HEAT STRESS

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Abstract

The impact of climate-induced temporary migration remains largely unexplored. Yet, this flow is widespread in developing countries and also responds to warming. The distinction from permanent migration is critical: because temporary migrants are often under-counted and unaccounted for in local administrative planning, they generate a distinct externality through the systematic under-provisioning of public services. Using a large-scale panel survey in India, we find that a one-degree rise in mean daily temperature increases temporary out-migration rates by 2%-6%. To investigate spatial spillovers under widespread climate change, we develop a model with both migration channels where temperature affects productivity and the under-provisioning of public services degrades local amenities for everyone. We use this framework to quantify the welfare costs of restricting each migration channel and compare different policy responses under climate change. Under the IPCC SSP 5-8.5 climate change scenario, restricting temporary migration generates welfare costs larger than restricting permanent migration, demonstrating that temporary flows are a critical but overlooked adaptation mechanism. Remedying the under-provisioning of services for temporary migrants delivers more than thrice the welfare gains than from cost-equivalent, place-based adaptation measures. These results have implications for the allocation of scarce climate adaptation funds in developing countries.

JEL Codes: Q54, O15, R23

Keywords: Internal migration, spatial equilibrium, heat stress, climate adaptation

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1 Introduction

Climate-induced migration is one among many profound consequences of climate change for lives and livelihoods everywhere. By 2050, there could be 143 million internal (or domestic) climate migrants in Sub-Saharan Africa, Latin America and South Asia (Rigaud et al., 2018). Empirical studies find that higher temperatures lead to distress migration from agriculture-dependent areas in South Asian, African, and South American countries (Berlemann and Steinhardt, 2017). While attention has focused on permanent relocation, temporary migration, which are shorter-term moves where workers maintain residential ties to their origins, is widely prevalent in many parts of the developing world (Sherbinin, 2020). This is also found to be a response to climate-change induced shocks like droughts, floods and extreme heat (Bharadwaj et al., 2021; Joarder and Miller, 2013; Kaczan and Orgill-Meyer, 2020).

The impacts of permanent migrants on local markets are well-studied (Card (2001); Peri (2016)). However, temporary migration can generate unique externalities. When populations relocate permanently, they formally integrate into destinations, gain documentation and political rights, and appear in official enumerations-creating incentives for policy responses like increased housing supply in order to to accommodate them. In contrast, temporary migrants often remain invisible to official counts and local politics (Sharma, 2014; Jayaram and Varma, 2020; Irudaya Rajan et al., 2020; Agarwal, 2022). This administrative and political invisibility generates a systematic underprovisioning of public goods (often reflected in the growth of informal settlements, strain on water and sanitation systems, and the like) that is distinct from general overcrowding (Gaikwad and Nellis, 2021). Furthermore, their transient nature can inhibit social integration, potentially contributing to local socio-political tensions that reduce a locations overall attractiveness (Gaikwad and Nellis, 2017; Thachil, 2017).

This paper investigates the role of temporary migration as an adaptation mechanism under heat and climate stress. We proceed by, first, providing new empirical estimates of the effect of temperature shocks on temporary outmigration using a novel panel dataset of temporary migration flows in India. Then, we build a spatial equilibrium model with endogenous choices between permanent and temporary migration that incorporates the unique negative externalities generated by temporary migrants. Productivity is modeled as a sector-specific function of temperature. Under this framework, we simulate the welfare effects of climate change and compare the effectiveness of different policy responses to climate-induced migration.

Despite its importance, the general equilibrium impact of temporary climate migration remains largely unknown because data on short-term movements are scarce and difficult to measure

(Foster and Rosenzweig, 2007). This paper uses data from the Consumer Pyramids Household Survey (CPHS), a large-scale household survey in India repeated three times a year. This dataset provides information on temporary migration that is typically unavailable in national Censuses or cross-sectional surveys. Two of its key advantages are (i) its panel nature allowing us to track individuals over time, and (ii) from September 2020, it provides information on both the origin and destination of migrants.[1]

Using this data, we explore the relationship between plausibly exogenous variation in daily mean temperatures and out-migration rates by employing a panel regression design with household and time fixed effects. A one-degree temperature increase during different seasons raises individual migration probabilities by 2.4%-6.1%, representing a 6%-18% increase over the mean outmigration rate. At the household level, the probability of having at least one migrant increases by 2.5%-5% for every degree rise in temperature, representing an increase of 7%-16% over the mean.

We then develop a spatial equilibrium model where households face a nested decision sequence to endogenously choose among staying, migrating temporarily, or migrating permanently. This model-based approach is necessary because reduced-form estimates, which are based on spatial variation in temperature shocks, cannot identify the welfare consequences of global climate change. In such a context, migration is not simply a response to local shocks but part of a broader spatial reallocation where all locations are simultaneously affected, generating spatial spillovers that empirical reduced-form methods do not capture. In our model, we incorporate temperature as a productivity factor that affects both the urban and the rural sectors.[2] A novel feature of the model is that local amenities deteriorate with a higher share of temporary migrants in the local labor force. This mechanism is designed to capture the unique externalities associated with temporary labor flows due to the underprovisioning of administrative services. The local quality of life depends thus not on population size per se (standard congestion in spatial models), but on the population composition, because of the failure of administrative systems to serve a subgroup for which they have not planned. The resultant strain on services like housing, water, sanitation degrades amenity value for the entire destination community.

We then use this to analyze impacts under climate change and a set of counterfactual policies. First, we simulate a climate shock corresponding to the IPCC AR 6 SSP 5-8.5 scenario. Using the model, we show that restricting migration is harmful to welfare, but crucially, restricting only

[1] To our knowledge, the only other paper using this dataset to study migration is Baseler et al. (2023).

[2] We estimate the model's temporary migration elasticity using the bilateral flows observed in the CPHS data. For productivity estimates under warming, we use high-resolution agronomic data from the FAO's Global Agro-Ecological Zones project for the rural sector, and experimental estimates from the literature for the urban sector.

temporary migration even while leaving the permanent migration channel fully open imposes a welfare cost of -2.73%. This is larger than the -2.12% welfare cost of restricting permanent migration, demonstrating that temporary migration is an important and distinct margin of adjustment. [3]

We also use our model to compare two distinct policy responses to these climate-induced welfare losses. Current policy frameworks on climate-related mobility are structured around a dual approach: averting or minimizing migration through in-place adaptation, or addressing and enabling migration when it occurs (UNFCCC, 2018; IOM, 2021). The first pillar, in-place (or in-situ) adaptation, aims to reduce the drivers of outmigration, through, for example, investments in climate-smart agriculture and protective infrastructure (Rigaud et al., 2018). The second pillar focuses on managing migration when it does occur, by formalizing migration pathways, ensuring access to rights and services and preventing overburdening of destination infrastructures. We conduct a comparative analysis of these two policies. We find that policies aimed at accommodating migrants by improving destination amenities are substantially more effective at raising welfare. Specifically, a policy that reduces the negative externalities from temporary migration boosts aggregate welfare by 0.72% compared to a world with climate change but no policy. This is more than thrice the welfare gain from a cost-equivalent in-place adaptation policy. However, these policies present a trade-off between maximizing welfare and maximizing output. While the externality-reducing policy yields the largest welfare gains, it results in a small decline in aggregate output (-0.41%). Conversely, the in-place adaptation policy, while less effective for welfare, generates a substantial output increase (+5.14%) by directly restoring productivity in climate-affected regions.

These findings have important implications for climate adaptation policy, particularly given severe constraints on adaptation finance. Developing countries need an estimated $215-$387 billion/year to finance climate adaptation, amounting to 0.6%-1% of their GDP (2021 prices). International public finance flows cover less than 5% of these needs (UNEP, 2024)[4], thus putting substantial pressure on national domestic budgets and policy priorities. Given these constraints, it is critical to identify which adaptation interventions deliver the highest welfare returns per dollar spent. Our results suggest that policies accommodating temporary migrants may offer a more effective use of scarce adaptation funds than in-place adaptation measures. The difference in wel-

[3]Shared Socioeconomic Pathways (SSPs) are climate change scenarios describing alternative future socio-economic developments and their associated greenhouse gas emissions trajectories. The IPCC Sixth Assessment Report (AR6) uses five main SSPs ranging from SSP1-1.9 (sustainability with very low emissions) to SSP5-8.5 (fossil-fuel intensive development with very high emissions). The four priority scenarios used in IPCC AR6 are SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5. We focus on SSP5-8.5 to understand the upper bounds of climate-driven economic responses under high-impact scenarios (Hsiang et al., 2017; Cruz and Rossi-Hansberg, 2021; Conte, 2022).

[4]The Glasgow Climate Pact urged developed nations to double adaptation finance to developing countries from $19 billion (2019 levels) to at least $38 billion by 2025, but even achieving this target would reduce the adaptation finance gap by only approximately 5% (UNEP, 2024).

fare gains between these approaches (0.72% versus 0.34%) is particularly striking given that both policies operate under the same fiscal budget. Moreover, the specific interventions that map to our counterfactual simulations (for example, registration systems that make temporary migrants visible to authorities and affordable rental housing programs) are often less capital-intensive than large-scale adaptation projects like climate-smart agricultural infrastructure or comprehensive heat-action plans.Importantly, our results highlight temporary migration as a critical adjustment mechanism in climate-stressed economies. Discussions of climate migration rarely distinguish between the unique externalities that temporary migrants generate at destinations. Our finding that restricting temporary migration imposes welfare costs as large as restricting permanent migration suggests that neglecting this channel could undermine adaptation efforts.

Our focus in this paper is on India, a suitable setting for three reasons. Firstly, India is highly climate vulnerable, susceptible to heatwaves, changing monsoon patterns, droughts and floods (Intergovernmental Panel On Climate Change (IPCC), 2023). Higher temperatures due to global warming adversely affect agricultural yields, labor productivity and living standards (Mani et al., 2018). Secondly, temporary migration is widespread (Morten, 2019). Compared to 97 million permanent migrants over 10 years (Census 2011, Govt. of India), there were an estimated 13.6 million short-term migrants in just one year (NSSO 64th round, 2007-'08, Govt. of India),[5] who are typically poorer, less educated, and from traditionally disadvantaged communities (Keshri and Bhagat, 2012; Coffey et al., 2015; Srivastava, 2019; Tiwari et al., 2022). Finally, there is growing evidence that climate vulnerability manifests through temporary migration, especially among households lacking resources to build alternative or resilient livelihoods (Iyer, 2021). A survey in three large Indian states found that more than two-thirds of the surveyed households had a member who migrated outwards for seasonal work due to droughts, floods, and/or heatwaves at the origin (Bharadwaj et al., 2021). They usually go to major cities for work in construction, or brick-kilns and cotton fields in neighbouring rural areas.

We contribute to two strands of literature. First, we advance the quantitative spatial economics literature that overwhelmingly focuses on permanent migration (Desmet and Rossi-Hansberg, 2009; Monte et al., 2018; Bryan and Morten, 2019; Morten and Oliveira, 2018). We build on two recent papers that distinguish between temporary migration and permanent migration in a nested choice framework (Imbert et al., 2023; Rai, 2024). We contribute to this emerging literature by incorporating a specific form of externality that is triggered by one of these migration channels, and use the model in a climate change context to evaluate relevant policies. Second, we contribute to the

[5]The NSSO defines short-term migrants as those who moved for six months or more- however, this definition is restrictive by not considering other time frames.

climate and environmental economics literature, in particular the studies on migration responses to climate and/or environmental triggers. (Oliveira and Pereda, 2020; Cruz and Rossi-Hansberg, 2021; Conte, 2022; Khanna et al., 2021). We identify a novel and understudied adaptation channel through temporary migration, and quantify its importance. Our policy conclusion- that enabling labor mobility is a critical component of adaptation- resonates with findings from other environmental contexts. Khanna et al. (2021), for instance, find that pairing pollution reduction with policies that ease migration frictions yields the largest welfare and productivity gains in China. While their mechanism focuses on skill-based productivity misallocation and ours on amenity loss from institutional failure, both papers arrive at a similar policy insight: the most effective response involves both mitigating the 'disamenity' directly and enhancing mobility.

