Globalization, Internal Migration, and Public Goods Provision in Emerging Economies

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Globalization, Internal Migration, and Public Goods Provision in Emerging Economies

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Abstract

Globalization can introduce new employment opportunities to emerging economies in multinational corporations and exporting firms. Who is best positioned to benefit, and what are the political consequences for "left behind" areas? We argue that primarily advantaged groups seize these opportunities through internal migration toward centers of global production – a costly activity not everyone can undertake. This selective out-migration creates demographic shifts in left-behind areas, weakening public goods provision. We test our argument in India, first documenting selective internal migration of advantaged groups. We then leverage the Indian IT export boom and explore its consequences for public goods provision. We find that the IT boom increased migration toward centers of production and away from left-behind localities. We also find that public goods provision was relatively weaker in unexposed localities, especially geographically distant ones. We identify migration as a mechanism through which globalization drives political change even in unexposed areas.

Verification Materials: The data and materials required to verify the computational reproducibility of the results, procedures and analyses in this article are available on the American Journal of Political Science Dataverse within the Harvard Dataverse Network, at: `https://doi.org/10.7910/DVN/E0BJIZ`.

The Cornell Center for Social Sciences verified that the data and replication code submitted to the AJPS Dataverse replicates the numerical results reported in the main text of this article.

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1 Introduction

Global economic integration – the spread of production across borders – is economically and politically disruptive. Rising import competition creates geographically concentrated economic dislocation that causes a political backlash in advanced economies (Colantone and Stanig, 2018; Baccini and Weymouth, 2021; Ballard-Rosa et al., 2022). Globalization is similarly disruptive for labor markets in emerging economies, though with divergent impacts. Integration can create new economic "winners" in these contexts via higher-wage employment opportunities in exporting firms and multinational corporations (Facchini et al., 2019; Helms, 2024). Yet these benefits for emerging economies are also highly geographically concentrated, producing large benefits in some areas and little in others (Fujita and Hu, 2001). When globalization creates new opportunities, who is best positioned to benefit? What are the political consequences, especially for areas "left behind"?

We develop a theory that proposes internal migration as a key mechanism linking positive globalization-induced labor market shocks to political change in emerging economies. Specifically, we identify how geographic mobility can change political outcomes even in localities that do not directly benefit from the shock. We argue that accessing globalization's benefits often requires migrating toward sites of global production (Bonifai et al., 2024). Yet because mobility is costly and disadvantaged groups often face discrimination in migrant destinations (Gaikwad and Nellis, 2017), relatively advantaged groups are best positioned to migrate and seek new opportunities. This *selective out-migration* produces demographic shifts in areas left behind by globalization, leaving a population relatively more composed of marginalized groups.

We unpack the consequences of this globalization-induced demographic shift for left-behind areas, focusing on local public goods provision. We suggest that the disproportionate exit of advantaged groups driven by globalization reduces provision in areas that do not experience direct economic benefits. Advantaged groups, due to their shared identity with extralocal policy makers, access to more powerful social networks, and higher political engagement, tend to attract more public goods (Kustov and Pardelli, 2018; Lee, 2018, 2023). We argue that their out-migration to pursue globalization's employment opportunities results in weaker provision for the localities they leave behind – the same areas left out of globalization's benefits.

We test our argument in India, a large emerging economy that has embraced globalization with geographically uneven impacts (Ghani et al., 2016; Tumbe, 2022). Using individual and household survey data, we find a pattern of selective out-migration consistent with our argument: upper-caste, wealthy, and educated Indians are far more likely to migrate than their disadvantaged counterparts. This mobility advantage is most pronounced for longer, more costly interstate moves.

We then zoom in on India's turn-of-the-century information technology (IT) boom, an external positive shock to labor demand in a globally competitive, export-oriented industry. We leverage subnational exogenous variation in exposure to the IT boom in a difference-in-differences research design (Shastry, 2012). We first find that this positive globalization shock generated internal migration from unexposed areas toward the handful of localities in which the IT boom was concentrated: we estimate that migration was 39 percent higher along this corridor, compared to other corridors, as a result of the IT boom. Internal migration into unexposed localities concomitantly declines.

We further leverage this design to identify global economic integration's effect on local public goods provision. Following the IT boom, left-behind localities experienced substantially weaker *per capita* provision of public health and education services than exposed areas. This relative decline in public goods provision is more pronounced in areas farther from exposed districts than in neighboring areas. Given that long-distance migration is costlier and therefore tends to be more selective, this finding is consistent with our argument that selective out-migration can lead to lower public goods provision. We focus on health and education, but find similar results for other local public goods like paved roads and electricity.