2 Background

2.1 Nature of Migration in India

Developing economies often have large disparities in productivity between regions and sectors Venables (2005). In the case of India, pre-existing social and caste networks (Munshi and Rosenzweig, 2016), state borders and the inability to transfer welfare entitlements across states (Kone et al., 2018), have been identified as inhibiting labor reallocation, leading to a relatively low rate of internal migration. These analyses focus on long-term migration rates over a period of 10 years or longer. In this paper, we turn our attention on a different form of internal migration- one that is short-term wherein the migrant moves out of his home in search of economic opportunities and eventually returns to his home in the place of origin. Temporary migrants typically maintain strong ties to their place of origin, with the intention of returning after a certain period.[6] This type of temporary migration is reflective of the uneven spatial distribution of economic opportunity; as well as the costs of relocating permanently(Srivastava, 2020). While permanent migration is important for capturing long-term demographic changes and associated structural transformations (Liu et al., 2023), the nature of permanent and temporary migration is different. For example, compared to 97 million permanent migrants over 10 years (Census 2011, Govt. of India), the National Sample Survey Office (NSSO 64th round, 2007-'08, Govt. of India) estimated 13.6 million short-term migrants in just one year[7]. In addition to being a quantitatively different phenomenon, several studies (Keshri and Bhagat (2012), Tiwari et al. (2022), Coffey et al. (2015), Srivastava (2019)) show that short-term

[6]In South Asia, migration is often seasonal or circular, involving the temporary relocation of certain family members to alternate locations to supplement household incomes. Rural communities depend on remittances sent back by family members who have migrated.(ActionAid, 2020)

[7]The NSSO defines short-term migrants as those who moved for six months or more- however, this definition is restrictive by not taking into account other time-frames.

migrants are poorer and belong to disadvantaged castes. They are, however, an important source of labor supply for urban markets (Imbert and Papp, 2020a). The government of India's report on internal migration[8] points to the estimated 13.6 million short-term migrants as of the National Sample Survey (NSS), 2007-08 and describes their concentration on building and construction sites, brick-kilns, and the like. It also expresses the need for better socio-economic measures (like food rationing services and health insurance) to protect the interests of vulnerable migrant populations. Studies[9, 10] point to how such workers, away from their usual places of residence and working in the urban informal sector, are excluded from state services, political representation, and worker protections (Sharma, 2014; Jayaram and Varma, 2020; Irudaya Rajan et al., 2020; Agarwal, 2022).

Despite their prevalence, temporary migration remains understudied primarily due to a lack of data. The existing data sources, such as the National Sample Survey (NSS) and the Indian Census, have limitations in providing accurate and timely information on the scale and direction of short-run internal migration flows in India (Ram Bhagat, 2008). The Census is conducted once in a decade and does not capture high-frequency data on migration. It captures permanent migration based on either the last known place of birth or place of residence. The National Sample Survey, on the other hand, does not have a defined frequency for carrying out migration-related surveys. Its restrictive definitions of short-term and seasonal migrants misses out on migrants who move for short durations other than 6 months. Another drawback of NSS data is the inability to identify the destination of migrants. Reliable estimates of the magnitude and patterns of internal migration in India are essential for designing effective social welfare policies and protections for vulnerable migrant populations.[11]

2.2 Vulnerability to warming

India is highly susceptible to increased heatwaves, changing monsoon patterns, droughts and floods (Intergovernmental Panel On Climate Change (IPCC), 2023). Climate assessments show a 0.7°C temperature rise since 1901-2018, with projections of a 1.4-2.7°C increase by 2040-2069 (Krishnan et al., 2020). Higher temperatures adversely affect agricultural yields, labor productivity and overall living standards (Mani et al., 2018). In 2021, heat exposure caused approximately $159 billion in annual lossesroughly 5.4% of GDP (ClimateTransparency, 2022). This makes India a suitable setting for studying migration and climate change. While studies document the link between adverse

[8] Report of the Working Group on Migration, Jan 2017, Govt. of India Retrieved on Mar 30, 2023

[9] Unlocking the Urban: Reimagining Migrant Lives in Cities Post-COVID 19 Retrieved on May 10, 2023

[10] Studies, Stories and a Canvas: Seasonal labor Migration and Migrant Workers from Odisha Retrieved on May 10, 2023

[11] The Economic Survey of India, 2016-17, GOI, draws on railway passenger traffic data in India to try and provide an estimate of work-related migrant flow. It estimated an annual flow of 9 million inter-state migrants in India since 2011. However, railway passenger data is at best a weak proxy for actual migratory flows.

weather events and outward migration (Kumar and Vishwanathan, 2012; Kumar and Viswanathan, 2013; Sedova and Kalkuhl, 2020; Dallmann and Millock, 2017; Liu et al., 2023), this literature focuses mostly on permanent migration [12]. However, temporary migration is widespread (Morten, 2019). Studies and surveys show that households affected by changing climatic conditions, which lack resources to build alternative or resilient livelihoods, often cope with these changes through temporary migration (Iyer, 2021) A survey amongst households in Uttar Pradesh, Madhya Pradesh, and Rajasthan noted that more than two-thirds of them reported having a member who migrated outwards for work due to droughts, floods and/or heatwaves at the origin (Bharadwaj et al., 2021). Sedova and Kalkuhl (2020) note how many individuals are prompted to relocate temporarily to other places, particularly large urban clusters, in search of work in response to weather-related shocks.

3 Data

3.1 Migration

The main source of data is the Consumer Pyramids household survey (CPHS) carried out by the Centre for Monitoring Indian Economy (CMIE). It is a continuous, large-scale panel survey of a nationally representative sample. Each household is surveyed three times a year, and every survey round is known as a Wave. A Wave spans 4 calendar months. We use the data for 8 waves covering the time period Sep 2021-April 2024. Starting in September 2020, this survey provides detailed migration data on individuals in and out of the sample households. The survey records when and if a member of a household is leaving the home to go elsewhere, and when they return. It also records the destination of the migrant. During any given survey round, approximately 33% of the adult, working-age population are outmigrants.[13] About 32% households reportedly send at least one outmigrant during this time period. The aggregate number masks considerable regional heterogeneity.

Some of the drawbacks of this survey are (i) the inability to measure migration when the entire household moves, (ii) as this is not a survey of migrants at the destination, we do not observe what the migrant is doing or how he/she is employed during the time they stay away from the rest of the household, and (iii) while the survey has been conducted on a regular frequency since 2014, the questions related to migration were only added relatively recently in 2020. Despite these drawbacks, the scale and frequency of this survey make this a unique source of migration data in this context,

[12] These studies rely on the decadal Census or other migration data sources where the individual changes the place of residence without maintaining links with the previous residence

[13] For comparison, the Periodic Labour Force Survey (PLFS) by the Indian Government in 2020-21 calculated the average outmigration rate to be 29%.

and because of its high frequency, it is well-suited to capturing the fast-moving nature of temporary migration.[14]

3.2 Historical Weather data

We use ERA5 Climate Reanalysis data from the Copernicus Climate Change Service (C3S0) at ECMWF to get surface temperature and rainfall data. ERA5 replaces the ERA-Interim reanalysis which has been used in, for example, Colmer (2021), Taraz (2018) and Sedova and Kalkuhl (2020). ERA5 provides gridded hourly estimates on a regular latitude-longitude grid of 0.25 degrees for a large number of atmospheric, ocean-wave and land-surface quantities. We aggregate the gridded data up to the district level and construct estimates of daily mean temperature and daily rainfall at the district level.

3.3 Climate projections

3.3.1 Temperature

This Copernicus Climate Change Service (C3S0) also catalogues daily and monthly global climate projections data from a large number of experiments, models and time periods computed in the framework of the sixth phase of the Coupled Model Intercomparison Project (CMIP6). This data underpins the IPCC 6th Assessment Report (AR6). Climate projection experiments follow the combined pathways of Shared Socioeconomic Pathway (SSP) and Representative Concentration Pathway (RCP). Shared Socioeconomic Pathways (SSPs) are climate change scenarios describing alternative future socio-economic developments and their associated greenhouse gas emissions trajectories. We extract the gridded data for India over the future period 2015-2100 to use as our estimates of future warming.

3.3.2 Crop yield projections

We leverage data from the Global Agro-Ecological Zones (GAEZ) project, version 5. This project was developed by the International Institute for Applied System Analysis (IIASA) and the UNs Food and Agriculture Organization (FAO). It draws on state-of-the-art agronomic models to calculate potential crop yields from high-resolution data on climatic and soil conditions under a set of assumptions about input use such as water, labor, and farm management.

[14] To our knowledge, the only other study to have used this dataset for studying migration is Baseler et al. (2023), which conducts a randomized control trial for investigating the link between short-term migration and food insecurity.

3.4 Empirical Results

We first measure the outmigration response to higher temperatures. Following the literature (Liu et al., 2023; Colmer, 2021; Oliveira and Pereda, 2020; Huang et al., 2020), we take the average of daily mean temperatures for every district. Like Colmer (2021); Liu et al. (2023), we use crop-growing seasons as our relevant time-frame for averaging. However, our focus is not only on rural-urban migration, but migration generally. By using the two main crop growing seasons in India (i) the 'kharif' rice season from June-September and (ii) the 'rabi' wheat season from October-March, we effectively capture averages over the summer and winter seasons- which is most analogous to the approach in Oliveira and Pereda (2020),and is suitable for studying broad seasonal variations in temperature that affect outcomes beyond the rural sector. Figure 1 shows the distributions of these temperature measures.

We exploit the panel structure of the data and regress the individual migration probabilities on the temperature measure, with household and time fixed effects, controlling for rainfall. We cluster standard errors at the district level.

$$\text{Migrate}_{ihdt} = \alpha + \beta \text{Temperature}_{dt} + \gamma \text{Rainfall}_{dt} + \mu_h + \lambda_t + \epsilon_{iht} \tag{3.1}$$

where Migrate_{iht} is the individual i or household h level migration outcome at time t in location d, Temperature_{dt} is the mean daily temperature during the relevant season, Rainfall_{dt} is the total rainfall during growing season, μ_h are household fixed effects, λ_t are year fixed effects and ϵ_{iht} is the error term. Our coefficient of interest is β, as it captures the migration response to temperature.

During the summer growing season, a one-degree temperature increase is associated with a 6.1% higher probability of individual outmigration, representing an 18.1% increase over the mean individual outmigration rate of 33.7%. Similarly, the likelihood of a household having an outmigrant increases by 5.0%, a 16.4% rise from the baseline household outmigration rate of 30.4%. The winter growing season shows more modest but still significant effects, with a 2.4% (5.7%) increase in individual outmigration and a 2.5% (7.9%) increase in household outmigration (refer Table 1).

Table 1: Effect of Daily Mean Temperatures in different seasons on Migration Outcomes

	Individual Is Outmigrant	**Household has Outmigrant**
	(1)	(2)
Summer (Growing Season)	0.061***	0.050***
	(0.016)	(0.014)
F-stat	28.325	16.488
Dep. Var. Mean	0.337	0.304
N	328454	78111
	(1)	(2)
Winter (Growing Season)	0.024***	0.025***
	(0.007)	(0.007)
F-stat	7.884	9.876
Dep. Var. Mean	0.349	0.318
N	303265	71587
Household FE	Yes	Yes
Year FE	Yes	Yes
Rainfall Controls	Yes	Yes

Notes: Standard errors clustered at district level in parentheses. A district is the smallest location identifier in our dataset. Each column shows results from two separate regressions. Column (1) regresses the individual temporary out-migration rate among the adult population on different seasons' daily mean temperatures, with controls for rainfall and household and time fixed effects. The dependent variable takes the value 1 if there the individual is away from his place of residence during that period, 0 otherwise. Column (2) regresses the household out-migration rate on different seasons' daily mean temperatures, with the same controls and fixed effects. The dependent variable takes the value 1 if there is at least one working age out-migrant in the household, 0 otherwise. The summer (growing season) corresponds to the months of May-August (approximately), which coincides with the *kharif* crop season's growing months in India. The winter (growing season) corresponds to the months of November-February (approximately), which coincides with the *rabi* crop season's growing months.
*** $p<0.01$, ** $p<0.05$, * $p<0.10$

4 Model

We develop a spatial equilibrium model of migration that incorporates two key features: temporary and permanent migration as distinct choices and a compositional externality proportional to the share of temporary migrants in the labor force. The model builds on the spatial migration literature (Oliveira and Pereda, 2020; Rai, 2024; Imbert et al., 2023) but adapts it to capture the unique characteristics of temporary migration flows and the impact of temperature with productivity. Our economy has a fixed number of locations, with each location comprising a rural and urban sector. Workers in each location decide to migrate to another place and sector, based on their utilities, which are a function of consumption, housing, amenities and idiosyncratic preferences. Once workers have distributed themselves over space, firms in every location and sector make production decisions. We assume that goods are not traded and that productivity is dependent on place-based factors, one of which is temperature. In equilibrium, this determines wages, rents, prices, outputs and migration rates.

4.1 Utility and migration decisions

We assume that the economy has N different locations. Each location comprises two sectors $s \in S$, one rural or agricultural (r); and one urban, or non-agricultural(u). Individuals do not choose where they are initially located, but can choose their destination location and sector if they wish to migrate.[15]This is similar to Bryan and Morten (2019), who take the initial place of residence as akin to a birthplace, which individuals have no control over. Each individual supplies one unit of labor inelastically. The initial place of residence is the 'origin' location. From this origin (o, s), each individual chooses among three options: (i) stay in the origin, (ii) migrate permanently to a destination (d, s'), or (iii) migrate temporarily to (d, s'). The distinction between permanent and temporary migration is crucial in our setting. Permanent migrants relocate their entire household and establish new roots at the destination, while temporary migrants maintain residential ties to their origin, working at the destination for a limited period before returning home.

Individuals have Cobb-Douglas preferences over a location-specific amenity $\tilde{b}$, a composite consumption good C and housing H:

$$U = \tilde{b} C^{\alpha} H^{1-\alpha}, \quad \alpha \in (0, 1) \tag{4.1}$$

As amenities are costless, an individual working in location-sector (d, s) faces the budget constraint:

$$W_{ds} = P_d C + q_d H \tag{4.2}$$

where W_{ds} is the nominal wage, P_d is the price index of the composite consumption good, and q_d is the rental price of housing. The wage income at every location-sector depends on the marginal productivity of labor at that location (expanded on in the next section). We assume that labor is perfectly homogeneous and there is no difference in skills or education that can fetch them a premium in the market.

In all cases, consumption is a CES aggregate of the goods produced in rural and urban sectors,$C_o = \left[\sum_{s \in S} c_{os}^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}$. This implies a corresponding price-dual $P_o = \left[\sum_{s \in S} p_{os}^{1-\sigma}\right]^{\frac{1}{1-\sigma}}$.

Standard utility maximisation yields the indirect utility function for an individual with wage W_{ds}

[15] This is different from Monte et al. (2018), where agents choose a pair of locations-one to live in and one to work in. In our study, we take the initial place of residence as given.

in location d, working in sector s:

$$V_{ds} = \tilde{b}_d \cdot \frac{\alpha^{\alpha}(1-\alpha)^{1-\alpha}W_{ds}}{P_d^{\alpha}q_d^{1-\alpha}} \tag{4.3}$$

If the individual initially located in place o wishes to move to a different location $d \in N$ ($\neq o$), then he or she has to incur a positive moving cost of m_{od}. We assume that $m_{od} > 1$, $m_{oo} = 1$ and $m_{od} = m_{do}$. The origin-destination moving cost is time invariant, implying that transport costs do not change substantially over the time period that we are studying (no large movements in prices or transport infrastructure). The deterministic component of utility for each migration choice is as follows. For an individual initially in origin (o) moving to destination d, sector s:

Permanent migration to (d, s):

$$V_{ods'}^{PM} = \frac{\tilde{b}_d}{m_{od}} \cdot \frac{\alpha^{\alpha}(1-\alpha)^{1-\alpha}W_{ds}}{P_d^{\alpha}q_d^{1-\alpha}} \tag{4.4}$$

Temporary migration to (d, s):

$$V_{ods'}^{TM} = \frac{\tilde{b}_d}{m_{od}} \cdot \frac{\alpha^{\alpha}(1-\alpha)^{1-\alpha}W_{ds}}{P_d^{\alpha}q_d^{1-\alpha}} \tag{4.5}$$

4.1.1 Compositional externality in Amenities

A key feature of our model is the treatment of location-specific amenities $\tilde{b}_d$, which depend on the composition of the local labor force. This departs from standard spatial models, which incorporate a congestion term as a function of total population, or population density. This is a scale effect where more people leads to more crowding, imposing a negative externality on everyone. However, we model the specific negative externality that arises from the population composition when there is a significant institutional or administrative failure to account (and hence provide) for one of those groups, in this case, temporary migrants. We model amenities as decreasing in the share of temporary migrants:

$$\tilde{b}_d = b_d \cdot (1 - \phi \cdot \frac{L_d^{TM}}{L_d}) \tag{4.6}$$

where b_d is the baseline amenity level, L_d^{TM} is the number of temporary migrants in location d, L_d is the total labor force in location d, and $\phi \in (0, 1)$ is a parameter that governs the sensitivity of amenities to temporary migrant concentration. This formulation represents the administrative frictions that arise from several institutional features of temporary migration. Temporary migrants are 'invisibilised' in official statistical counts and local politics (Sharma, 2014; Jayaram and Varma, 2020; Irudaya Rajan et al., 2020; Agarwal, 2022). This invisibility, because it does not trigger an expansion of public services, can lead not just to general overcrowding (which is standard congestion effects in the migration literature) but to a systematic underprovisioning of those non-excludable public services and related infrastructure (Gaikwad and Nellis, 2021). This can potentially foster the growth of informal settlements that strain public health and sanitation systems for the entire destination community. Furthermore, their transient nature can inhibit deep social integration, potentially contributing to local social and political tensions that reduce a location's overall attractiveness. A higher ϕ thus represents more severe administrative frictions. This means that a rising share of unaccounted-for temporary migrants translates into higher strain on amenity valuations and a lower quality of life for the entire destination population.

4.1.2 Nested Preferences

Individuals have idiosyncratic preferences over locations and migration types. Drawing closely from (McFadden et al., 1978; Rai, 2024; Imbert et al., 2023), we assume these preferences follow a nested Frechet distribution, which allows for flexible substitution patterns. Specifically, let ε_i^S, ε_i^{PM}, and ε_i^{TM} denote individual i's idiosyncratic preference shocks for staying, permanent migration, and temporary migration, respectively. The joint distribution is:

$$F(\varepsilon^S, \{\varepsilon_{ds}^{PM}\}_{d,s}, \{\varepsilon_{ds}^{TM}\}_{d,s}) = \exp\left\{-\left[\left(\varepsilon^S\right)^{-\theta^u} + \left(\sum_{d,s}(\varepsilon_{ds}^{PM})^{-\theta^{PM}}\right)^{\theta^u/\theta^{PM}} + \left(\sum_{d,s}(\varepsilon_{ds}^{TM})^{-\theta^{TM}}\right)^{\theta^u/\theta^{TM}}\right]\right\} \tag{4.7}$$

where θ^u controls substitution across migration types (stay, permanent, temporary), while θ^{PM} and θ^{TM} control substitution across destinations within each migration type.

This nested structure implies a two-stage decision process. First, individuals choose between staying, permanent migration, and temporary migration. Second, conditional on choosing to migrate (permanently or temporarily), they select their destination.

Conditional on choosing migration type $k \in \{PM, TM\}$, the probability of selecting destination (d, s') is:

$$T_{ods'|k} = \frac{\left(V_{ods'}^k\right)^{\theta^k}}{\sum_{j=1}^N \sum_{r\in\{R,U\}} \left(V_{ojr}^k\right)^{\theta^k}} \tag{4.8}$$

The unconditional probability of migrating from (o, s) to (d, s') via migration type k is:

$$\pi_{ods'}^k = T_o^k \times T_{ods'|k} \tag{4.9}$$

Migration flows are increasing in destination wages and amenities, decreasing in destination living costs, and decreasing in bilateral migration costs.

4.2 Housing Market

Following Morten and Oliveira (2018), we model the price of housing as depending on the underlying cost of producing housing units. The price of housing is determined by the marginal cost of construction, which includes the interest rate ι_t, construction costs CC, and land costs LC_d. We assume as in Morten and Oliveira (2016) that all housing supply is owned by absentee landlords. Equilibrium rent is the discounted value of house prices:

$$q_d = \iota \cdot MC(CC, LC_d) \tag{4.10}$$

The cost of land is a function of the demand for housing. The demand for housing is determined by the total expenditure on housing:

$$H_d = \frac{(1-\alpha)\sum_{s\in\{R,U\}} W_{ds}L_{ds}}{q_d} \tag{4.11}$$

As a result, the equilibrium price of housing in location d is given by:

$$q_d = \bar{\iota} H_d^{\lambda} \tag{4.12}$$

where $\bar{\iota}$ is a measure of construction costs (inclusive of interest), and λ is the inverse housing supply elasticity [16]. Substituting the two equations together yields the equilibrium rent as a function of local income:

$$q_d^{1+\lambda} = \bar{\iota}(1-\alpha)^{\lambda}\left[\sum_{s\in\{R,U\}} W_{ds}L_{ds}\right]^{\lambda} \tag{4.13}$$

4.3 Firms and general equilibrium

There are a large number of identical firms operating in every location. They all produce a single, non-differentiated good with the labor as the only factor of production. Employers do not distinguish between migrant laborers and residential laborers as both are equally skilled and hence, both are compensated at the same wage rate. In every location and each sector, firms hire labor to produce a single good using the same Cobb-Douglas production function:

[16] The parameter λ captures the responsiveness of housing supply to price changes: higher values indicate more inelastic supply, meaning housing costs rise more sharply with increased demand.

$$Y_{ds} = A_{ds} L_{ds}^{\beta} \tag{4.14}$$

where β is labor input share and $\beta < 1$ to satisfy standard assumptions of diminishing marginal product. We assume for simplicity that every location has the same production function. We also assume that the same goods are being produced in each location, so that there is no inter-regional trade in goods. Only factors, specifically labor, are mobile between regions. Since markets are competitive, firms earn zero profit in equilibrium and labor is paid its marginal product. Hence, the real wage rate w_{ds} in every location d, sector s is the marginal productivity of labor in that location and sector. This implies that:

$$\frac{W_{ds}}{p_{ds}} = \beta A_{ds} L_{ds}^{\beta-1} \tag{4.15}$$

where W_{ds} is the real wage rate prevailing in sector s in place d and p_{ds} and L_{ds}^{D} are the corresponding price and labor demand. A_{ds} is a location and sector-specific productivity factor[17].

A_{ds} is a key component of this model. We assume that this depends critically on temperature.[18] We impose the following functional form on A_d:

$$A_d = \varphi_d f_s(T_d) \tag{4.16}$$

where φ_d is the time-invariant component of productivity, $f_s(T_d)$ is some sector-specific function of temperature at place d.

An equilibrium is characterized by the clearing of all markets, given an initial distribution of labor and a preference draw. A negative productivity shock in a location reduces local wages, inducing out-migration. However, this out-migration affects destination locations through three channels: increased labor supply (depressing wages), increased housing demand (raising rents), and changes in labor composition at destinations (affecting amenities).

[17]This is on the lines of place-based productivities found in spatial equilibrium models in (Desmet et al., 2021; Cruz and Rossi-Hansberg, 2021; Peri and Sasahara, 2019; Oliveira and Pereda, 2020; Bryan and Morten, 2019; Khanna et al., 2021; Morten and Oliveira, 2018)

[18]Temperature impacts economic growth(Dell et al., 2012), labor productivity (Parsons et al., 2021) and mortality (Deschênes and Greenstone, 2011). The link between temperature and output has been documented for both in the agricultural sector (Taraz, 2018; Colmer, 2021; Burke and Emerick, 2016) as well as for the non-agricultural sector (Somanathan et al., 2021; Chen and Yang, 2019).

5 Solving for model's structural parameters

5.1 Estimating Frechet parameters

The bilateral migration data that is available in CPHS is very well-suited for the estimation of a gravity-type equation of migration flows.

We parameterise moving costs using 3 observable factors,(Kone et al., 2018; Dallmann and Millock, 2017)- (i) distance between the origin and destination districts, [19] (ii) whether or not the two districts are located in the same state, and (iii) linguistic distance between the two districts (see A.1 for details), (iii) whether the worker is switching sectors. We impose the following functional form on the moving cost:

$$\begin{aligned} m_{od} = \exp[&Distance_{od} + \mu_2 \mathbf{I}(o,d \text{ in different state}) + \\ &\mu_3 \mathbf{I}(\text{linguistic distance between } o,d) + \\ &\mu_4 \mathbf{I}(\text{worker switching sectors})] \end{aligned} \tag{5.1}$$

We estimate the temporary migration gravity equation using the method of Poisson pseudo-maximum likelihood (PPML) (Silva and Tenreyro, 2006). This method can rationalize zero migration flows between districts, which is relevant in our context [20]. The estimation results are given in Table 6. Similarly to Kone et al. (2018) we find that state borders and linguistic distances play a significant inhibitory role on district-to-district migration. Following the standard 2-step model in the literature (Morten and Oliveira, 2016, 2018; Rai, 2024), we use the estimated destination-sector fixed effects from the gravity model and regress it on destination-sector specific wages, and destination specific prices and amenities. We use a Bartik-style wage shifter to estimate the impact of wages on destination-sector utlities, after absorbing the prices and amenities as fixed effects. The final estimated parameter, θ_{TM}, is given in Table 7.

For other structural parameters, we assume values or set them from the literature. Crucially, we use estimates of θ_u and θ_{PM} from Rai (2024). The list of model parameters is given in Table 8. We find that our estimated value of θ_{TM} is around 8.07, which is lower than but still comparable to the estimates value in Rai (2024), which is around 9.

[19] Strictly speaking, we calculate the distance between the centroid of each district. See Table **??** for a summary.

[20] The other margin of migration that is present in our data but we do not consider is intra-district or within-district migration.

5.2 Estimating the impact of temperature on productivity

The key aspect of our model is the impact of temperature on productivity. This varies widely based both on prevailing local conditions and the nature of the work involved (Tord Kjellstrom, 2019).[21] We model the impact of temperature separately for the rural and urban sectors based on the data sources outlines in Section 3.

Rural sector: For the rural or agricultural sector, we aim to estimate $f_r(T_{dt})$. To do this, we leverage high-resolution spatial data from the FAO's Global Agro-Ecological Zones project (Costinot et al., 2016; Oliveira and Pereda, 2020; Aggarwal et al., 2022). This database combines agronomic models with geographic characteristics to predict crop yields under each Shared Socio-Economic Pathway (SSP) outlined in the IPCC's Sixth Assessment Report (AR6). Each pathway is associated with a degree measure of average global temperature increase. Hence, this predicts potential agricultural productivity in every region under different degrees of warming. We specifically use the potential crop yields under SSP 5-8.5. We calculate relative yields by comparing historical and projected crop yields, aggregating the gridded data upto districts. We then weight districts' yield changes by their historical production levels to capture differential impacts across India's agricultural landscape. We consider the two major food crops grown in India, rice (wetland and dryland) and wheat.

Urban sector: For the non-agricultural sector, we need to estimate $f_u(T_{dt})$, which represents the effect of temperature on urban productivity. This is based on the findings in Adhvaryu et al. (2020), which examines the impact of heat on labor productivity among garment factory workers in Bangalore, India. The key findings from this study that we have used are that (i) Mean productivity (actual/targeted output) in the sample is approximately 53 (ii) For temperatures $> 27°$C: efficiency decreases by 2.1% for every 1°C increase. We extract gridded temperature data for two key periods, (i) a historical 'baseline' (2015-2024), and (ii) future (2041-2060) climate model projections under the high-emissions SSP5-8.5 scenario. By comparing these periods and aggregating gridded data, we construct district-level temperature distributions to estimate shifts in non-agricultural labor productivity. As the temperature distribution is each location shifts by a certain degree Celsius, we calculate the expected reduction in labor efficiency from the mean.

[21] The relationship between temperature and productivity is complex, and different papers have taken different approaches to modelling it. Oliveira and Pereda (2020) have not opted for a parametric approach, instead they draw on grid-level data from the Global Agro-Ecological Zones (GAEZ) project, like we have. Peri and Sasahara (2019) assume that urban productivity is not affected by an increase in temperatures but that rural productivity decreases at a constant rate (assumed to be 10%) if temperatures rise above a certain threshold. Cruz and Rossi-Hansberg (2021) frame a 'damage' function that impacts location amenities and productivities through temperature and estimate it using a panel fixed effects empirical specification with temperature entering the regression in a flexible non-parametric way.

5.3 Calibrating ϕ

Our model formulates amenities to capture a novel composition-based externality that extends beyond traditional congestion effects, highlighting how the presence of temporary migrants creates systemic challenges in local service provision. The negative impact on amenity from a higher share of temporary migrants in the labor force (and not just total labor) stems from the institutional infrastructure's inability to adequately recognize and respond to their transient status. We calibrate the amenities to justify the observed migration flows in the data under an assumed equilibrium. We do this by minimizing the discrepancies between observed and predicted migration probabilities using the CPHS data on bilateral temporary migration flows, initial labor allocations (due to data limitations, we assume the observed baseline labor is the sum of natives and permanent migrants) and location-sector specific wages. The objective function compares the model's predicted migration probabilities with the empirically observed migration patterns across districts, effectively backing out the implied amenity levels that rationalize observed labor mobility. We employ a standard numerical optimization procedure for this. We derive a value of ϕ that is approximately 0.126.

This indicates that a 10 percentage point increase in the share of temporary migrants causes the amenities to degrade by 1.26%. As the amenities enter the utility function directly, this 10 percentage point increase in the share of temporary migrants translates into a utility loss of 1.26%. While the existing literature does not allow for a direct comparison, we try to benchmark this value against measures of subjective valuations of public amenities. This is a very conservative estimate when contrasted against, say, Gonzalez-Navarro and Quintana-Domeque (2010), who find that providing significant infrastructure improvements in slums (paved roads) causes property valuations to increase by 15-17%. A closer benchmark is welfare-equivalent household willingness-to-pay for important local amenities like clean air and clean water. In Ito and Zhang (2020), households are willing to pay about $190 to eliminate disamenity from severe air-pollution, implying a welfare cost equivalent to 1.7% of household income. In Burlig et al. (2025), Indian households are willing to pay upto 1.5% of their household expenditure to eliminate a disamenity from unsafe drinking water. Both of these estimates are somewhat comparable to our calibrated ϕ value- wherein a large institutional shock, such as a 10 percentage point increase in the share of temporary migrants, would generate a welfare loss of 1.26% due to the degradation of non-excludable public goods.

6 Counterfactual Results

6.1 Effect of increase in temperature under climate change

We use the calibrated model to evaluate the impact of climate-induced productivity shocks on migration patterns, spatial outcomes, and welfare.[22] Our counterfactual analysis compares three policy regimes: (i) unrestricted migration, where workers are free to choose between staying, moving permanently, and moving temporarily; (ii) restricted temporary migration, where temporary migration is rendered prohibitively costly but permanent migration remains feasible; and (iii) restricted permanent migration, where permanent migration is effectively prohibited but temporary migration remains feasible.

We simulate productivity shocks corresponding to the Shared Socioeconomic Pathway 5-8.5 (SSP5-8.5) from the IPCC Sixth Assessment Report (AR6) (AR6, 2023).[23] SSP5-8.5 represents a high-emissions scenario with continued reliance on fossil fuels and limited climate mitigation, resulting in substantial global warming by mid-century. Under this scenario, mean temperatures are projected to increase by approximately 2.4° C (range: 2.1-2.8° C) relative to the 1850-1900 baseline by 2041-2060.[24] The productivity impacts of this temperature increase vary across locations and sectors. Under SSP 5, approximately 75%-80% of location-sectors experience negative productivity shocks, with mean productivity decline of around 10% in affected areas and overall productivity declines of 7.7%-7.8% across all areas (Table 2).

Table 2: Productivity Changes Across Location-Sectors under SSP 5-8.5

Sector type	Locations with Productivity Hat < 1	Mean Productivity Change
Rural	392 (80.5%)	-7.7%
Urban	367 (75.4%)	-7.8%

We find that, first, even with unrestricted migration, the climate shock imposes substantial costs (Table 3). Aggregate welfare declines by 0.28%, while output falls by 4.52%.[25] Both tempo-

[22] Appendix .3 details the exact-hat system used to solve for the equilibrium steady-state under a shock.

[23] Shared Socioeconomic Pathways (SSPs) are climate change scenarios describing alternative future socio-economic developments and their associated greenhouse gas emissions trajectories. The IPCC Sixth Assessment Report (AR6) uses five main SSPs ranging from SSP1-1.9 (sustainability with very low emissions) to SSP5-8.5 (fossil-fuel intensive development with very high emissions). The four priority scenarios used in IPCC AR6 are SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5.

[24] We focus on SSP5-8.5 to understand the upper bounds of climate-driven economic responses under high-impact scenarios (Hsiang et al., 2017; Cruz and Rossi-Hansberg, 2021; Conte, 2022). While some research questions the likelihood of SSP5-8.5 emissions trajectories, this scenario remains valuable for assessing adaptation needs under severe climate stress, particularly in climate-vulnerable regions like India where adaptation capacity is limited.

[25] As a benchmark, the ClimateTransparency (2022) report finds that the heat-related reduction in labor capacity

rary and permanent migration rates increase modestly (0.41% and 0.07% respectively) as workers seek to escape adversely affected areas. Second, restricting only temporary migration while leaving the permanent migration channel fully open imposes a substantial welfare and output cost. When temporary migration is limited, aggregate welfare declines by 2.73%, which is nearly ten times larger than under unrestricted migration. Output falls by 10.11%, more than double the decline under unrestricted migration. Restricting permanent migration also increases welfare losses, though the welfare effect is somewhat smaller in magnitude. With limited permanent migration, welfare declines by 2.12% and output falls by 12.11%. Third, the temporary and permanent migration channels are not perfect substitutes. Under unrestricted migration, both temporary and permanent migration rates increase modestly (0.41% and 0.07% respectively) as workers seek to escape adversely affected areas. When temporary migration is restricted, permanent migration increases by 77.74% as workers substitute toward this remaining margin, though this substitution is far from complete- the total migration rate still declines by 3.40%. Conversely, when permanent migration is restricted, temporary migration more than doubles (107.22%), but total migration rate falls.

These results reveal a divergence between the drivers of aggregate output and aggregate welfare. Restricting permanent migration creates the largest output loss (-12.11%), presumably because of the negative externality modeled in the amenity. When the only adjustment channel left is temporary migration (which increases by 107%), the labor composition at destinations skews in favor of temporary migrants. However, this causes a reduction in destination amenities, possibly so severely that it cuts off reallocation of labor from shocked to productive regions. The resultant, exacerbated labor misallocation stunts national output. On the other hand, restricting temporary migration is most damaging to welfare (-2.73%) because it removes the most accessible and flexible coping mechanism for households. Under a climate shock, temporary migration responds more than permanent migration (0.41% increase against 0.07%). When this channel is shut down, households that would have otherwise moved remain trapped in their origins, which drives the large aggregate welfare loss. Taken together, these results imply that temporary migration is an important and distinct margin of adjustment to negative climate shocks.[26]

The shock also affects the spatial distribution of economic activity. Under unrestricted migration, spatial wage dispersion increases slightly (0.05%) as productivity shocks vary across locations. Rent dispersion actually decreases (-0.26%), likely reflecting the dampening effect of out-migration from the most affected areas. Amenity dispersion decreases substantially (-1.93%) as workers reallocate away from locations with the largest climate-induced productivity losses.

in India caused a loss of 5.4% of GDP in 2021.

[26]These findings are consistent with Rai (2024), who underscores the importance of temporary migration in reallocating labor in the face of economic shocks, and that it generates larger gains in welfare than permanent migration. Other literature have pointed to the high degree of responsiveness of temporary migrants to economic shocks (Imbert and Papp, 2020b) and the use of seasonal migration as a consumption-smoothing mechanism (Bryan et al., 2014).

Table 3: Changes in outcomes under SSP 5-8.5 Scenario (Baseline: No Climate Change)

Metric	All migration allowed (1)	No TM (2)	No PM (3)
Panel A: Aggregate Metrics			
% change in aggregate welfare	-0.28%	-2.73%	-2.12%
% change in total output	-4.52%	-10.11%	-12.11%
% change in total migration rate	0.23%	-3.40%	-5.20%
% change in temporary migration rate	0.41%	-99.97%	107.22%
% change in permanent migration rate	0.07%	77.74%	-99.67%
% change in spatial wage dispersion	0.05%	2.80%	2.54%
% change in spatial rent dispersion	-0.26%	-1.39%	2.83%
% change in spatial amenity dispersion	-1.93%	-82.31%	1.01%
Panel B: Aggregate Welfare in Selected Places			
10 most affected location-sectors	-0.93%	-6.68%	-6.39%
10 least affected location-sectors	0.20%	-1.44%	2.44%

Notes: This table shows the percentage change in aggregate metrics under a warming scenario relative to the scenario with no climate change. Each column corresponds to a particular counterfactual. Column (1)represents a scenario with climate change and no migration restrictions, ie, all channels of spatial adjustment are open. Column (2) represents a scenario with climate change and no temporary migration, which means only the permanent migration channels remains open. Column (3) represents a scenario with climate change and no permanent migration, which means only the temporary migration channels remains open. Panel A reports economy-wide metrics. Panel B reports the outcomes from selected location-sectors only, with the 10 most (least) affected location-sectors being the ones with the highest (lowest) change in relative productivity under climate change.

Distributional Impacts: Under unrestricted migration, the most affected location-sectors experience welfare losses of 0.93%, while the least affected locations actually see small welfare gains of 0.20%. This divergence reflects both the direct productivity effects and the general equilibrium adjustments: adversely affected locations lose workers through outmigration, while less affected locations receive in-migrants who expand local labor supply and economic activity. When temporary migration is restricted, welfare losses become much more severe and spatially concentrated. The most affected location-sectors now experience welfare losses of 6.68%, which is more than seven times larger than under unrestricted migration. Even the least affected locations now suffer welfare losses of 1.44%, as the inability to use temporary migration limits the economy's capacity to reallocate labor efficiently in response to the shock. These distributional results highlight that while aggregate welfare losses from climate change are substantial, the burdens fall disproportionately on already vulnerable populations in adversely affected areas. Migration- particularly temporary migration - serves as a mechanism for spreading these costs more broadly and providing outside options for those facing the most severe shocks.

6.2 Effect of policies under climate change

Having established the importance of temporary movements as an adjustment mechanism in the face of climate shocks, we now evaluate alternative adaptation policies. Policy frameworks on climate-related mobility are structured around a dual approach: averting or minimizing migration through in-place adaptation, or addressing and enabling migration when it occurs (UNFCCC, 2018; IOM, 2021). The first pillar, in-place (or in-situ) adaptation, aims to reduce the drivers of outmigration, through, for example, investments in climate-smart agriculture and protective infrastructure (Rigaud et al., 2018). The second pillar focuses on managing migration when it does occur, by formalizing migration pathways, ensuring access to rights and services and preventing overburdening of destination infrastructures.

We layer a government tax-and-spend approach on our model to compare the impacts of three cost-equivalent policy measures under the SSP5-8.5 climate shock: (i) productivity-focused policy, allocating the entire budget to in-place adaptation; (ii) externality-reduction policy, allocating the entire budget to the management of migration by reducing negative externalities at destinations; and (iii) balanced policy, splitting the budget equally between both approaches. All three policies are evaluated relative to the baseline of climate shock with no government intervention. These allocation rules are benchmarks we construct to evaluate the comparative effectiveness of the two policy approaches- we do not claim to be solving for the 'optimal' policy mix.

We thus introduce a government that raises revenue through a national ad-valorem tax τ on the wage bill. The total government revenue, G_{total}, is held constant across the three policy scenarios by calculating it based on the wage bill of the economy with climate shock but no government. Next, we make some assumptions to translate government spending into (i) place-based; and (ii) friction-reduction policies.[27]

1. For in-place climate adaptation, we direct money towards places that experienced a negative productivity shock under SSP 5-8.5. This raises the local productivity term A_{ds} from what it was under climate change. We use benefit-cost ratios (BCRs)[28] from studies of climate adaptation interventions to discipline how this spending translates into better productivity.

2. For the externality-reduction policy, we direct money towards reducing the compositional externality parameter ϕ across all locations in the economy, thereby increasing the effective local amenity value. We use experimental estimates of people's valuation of public services to discipline how this spending translates into increased welfare.[29]

Table 4 provides a summary of the parameters affected by the 3 allocation rules.

We find that, first, while all three adaptation policies generate welfare gains relative to inaction

Table 4: Policy Scenarios under Climate Change

Scenario	Productivity Increases	Reduction in ϕ
Productivity-focused policy	7% from SSP 5 scenario	None
Friction-reduction policy	None	11% from baseline
50:50 Policy	5% from SSP 5 scenario	10% from baseline

under climate change, reducing ϕ delivers the largest gains among single-instrument approaches (Table 5). Allocating the entire government budget to reducing ϕ leads to welfare improvement of 0.72%, which is more than twice the welfare gains of 0.23% from cost-equivalent in-place adaptation. This suggests that remedying the systematic underprovisioning of services for temporary migrants unlocks considerable efficiency gains by improving labor allocation and reducing the negative externalities that everyone experiences at their destinations. Second, the two policy instruments operate through distinct channels. Productivity-focused adaptation directly restores output capacity in

[27] Appendix .4 contains more details.

[28] A Benefit-Cost Ratio (BCR) is an indicator used in cost-benefit analysis to evaluate the economic viability of a project or policy. It is calculated by dividing the total expected benefits of the project by its total expected costs, all typically expressed in present-value terms.

[29] Place-based adaptation corresponds to programs like heat action plans and climate-resilient agricultural practices. Friction-reduction policies corresponds to initiatives like India's Affordable Rental Housing Complexes (ARHC) scheme launched in 2020 to provide formal housing for migrant workers.

climate-affected regions, generating a 5.14% increase in total output. However, this approach provides limited relief for the spatial frictions that impede efficient labor reallocation. By contrast, reducing ϕ improves welfare for everyone at destinations, but cannot directly reverse the underlying productivity losses from climate change, resulting in output decline of 0.41%. The balanced policy combines both mechanisms, achieving both welfare improvement 0.89% and substantial output gains (3.52%). Third, the welfare gains from the policies are large enough to more than offset the initial -0.28% welfare damage from the climate shock, leaving the economy better off than in the pre-shock baseline. This 'overshooting' is a direct result of reducing the institutional frictions embodied in the amenity formulation through ϕ. Amenities (and hence welfare) are a decreasing function of the share of temporary migrants in the labor force, with ϕ governing the sensitivity of amenities to this share. The friction-reduction policy of reducing ϕ not only plugs the welfare gaps caused by a climate shock, but also attenuates a significant pre-existing institutional failure. This produces the dual benefit of both climate adaptation and structural welfare improvement.

Finally, the balanced policy achieves a 0.89% welfare improvement, which is lower than the sum of the two individual policies, indicating some degree of substitutability when resources are divided between both instruments. Output increases by 5.14% under adaptation alone and falls by -0.41% under friction-reduction investments alone, with the balanced approach achieving 3.52% gain.[30] This speaks to the different characteristics of the policy instruments-in-place adaptation restores productivity but cannot fix spatial frictions; friction-reduction enables efficient labor reallocation but cannot fix lost productivity. These illustrates the importance of addressing institutional frictions alongside direct productivity losses in climate adaptation policy.

The policies also generate distinct effects on migration patterns and spatial inequality. Friction-reduction policies encourage marginally more migration (total migration rate increases by 0.14% versus 0.04% under productivity-focused policy), with temporary migration rising more sharply (0.45% versus 0.35%). This reflects that reducing administrative frictions makes temporary migration more attractive by improving conditions at destination locations. The balanced policy produces an intermediate migration response (0.09% increase in total migration rate). All three policies reduce spatial wage dispersion, with the balanced approach achieving the largest reduction (2.43%), indicating more efficient spatial allocation of labor. However, rent dispersion increases under all policies (ranging from 1.09% to 3.75%), as adaptation spending and the resulting economic activity drive up housing costs in productive locations. Amenity dispersion patterns differ sharply: friction-reduction policies substantially compress amenity differences across space (1.82% reduction),

[30]However, we emphasize that this result reflects a simple equal-allocation rule rather than a policy solution that maximises total welfare. A richer policy analysis would endogenize the tax rate, allow the government to respond to migration and productivity outcomes.

Table 5: Changes in outcomes under alternative policies (Baseline: SSP 5-8.5 Climate Scenario)

Metric	No migration restrictions (Baseline)	50-50 Policy (1)	Externality-Reduction (2)	In-place Adaptation (3)
% change in aggregate welfare	-0.28	0.89	0.72	0.23
% change in total output	-4.52	3.52	-0.41	5.14
% change in total migration rate	0.23	0.09	0.14	0.04
% change in temporary migration rate	0.41	0.34	0.45	0.35
% change in permanent migration rate	0.07	-0.14	-0.31	-0.27
% change in spatial wage dispersion	0.05	-2.43	-2.03	-1.75
% change in spatial rent dispersion	-0.26	3.75	1.09	1.55
% change in spatial amenity dispersion	-1.93	-1.82	-0.63	0.01

Notes: This table shows the percentage change in aggregate metrics under a warming scenario with alternative, cost-equivalent policies relative to the scenario with climate change, but no policy. The baseline column in grey represents the percentage change in outcomes under climate change and no policy intervention relative to the scenario with no climate change. Each of the remaining columns corresponds to a particular policy counterfactual. Column (1) represents a policy with 50% of the budget being allocated towards friction-reduction (reducing ϕ) and the remaining 50% of the budget is allocated towards improving productivity in climate-affected location-sectors. Column (2) represents a policy where the entire government budget is spent on reducing the negative externalities through amenity frictions caused by the share of temporary migrants in the local labor force, ie, reducing ϕ. Column (3) represents a policy where the entire government budget is spent on improving the productivity in location-sectors that are adversely impacted by climate change. Under all policy scenarios, the government budget is the same and is derived from imposing an ad-valorem sales tax on consumption.

while productivity-focused policies leave amenity dispersion essentially unchanged (0.01% increase), reflecting that the latter addresses productivity but not the quality-of-life impacts of temporary migration.

7 Discussion

This paper develops and estimates a spatial model of temporary and permanent migration to evaluate the impacts of warming and the effectiveness of alternative adaptation policies. Our key contribution lies in identifying and modeling a distinct externality generated by temporary migrants at destination locations that arises from their systematic exclusion from administrative systems and public service planning. Being undercounted in official data and lacking political representation at their temporary residences, temporary migrants face a systematic underprovisioning of administrative services. This creates strains on local infrastructure that negatively affect all residents. This institutional failure produces welfare costs that conventional migration models- which typically only account for permanent migration and focus on congestion costs from total populations- fail to capture.

Our results demonstrate the importance of distinguishing between temporary and permanent migrants in the face of climate shocks. Under a climate shock (SSP5-8.5), we find that restricting temporary migration reduces aggregate welfare by 2.73%. This loss is nearly ten times larger than the welfare loss under unrestricted migration (0.28%) and is comparable in magnitude to the cost of restricting permanent migration (2.12%). When this channel is blocked, the remaining migration options cannot fully compensate. We observe that workers substitute toward permanent migration when temporary moves are restricted (permanent migration increases by 77.74%), but this substitution is incomplete, leaving workers who would have benefited most from temporary mobility worse off. This finding- that temporary migration is a distinct and important adaptation channel- is consistent with Rai (2024), who also finds that temporary migration generates larger welfare gains than permanent migration in response to economic shocks.

We further show that the negative externality due to the composition of the labor force has substantial economic consequences. Investments that reduce the negative externalities from temporary migrants- through initiatives like migrant registration systems, temporary housing programs, and enhanced public service capacity- generate welfare gains (0.72%) that are more than thrice the gains from cost-equivalent in-place adaptation measures (0.23%). This highlights that adaptation policy must account for both direct productivity impacts and the institutional constraints on spatial adjustment. This does not imply that in-place adaptation is unimportant; rather, it recommends a balanced policy portfolio that addresses the institutional frictions that constrain mobility.[31] In this paper, we focus on one such friction that has been largely overlooked, that is, the negative externality that arises from a higher share of temporary migrants at the destination. The welfare-augmenting results of reducing ϕ reflect that in economies where temporary migration prevails but is 'invisibilised' due to high administrative frictions, such interventions unlock efficiency gains by facilitating a more efficient labor reallocation. Crucially, these gains are large enough to make the post-policy economy better off than it was before the climate shock, because the policy attenuates a significant, pre-existing institutional failure. In contrast, in-place adaptation, while directly restoring productivity in climate-affected areas, cannot address the administrative frictions that inhibit efficient spatial adjustment.

The policy implications extend beyond the specific allocation question. Presently, there are massive funding gaps for climate adaptation. Developing countries need an estimated \$215-\$387

[31] This echoes findings from Khanna et al. (2025), who show that combining pollution mitigation measures with policies to relax migration frictions (like the 'hukou' restrictions in China) yields the largest welfare and productivity gains. While their mechanism focuses on productivity losses from skill-based spatial misallocation and ours focuses on amenity losses from institutional failure, both papers hint towards a similar policy insight: addressing the underlying disamenity (warming or pollution) is most effective when paired with policies that enhance labor mobility.

billion/year to finance climate adaptation, amounting to 0.6%-1% of their GDP (2021 prices). International public finance flows cover less than 5% of these needs (UNEP, 2024), thus putting substantial pressure on national domestic budgets and policy priorities.[32]Given these severe resource constraints, identifying which interventions deliver the highest returns per dollar is critical. Our results suggest that policies remedying the underprovisioning of services for temporary migrants may offer a more cost-effective use of scarce adaptation funds. Importantly, many of these friction-reducing interventions are often less capital-intensive than comprehensive in-place adaptation. For instance, digital-first initiatives like Indias E-Shram portal for registering unorganized workers leverage technology to serve migrants at a national scale with relatively low capital costs. Similarly, targeted policies like the Affordable Rental Housing Complexes (ARHCs) scheme focus investment on a specific need, in contrast to the vast capital required to implement climate-smart agricultural infrastructure across millions of hectares or city-wide heat action plans.

Our focus on India reflects its high climate vulnerability, widespread temporary migration, and evidence that climate shocks manifest through temporary mobility. However, the mechanisms we identify are relevant in other climate-vulnerable countries too. In many developing countries, widespread internal migration is often climate or weather-induced and is circular and/or temporary in nature (Sherbinin, 2020; Bharadwaj et al., 2021; Joarder and Miller, 2013; Kaczan and Orgill-Meyer, 2020). With limited administrative capacity to track and serve mobile populations, temporary migrants in these regions are left outside social protection nets (WBG, 2018), creating the specific externality we have modeled in this paper. Our framework and findings may therefore provide insights for climate adaptation planning well beyond the Indian case.

8 Conclusion

Climate adaptation policy must grapple with the complex institutional context in which behavioral responses unfold. This paper highlights that temporary migration represents a critical yet understudied adaptation mechanism through which households cope with climate-induced economic shocks. The effectiveness of this mechanism depends fundamentally on whether destination institutions can accommodate temporary migrants or whether their presence creates negative externalities that reduce welfare for all residents.

Our analysis demonstrates that temporary migration is active adaptation strategy, which is not a perfect substitute for permanent migration. Restricting temporary migration can reduce

[32]Under the principle of Common But Differentiated Responsibilities and Respective Capabilities (CBDR), developed nations are to provide resources to assist developing countries in their adaptation efforts.

aggregate welfare by 2.73%, a loss nearly ten times larger than under unrestricted migration and comparable to the welfare cost of restricting permanent migration. This underscores the importance of temporary migration as a distinct and crucial margin of economic adjustment.

Crucially, our findings reveal that the institutional handling of temporary migrants generates substantial economic consequences. Policies that reduce negative externalitiessuch as migrant registration systems, temporary housing programs, and enhanced public service capacitycan generate welfare gains that are more than three times larger than equivalent place-based adaptation measures. These results highlight the critical need for a comprehensive adaptation strategy that simultaneously addresses both direct climate impacts and the institutional frictions that constrain labor mobility.

The broader contribution of this research lies in demonstrating that effective policy responses to climate migration requires a recognition of the different kinds of mobilities that are prevalent in developing economies, and the distinct policy responses that each demand. Temporary migration is widely prevalent in developing countries, and responds to warming. We show in this paper using a novel dataset of temporary migration in India, that a degree rise in mean daily temperatures leads to a 2%-6% increase in temporary outmigration rates from affected areas. Policies that focus exclusively on managing permanent migration or restoring local productivity miss the opportunity to enhance the efficiency of temporary migration as an adaptation channel.

A comprehensive adaptation strategy must therefore address both dimensions: mitigating climate impacts at their source while simultaneously ensuring that mobility-based adaptation can function effectively. By understanding and addressing the institutional barriers that temporary migrants face, policymakers can unlock more efficient responses to climate-induced mobility challenges.

References

Adhvaryu, A., N. Kala, and A. Nyshadham (2020, October). The Light and the Heat: Productivity Co-Benefits of Energy-Saving Technology. *The Review of Economics and Statistics* 102(4), 779–792.

Agarwal, P. (2022, June). State-Migrant Relations in India: Internal Migration, Welfare Rights and COVID-19. *Social Change* 52(2), 239–256.

Aggarwal, S., B. Giera, D. Jeong, J. Robinson, and A. Spearot (2022, November). Market Access, Trade Costs, and Technology Adoption: Evidence from Northern Tanzania. *The Review of Economics and Statistics, 1–45.*

Allcott, H., A. Collard-Wexler, and S. D. O'Connell (2016, March). How Do Electricity Shortages Affect Industry? Evidence from India. American Economic Review *106(3), 587–624.*

AR6, I. (2023). IPCC AR6 Working Group 1: Summary for Policymakers.

Baseler, T., A. Narayan, O. Ng, and S. Sinha Roy (2023, August). Does Food Insecurity Hinder Migration?: Experimental Evidence from the Indian Public Distribution System. Publisher: World Bank, Washington, DC.

Berlemann, M. and M. F. Steinhardt (2017, December). Climate Change, Natural Disasters, and Migrationa Survey of the Empirical Evidence. CESifo Economic Studies *63(4), 353–385.*

Bharadwaj, R., S. Hazra, M. Reddy, S. Das, and D. Kaur (2021, October). Connecting the dots: climate change, migration and social protection. Working Paper, International Institute for Environment and Development (IIED), London, UK. ISBN: 9781784319311 Publisher: IIED.

Bryan, G., S. Chowdhury, and A. Mobarak (2014). Underinvestment in a Profitable Technology: The Case of Seasonal Migration in Bangladesh. Econometrica *82*, 1671–1748. Publisher: Econometric Society.

Bryan, G. and M. Morten (2019, October). The Aggregate Productivity Effects of Internal Migration: Evidence from Indonesia. *Journal of Political Economy* 127(5), 2229–2268.

Burke, M. and K. Emerick (2016, August). Adaptation to Climate Change: Evidence from US Agriculture. *American Economic Journal: Economic Policy* 8(3), 106–140.

Burlig, F., A. Jina, and A. Sudarshan (2025, March). The Value of Clean Water: Experimental Evidence from Rural India. Technical Report w33557, National Bureau of Economic Research.

Card, D. (2001). Immigrant Inflows, Native Outflows, and the Local Labor Market Impacts of Higher Immigration. *Journal of Labor Economics* 19(1), 22–64. Publisher: [The University of Chicago Press, Society of Labor Economists, NORC at the University of Chicago].

Chen, X. and L. Yang (2019, May). Temperature and industrial output: Firm-level evidence from China. *Journal of Environmental Economics and Management* 95*, 257–274.*

ClimateTransparency (2022, October). Climate Transparency Report 2022-India. Technical report, Climate Transparency.

Coffey, D., J. Papp, and D. Spears (2015, June). Short-Term Labor Migration from Rural North India: Evidence from New Survey Data. Population Research and Policy Review *34(3), 361–380.*

Colmer, J. (2021, October). Temperature, Labor Reallocation, and Industrial Production: Evidence from India. American Economic Journal: Applied Economics *13(4), 101–124.*

Conte, B. (2022). Climate Change and Migration: The Case of Africa.

Costinot, A., D. Donaldson, and C. Smith (2016, February). Evolving Comparative Advantage and the Impact of Climate Change in Agricultural Markets: Evidence from 1.7 Million Fields around the World. Journal of Political Economy. Publisher: University of Chicago PressChicago, IL.

Cruz, J.-L. and E. Rossi-Hansberg (2021, February). The Economic Geography of Global Warming.

Dallmann, I. and K. Millock (2017, December). Climate Variability and Inter-State Migration in India. *CESifo Economic Studies* 63(4), 560–594.

Dekle, R., J. Eaton, and S. Kortum (2008, July). Global Rebalancing with Gravity: Measuring the Burden of Adjustment. *IMF Staff Papers* 55(3), 511–540.

Dell, M., B. F. Jones, and B. A. Olken (2012, July). Temperature Shocks and Economic Growth: Evidence from the Last Half Century. *American Economic Journal: Macroeconomics* 4(3), 66–95.

Deschênes, O. and M. Greenstone (2011, October). Climate Change, Mortality, and Adaptation: Evidence from Annual Fluctuations in Weather in the US. *American Economic Journal: Applied Economics* 3(4), 152–185.

Desmet, K., R. E. Kopp, S. A. Kulp, D. K. Nagy, M. Oppenheimer, E. Rossi-Hansberg, and B. H. Strauss (2021, April). Evaluating the Economic Cost of Coastal Flooding. *American Economic Journal: Macroeconomics* 13(2), 444–486.

Desmet, K. and E. Rossi-Hansberg (2009, November). Spatial growth and industry age. *Journal of Economic Theory* 144(6), 2477–2502.

Dutta, A., S. Gandhi, and R. K. Green (2021, April). Distant Shocks, Migration, and Housing Supply in India.

Foster, A. D. and M. R. Rosenzweig (2007, January). Chapter 47 Economic Development and the Decline of Agricultural Employment. In T. P. Schultz and J. A. Strauss (Eds.), *Handbook of Development Economics*, Volume 4, pp. 3051–3083. Elsevier.

Gaikwad, N. and G. Nellis (2017). The Majority-Minority Divide in Attitudes toward Internal Migration: Evidence from Mumbai. *American Journal of Political Science* 61(2), 456–472. Publisher: [Midwest Political Science Association, Wiley].

Gaikwad, N. and G. Nellis (2021). Do Politicians Discriminate Against Internal Migrants? Evidence from Nationwide Field Experiments in India. *American Journal of Political Science* 65(4), 790–806. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/ajps.12548.

Gonzalez-Navarro, M. and C. Quintana-Domeque (2010, February). Roads to Development: Experimental Evidence from Urban Road Pavement.

Hallegatte, S., J. Rentschler, and J. Rozenberg (2019). Lifelines: The Resilient Infrastructure Opportunity. Sustainable Infrastructure. Technical report, World Bank.

Hsiang, S., R. Kopp, A. Jina, J. Rising, M. Delgado, S. Mohan, D. J. Rasmussen, R. Muir-Wood, P. Wilson, M. Oppenheimer, K. Larsen, and T. Houser (2017, June). Estimating economic damage from climate change in the United States. *Science* 356(6345), 1362–1369.

Huang, K., H. Zhao, J. Huang, J. Wang, and C. Findlay (2020, November). The impact of climate change on the labor allocation: Empirical evidence from China. *Journal of Environmental Economics and Management* 104*, 102376.*

Imbert, C., J. Monras, M. Seror, and Y. Zylberberg (2023, August). Floating Population: Migration With(Out) Family and the Spatial Distribution of Economic Activity. Federal Reserve Bank of San Francisco Working Paper.

Imbert, C. and J. Papp (2020a, September). Costs and benefits of rural-urban migration: Evidence from India. *Journal of Development Economics* 146*, 102473.*

Imbert, C. and J. Papp (2020b, April). Short-term Migration, Rural Public Works, and Urban Labor Markets: Evidence from India. Journal of the European Economic Association *18(2), 927–963.*

Intergovernmental Panel On Climate Change (IPCC) (2023, June). Climate Change 2022 Impacts, Adaptation and Vulnerability: Working Group II Contribution to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change (1 ed.). Cambridge University Press.

IOM (2021). *Institutional Strategy on Migration, Environment and Climate Change 20212030 For a comprehensive, evidence and rights-based approach to migration in the context of environmental degradation, climate change and disasters, for the benefit of migrants and societies.* Geneva: International Organization for Migration (IOM).

Irudaya Rajan, S., P. Sivakumar, and A. Srinivasan (2020). The COVID-19 Pandemic and Internal Labour Migration in India: A 'Crisis of Mobility'. *The Indian Journal of Labour Economics: The Quarterly Journal of the Indian Society of Labour Economics* 63(4), 1021–1039.

Ito, K. and S. Zhang (2020, May). Willingness to Pay for Clean Air: Evidence from Air Purifier Markets in China. *Journal of Political Economy* 128(5), 1627–1672. Publisher: The University of Chicago Press.

Iyer, K. (2021). *Landscapes of Loss: The Story of an Indian Drought.* HarperCollins Publishers India. Google-Books-ID: trclzgEACAAJ.

Jayaram, N. and D. Varma (2020, December). Examining the Labour in Labour Migration: Migrant Workers Informal Work Arrangements and Access to Labour Rights in Urban Sectors. *The Indian Journal of Labour Economics* 63(4), 999–1019.

Joarder, M. A. M. and P. W. Miller (2013, December). Factors affecting whether environmental migration is temporary or permanent: Evidence from Bangladesh. *Global Environmental Change* 23(6), 1511–1524.

Kaczan, D. J. and J. Orgill-Meyer (2020, February). The impact of climate change on migration: a synthesis of recent empirical insights. *Climatic Change* 158(3-4), 281–300.

Keshri, K. and R. B. Bhagat (2012). Temporary and Seasonal Migration: Regional Pattern, Characteristics and Associated Factors. *Economic and Political Weekly* 47(4), 81–88. Publisher: Economic and Political Weekly.

Khanna, G., W. Liang, A. M. Mobarak, and R. Song (2021, January). The Productivity Consequences of Pollution-Induced Migration in China.

Khanna, G., W. Liang, A. M. Mobarak, and R. Song (2025, April). The Productivity Consequences of Pollution-Induced Migration in China. *American Economic Journal: Applied Economics* 17(2), 184–224.

Kone, Z. L., M. Y. Liu, A. Mattoo, C. Ozden, and S. Sharma (2018, April). Internal borders and migration in India*. *Journal of Economic Geography.*

Krishnan, R., J. Sanjay, C. Gnanaseelan, M. Mujumdar, A. Kulkarni, and S. Chakraborty (Eds.) (2020). Assessment of Climate Change over the Indian Region: A Report of the Ministry of Earth Sciences (MoES), Government of India. *Singapore: Springer Singapore.*

Kumar, K. and B. Vishwanathan (2012). Weather variability and agriculture: Implications for long and short-term migration in India. Centre for Development Economics Department of Economics, Delhi School of Economics, 1–27.

Kumar, K. S. and B. Viswanathan (2013, May). Influence of weather on temporary and permanent migration in rural india. *Climate Change Economics* 04(02), 1350007. Publisher: World Scientific Publishing Co.

Liu, M., Y. Shamdasani, and V. Taraz (2023, May). Climate Change and Labor Reallocation: Evidence from Six Decades of the Indian Census. *American Economic Journal: Economic Policy* 15(2), 395–423.

Mani, M., S. Bandyopadhyay, S. Chonabayashi, A. Markandya, and T. Mosier (2018, June). *South Asia's Hotspots.* Washington, DC: World Bank.

McFadden, D., A. Karlqvist, L. Lundqvist, and F. Snickars (1978). Modeling the Choice of Residential Location. *Spatial Interaction Theory and Planning Models* 25*, 75–96.*

Monte, F., S. J. Redding, and E. Rossi-Hansberg (2018, December). Commuting, Migration, and Local Employment Elasticities. American Economic Review *108(12), 3855–3890.*

Morten, M. (2019, February). Temporary Migration and Endogenous Risk Sharing in Village India. Journal of Political Economy *127(1), 1–46.*

Morten, M. and J. Oliveira (2016, April). Paving the Way to Development: Costly Migration and Labor Market Integration.

Morten, M. and J. Oliveira (2018). The Effects of Roads on Trade and Migration : Evidence from a Planned Capital City .

Munshi, K. and M. Rosenzweig (2016, January). Networks and Misallocation: Insurance, Migration, and the Rural-Urban Wage Gap. American Economic Review *106(1), 46–98.*

Oliveira, J. and P. Pereda (2020, September). The impact of climate change on internal migration in Brazil. Journal of Environmental Economics and Management *103*, 102340.

Parsons, L. A., D. Shindell, M. Tigchelaar, Y. Zhang, and J. T. Spector (2021, December). Increased labor losses and decreased adaptation potential in a warmer world. *Nature Communications* 12(1), 7286. Number: 1 Publisher: Nature Publishing Group.

Peri, G. (2016, November). Immigrants, Productivity, and Labor Markets. *Journal of Economic Perspectives* 30(4), 3–30.

Peri, G. and A. Sasahara (2019, April). The Impact of Global Warming on Rural-Urban Migrations: Evidence from Global Big Data. Technical Report w25728, National Bureau of Economic Research, Cambridge, MA.

Rai, A. (2024). Temporary vs Permanent Migration in a spatial economy.pdf.

Ram Bhagat (2008). Assessing the measurement of internal migration in India. *Asian and Pacific Migration Journal* 17*, 91–102.*

Rigaud, K. K., A. de Sherbinin, B. Jones, J. Bergmann, V. Clement, K. Ober, J. Schewe, S. Adamo, B. McCusker, S. Heuser, and A. Midgley (2018, March). Groundswell: Preparing for Internal Climate Migration. Publisher: World Bank, Washington, DC.

Sedova, B. and M. Kalkuhl (2020, May). Who are the climate migrants and where do they go? Evidence from rural India. World Development *129*, 104848.

Sharma, A. (2014). *Their own country: A profile of labour migration from Rajasthan.* Centre for Migration and Labour Solutions, Aajeevika Bureau.

Sherbinin, A. d. (2020, October). Climate Impacts as Drivers of Migration.

Silva, J. M. C. S. and S. Tenreyro (2006, November). The Log of Gravity. *The Review of Economics and Statistics* 88(4), 641–658.

Somanathan, E., R. Somanathan, A. Sudarshan, and M. Tewari (2021, June). The Impact of Temperature on Productivity and Labor Supply: Evidence from Indian Manufacturing. *Journal of Political Economy* 129(6), 1797–1827.

Srivastava, R. (2019, June). Emerging Dynamics of Labour Market Inequality in India: Migration, Informality, Segmentation and Social Discrimination. *The Indian Journal of Labour Economics* 62(2), 147–171.

Srivastava, R. (2020, October). Growing Precarity, Circular Migration, and the Lockdown in India. *The Indian Journal of Labour Economics* 63(1), 79–86.

Taraz, V. (2018, December). Can farmers adapt to higher temperatures? Evidence from India. *World Development* 112*, 205–219.*

Thachil, T. (2017). Do Rural Migrants Divide Ethnically in the City? Evidence from an Ethnographic Experiment in India. American Journal of Political Science *61(4), 908–926. Publisher: [Midwest Political Science Association, Wiley].*

Tiwari, C., S. Bhattacharjee, P. Sethi, and D. Chakrabarti (2022, August). Internal Migration and Rural Inequalities in India. Population Research and Policy Review *41(4), 1673–1698.*

Tord Kjellstrom, N. M. (2019, July). Working on a warmer planet: The effect of heat stress on productivity and decent work. Report, International Labour Organisation. ISBN: 9789221329671.

UNEP (2024, October). Adaptation Gap Report 2024 | UNEP - UN Environment Programme. Technical report, United Nations Environment Programme. Section: publications.

UNFCCC (2018). 2018 Report of the Task Force on Displacement | UNFCCC. Technical report, UNFCCC Task Force on Displacement.

Venables, A. J. (2005, January). Spatial disparities in developing countries: cities, regions, and international trade. Journal of Economic Geography *5(1), 3–21.*

WBG (2018). The State of Social Safety Nets. Technical report, World Bank.

WRI and GCA (2019). Three Revolutions to Accelerate Adaptation | Adapt Now Report | World

Resources Institute. Technical report, Global Commision on Adaptation; World Resources Institute.

Figures

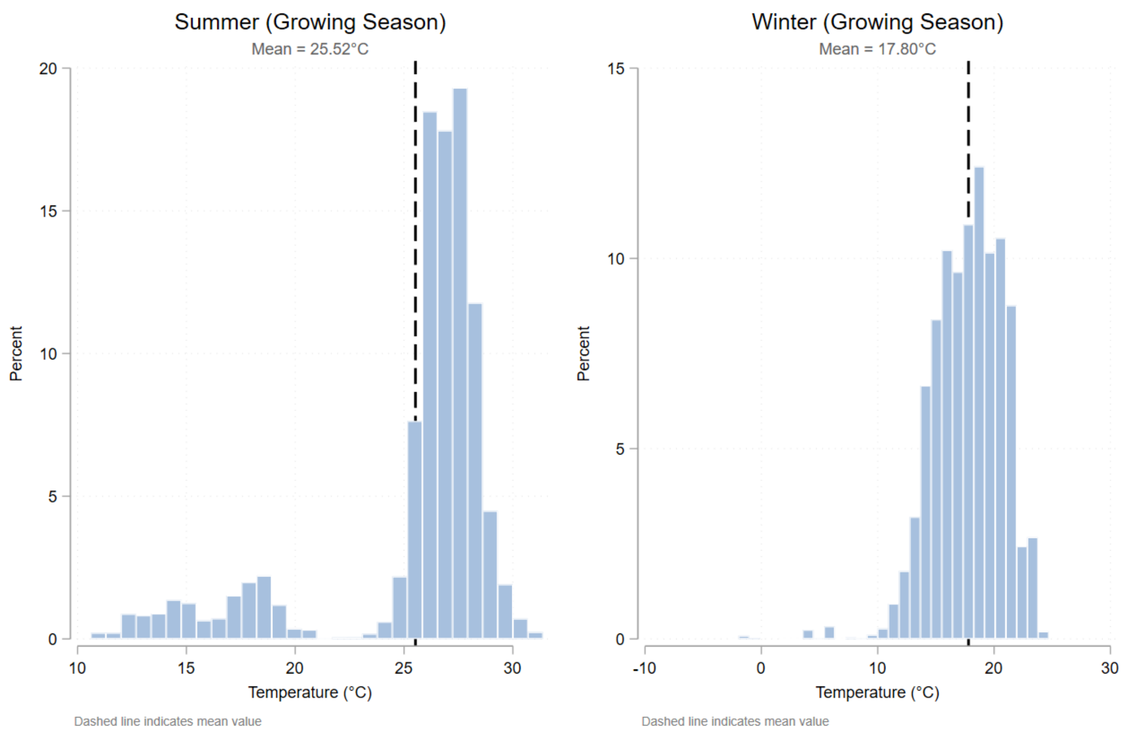

Figure 1: Distributions of daily mean temperature

Appendix

.1 Linguistic distance

We measure linguistic proximity between districts using the measures outlined in Kone et al. (2018). The data source is the language census conducted by the Indian government in 2011, which captures the mother tongues (the language spoken in childhood to the person by the person's mother) of residents in every district. We construct two different measures of linguistic proximity between two districts as follows: Let s_i^l and s_j^l be the share of individuals speaking mother tongue l in districts i and j, respectively. Then $s_i^l * s_j^l$ is the probability that an individual from i can speak to an individual from j in language l. Aggregating over all possible mother tongues, the likelihood of any two individuals being able to communicate in a common language is given by:

$$\text{Common Language}_{ij} = \sum_l s_i^l \cdot s_j^l \tag{.1}$$

Similarly, the following measures the degree of overlap in languages spoken at any pair of districts:

$$\text{Language Overlap}_{ij} = \sum_l \min\{s_i^l, s_j^l\} \tag{.2}$$

This is because $\min\{s_i^l, s_j^l\}$ represents the intersection of people from each district who speak the same language l (note that every individual speaks only one mother tongue). The alternative measures of linguistic distance/proximity give us similar results.

.2 Estimation results

Table 6: Estimating temporary migration elasticity: Step 1

	(1) Migration Proportion	(2) Migration Proportion	(3) Migration Proportion
Log Distance	-1.405***		
	(0.084)		
Common Language	0.378***	0.432***	0.597***
	(0.083)	(0.080)	(0.085)
State Border Dummy	-1.538***	-1.749***	-2.577***
	(0.161)	(0.164)	(0.188)
Distance Inverse Sine Hyperbolic		-1.097***	
		(0.056)	
Constant	-1.466***	-1.608***	-1.629***
	(0.222)	(0.213)	(0.265)
Observations	2088834	2088902	2088902

Standard errors in parentheses

Standard errors are clustered at origin-destination-region pair. All regressions have fixed effects for origin-region-district-time and destination-region-district-time.

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

Table 7: Estimating temporary migration elasticity: Step 2

	Destination FE
Mean Wage (standardised)	8.072
	(18.254)
Observations	782
R-squared	0.989

$^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$

Table 8: Model Parameters

Parameter	Value
α	0.5
β	0.07 (Allcott et al., 2016)
σ	5.0
λ	0.6 (Dutta et al., 2021)
θ_{PM}	5.5 (Rai, 2024)
θ_{TM}	8.07
θ_u	1.4 (Rai, 2024)

.3 Counterfactual system solution

.3.1 Inclusive value notation

Based on the preference structure outlined in Section 4, discrete choice theory yields the following migration probabilities. The probability that an individual from origin (o, s) chooses migration type $k \in \{S, PM, TM\}$ is:

$$T_o^k = \frac{\left(IV_o^k\right)^{\theta^u}}{(IV_o^S)^{\theta^u} + (IV_o^{PM})^{\theta^u} + (IV_o^{TM})^{\theta^u}} \tag{.3}$$

where the inclusive values are:

$$IV_o^S = V_{os}^S \tag{.4}$$

$$IV_o^{PM} = \left[\sum_{d=1}^{N} \sum_{s' \in \{R,U\}} \left(V_{ods'}^{PM}\right)^{\theta^{PM}}\right]^{1/\theta^{PM}} \tag{.5}$$

$$IV_o^{TM} = \left[\sum_{d=1}^{N} \sum_{s' \in \{R,U\}} \left(V_{ods'}^{TM}\right)^{\theta^{TM}}\right]^{1/\theta^{TM}} \tag{.6}$$

Conditional on choosing migration type $k \in \{PM, TM\}$, the probability of selecting destination (d, s') is:

$$T_{ods'|k} = \frac{\left(V_{ods'}^k\right)^{\theta^k}}{\sum_{j=1}^{N} \sum_{r \in \{R,U\}} \left(V_{ojr}^k\right)^{\theta^k}} \tag{.7}$$

The unconditional probability of migrating from (o, s) to (d, s') via migration type k is:

$$\pi_{ods'}^k = T_o^k \times T_{ods'|k} \tag{.8}$$

.3.2 Hat algebra for evaluating counterfactuals

Following conventional (exact hat algebra) notation (Dekle et al., 2008), we denote the new value of a variable X by X' such that $\hat{X} = \frac{X'}{X}$. Given a climate-induced productivity shock $\hat{A}_{ds}$, we solve for the proportional changes in all endogenous variables using the complete equilibrium system. All variables highlighted in blue indicate that I observe those variables in my baseline equilibrium.

1. Goods Market Clearing:

$$\hat{A}_{ds}(\hat{L}_{ds})^{\beta} = (\hat{p}_{ds})^{-\sigma}(\hat{P}_d)^{\sigma-1}\left[\sum_{k\in\{R,U\}} \phi_{dk}\hat{W}_{dk}\hat{L}_{dk}\right] \tag{.9}$$

where $\phi_{dk} = \frac{W_{dk}L_{dk}}{\sum_{j\in\{R,U\}} W_{dj}L_{dj}}$ is the baseline expenditure share of sector k in destination d.

2. Wage Determination:

$$\hat{W}_{ds} = \hat{p}_{ds}\hat{A}_{ds}(\hat{L}_{ds})^{\beta-1} \tag{.10}$$

3. Composite Price Index:

$$\hat{P}_d = \left[\sum_{s\in\{R,U\}} \xi_{ds}(\hat{p}_{ds})^{1-\sigma}\right]^{\frac{1}{1-\sigma}} \tag{.11}$$

where $\xi_{ds} = \frac{p_{ds}^{1-\sigma}}{\sum_{k\in\{R,U\}} p_{dk}^{1-\sigma}}$ is the baseline CES price share.

4. Housing Market Equilibrium:

$$\hat{q}_d = \left[\sum_{s\in\{R,U\}} \phi_{ds}\hat{W}_{ds}\hat{L}_{ds}\right]^{\frac{\lambda}{1+\lambda}} \tag{.12}$$

where $\phi_{ds} = \frac{W_{ds}L_{ds}}{\sum_{k\in\{R,U\}} W_{dk}L_{dk}}$ is the baseline wage bill share.

5. Labor Market Clearing: We modify the labor market clearing condition sightly to account for the data constraints. Since I do not observe permanent migration flows in my data, I assume that the observed labor force is the sum of natives and permanent migrants.

$$\hat{L}_{ds} = \frac{L_{ds}^{native} + \sum_{o\neq d} L_{os}\pi_{ods}^{\prime PM} + \sum_{o\neq d} L_{os}\pi_{ods}^{\prime TM}}{L_{ds}} \tag{.13}$$

6. Migration Probabilities:

$$\hat{\pi}_{ods}^{TM} = \hat{T}_o^{TM} \times \hat{T}_{ods|TM} \tag{.14}$$

where:

$$\hat{T}_{ods|TM} = \left(\frac{\hat{V}_{ods}^{TM}}{I\hat{V}_{o}^{TM}}\right)^{\theta^{TM}} \tag{.15}$$

$$I\hat{V}_{o}^{TM} = \left[\sum_{j,k} \omega_{ojk}^{TM} (\hat{V}_{ojk}^{TM})^{\theta^{TM}}\right]^{1/\theta^{TM}} \tag{.16}$$

$$\hat{T}_{o}^{TM} = \left(\frac{I\hat{V}_{o}^{TM}}{\sum_{j\in\{S,PM,TM\}} \omega_{o}^{j} (I\hat{V}_{o}^{j})^{\theta^{u}}}\right)^{\theta^{u}} \tag{.17}$$

with $\omega_{ojr}^{k} = \frac{(V_{ojr}^{k})^{\theta^{k}}}{\sum_{j',r'} (V_{oj'r'}^{k})^{\theta^{k}}}$ and $\omega_{o}^{j} = \frac{(IV_{o}^{j})^{\theta^{u}}}{\sum_{j'} (IV_{o}^{j'})^{\theta^{u}}}$ baseline shares.

7. Indirect Utility Changes:

$$\hat{V}_{ods}^{TM} = \hat{\hat{b}}_{d} \frac{\hat{W}_{ds}}{(\hat{P}_{d})^{\alpha} (\hat{q}_{d})^{1-\alpha}} \tag{.18}$$

8. Temporary Migrant Share Update:

$$s_{d}^{TM'} = \frac{\sum_{s\in\{R,U\}} \sum_{o\neq d} L_{ods}^{TM} \hat{\pi}_{ods}^{TM}}{\sum_{s\in\{R,U\}} L_{ds} \hat{L}_{ds}} \tag{.19}$$

9. Amenity Update with Congestion:

$$\hat{\hat{b}}_{d} = \frac{1-\phi s_{d}^{TM'}}{1-\phi s_{d}^{TM}} \tag{.20}$$

.3.3 Solution Algorithm

The exact hat algebraic system described above reduces the dimensionality of the system by expressing all endogenous variables as proportional changes relative to the baseline equilibrium. We use this to numerically for the equilibrium under a climate shock. The collapsed system solves simultaneously for wage changes ($\hat{W}_{ds}$) and price changes ($\hat{p}_{ds}$) across all location-sector pairs, which together constitute a $2NS$-dimensional vector. We solve for two market-clearing conditions, ie, the labor market clearing (equating labor supply from migration choices to labor demand from firms) and goods market clearing (equating sectoral production to consumption demand) conditions. The inputs from our data our (i) location-sector labor (ii) location-sector wages (iii) temporary migration shares. We start with an initial 'guess' for wages and prices. We then apply MATLAB's 'fsolve' function to iterate until both residuals fall below the specified tolerance (10^{-5}), at which point we recover all remaining counterfactual variablesincluding migration flows, labor allocations, output levels, and welfareusing the closed-form relationships derived from the model's equilibrium conditions.

.4 Counterfactual government budget and policy allocations

The government levies a national-level, ad-valorem sales tax τ on the total consumption to fund a national budget, which is used to finance climate adaptation policies.

$$G_{total} = \tau\alpha \sum_{d=1}^{N} \sum_{s\in\{R,U\}} W_{ds}L_{ds} \tag{.21}$$

The government allocates a share $\kappa_A \in [0, 1]$ of its budget to "place-based" adaptation (boosting productivity) and the rest, $1 - \kappa_A$, to "people-based" adaptation (reducing composition-based negative externalities by reducing the parameter ϕ). Spending on productivity adaptation is $G_{adapt} = \kappa_A G_{total}$. This spending can offset a negative climate shock, $\hat{A}_{ds}^{climate}$. The final productivity is:

$$A'_{ds} = A_{ds} \cdot \hat{A}_{ds}^{climate} \cdot (1 + \eta_a G_{adapt}) \tag{.22}$$

where η_a is elaborated on below. Spending on reducing ϕ is $G_\phi = (1 - \kappa_A)G_{total}$. This spending endogenously determines the new value of this parameter, $\phi^{'}$:

$$\phi^{'} = \frac{\phi}{1 + \eta_\phi G_\phi} \tag{.23}$$

where ϕ is the baseline sensitivity of amenities to composition of labor force with no government intervention.

.4.1 Parameter determination

We set the national tax rate τ to be equal to 11%, in line with the average effective Goods and Services tax (GST) rate in India[33].

The parameters η_a and η_ϕ govern the translation of public expenditure on productivity enhancement and amenity improvement, respectively. As direct estimates of these specific parameters are not available, we calibrate them externally by drawing on estimates from relevant studies that evaluate analogous real-world programs and investments.

[33] Refer The Hindu Business Line, accessed in September 2025

The value for η_A is disciplined by the benefit-cost ratio (BCR) estimates for climate-resilient investments, with a focus on climate-smart agriculture and urban heat action planning. Our chosen BCR of 2:1 is a conservative stance that reflects the wide variability and context-specificity emphasized in the literature. WRI and GCA (2019) finds that the overall BCR for investments in resilience ranges from 2:1 to 10:1. Hallegatte et al. (2019) notes that 77% of its modeled scenarios yielded a BCR greater than 2:1. While a precise BCR for urban heat planning is lacking, the WRI and GCA (2019) report highlights the high effectiveness of such programs through a case study of the Ahmedabad Heat Action Plan in India, supporting the plausibility of positive returns. Within our model, η_A translates the flow of adaptation expenditure (G_A) into an increase in the local productivity parameter (A_{ds}) for places that are initially negatively affected by the climate shock.

Next, we calibrate η_ϕ, which governs the translation of government spending, G_ϕ, on reducing ϕ. The parameter is pinned down by targeting an empirical moment from the experimental literature on the valuation of local amenities and/or willingness-to-pay estimates for amenity improvements resulting from public spending. Our calibration is anchored by the findings of Burlig et al. (2025), who conduct a large-scale field experiment in rural India to measure household valuation for clean water. Their study is a relevant benchmark for two key reasons. First, it evaluates a real-world program that reduces a major local disamenity (lack of safe drinking water). Second, it provides a direct estimate of households' Willingness-to-Pay (WTP) to eliminate this disamenity, which they find to be approximately 1.5% of monthly household expenditure, at a program cost of roughly 210.77 INR per household-month. We therefore target a 1.5% increase in the population-weighted national average amenity value per 210.77 INR of public spending. To do this, first, we calculate the national average amenity value in the model's baseline equilibrium. Second, we numerically solve for the single post-policy congestion parameter, ϕ_{new}, that is required to achieve a 1.5% increase in this national average. Finally, using the policy function from our model, we algebraically solve for η_ϕ using the target ϕ_{new} and the associated program cost from Burlig et al. (2025). This results in $\eta_\phi \approx 0.006$, with units of 1/INR.