Our article makes a few key contributions. First, we expand the literature on the political consequences of global economic integration. With some notable exceptions, most existing research focuses on advanced economies, especially in areas directly affected by negative external shocks. We shift the focus by investigating how *positive* shocks shape politics in emerging economies, with a novel theoretical focus on areas not directly affected by the shock itself. Our article is an attempt to expand our understanding of globalization's political consequences to a less studied context, which complements extant research by exploring the other side of the globalization coin.

Second, our study identifies internal migration as a key mechanism linking globalization to political change in emerging economies (Helms, 2024). We highlight how shocks with disparate geographic impacts might influence localities that are not directly exposed to the shock. This dynamic may complicate existing accounts that identify the political consequences of globalization for places directly experiencing its benefits or harms. Via internal migration, political change could occur in exposed as well as unexposed areas. This is especially the case when those who migrate systematically differ from those who remain (Lim, 2023). More broadly, our study contributes to a growing literature on the political consequences of out-migration for emerging economies (Gaikwad et al., 2024).

Finally, our findings suggest an alternative mechanism by which global economic integration contributes to inequality in developing countries (Goldberg and Pavcnik, 2007; Rudra, 2008). If geographic mobility is prerequisite to accessing economic opportunity, but the mobility of disadvantaged groups is constrained, globalization's largest benefits may accrue to advantaged groups. In other words, the benefits of globalization accrue to people who were already "winners" in the domestic economy, while those left behind suffer from weaker public goods provision. This logic would suggest policies that increase the mobility of disadvantaged groups and targeted public goods provision in left-behind areas.

2 Theoretical Framework

While the backlash to globalization in advanced economies is well-documented (Colantone and Stanig, 2018; Baccini and Weymouth, 2021), less appreciated are the potential *positive* labor market consequences for workers in emerging economies. Standard trade theories predict that global economic integration creates new, higher-paying employment opportunities for these workers (McCaig and Pavcnik, 2018).[1] We know far less about how positive globalization shocks shape political outcomes in emerging economies (Helms, 2024). We explore the political consequences of positive labor market shocks from a new angle. Specifically, we ask the following questions: when globalization brings new labor market opportunities to emerging economies, how do workers access them? Related, who is best positioned to access the economic benefits of globalization? What are the political consequences?

We build a framework that centers internal migration as a key mechanism linking globalization to political change in emerging economies. Furthermore, we focus on the consequences of globalization for areas "left behind" by those who migrate to seek new opportunity, *not* on areas that experience the shock. In other words, we derive predictions about the consequences of a positive external shock for localities that do not directly benefit, focusing on out-migration as a driver of political change. We first discuss how accessing globalization's opportunities often requires internal migration. But we highlight that some people – particularly those belonging to advantaged groups – are more geographically mobile and better able to capture globalization's largest benefits. We then identify the consequences of advantaged groups' out-migration from left-behind localities, focusing on local public goods provision.

[1] Globalization may have other negative consequences for emerging economies (Fischer, 2003). Our argument focuses solely on its labor market consequences, which most economic models suggest should be positive.

2.1 Accessing Global Opportunity (Often) Requires Migration

Standard models of trade and investment predict that global economic integration creates new, higher-paying employment opportunities in emerging economies. Yet these opportunities are rarely distributed evenly across space. Structural conditions prevent many localities from reaping the labor market benefits of globalization. Infrastructure that is prerequisite to competing in global markets, such as roads, railroads, ports, telecommunications, and electricity, is severely underprovided in most areas (Schwab, 2017). Because only a handful of localities possess the conditions necessary for export-oriented production, global employment opportunities cluster in a small number of locations. Many globally oriented industries also benefit heavily from agglomeration externalities, further driving concentration of globalization's benefits in areas with preexisting industry (Fujita and Hu, 2001).

As a result, while global economic integration increases labor demand in emerging economies, it does so highly unequally across space. Localities with sufficient infrastructure provision, a concentration of globally competitive industry, and connections to world markets will see large increases in labor demand. Other areas without these preconditions will likely be "left behind" by this positive economic shock, experiencing few or even no direct benefits.

We argue that for people who live in localities left behind by global economic integration, accessing new labor market opportunities requires internally migrating toward centers of global production (Helms, 2024). Those who already live in or near exposed places can access new opportunities without migrating. However, for those who live distant from globalization's direct economic impacts, migration is necessary to access these opportunities.

A wealth of evidence demonstrates that out-migration is a common strategic reaction to global economic integration. In China, market-oriented reforms generated migration out of unexposed areas and into centers of export-oriented production (Liang, 1999). China's entry into the World Trade Organization and Permanent Normal Trade Relations with the United States stimulated internal labor mobility toward centers of global production (Potlogea and Cheng, 2017; Facchini et al., 2019). Global economic integration also led the Chinese government to relax *hukou*, China's restrictive internal migration regulations, to allow for labor mobility from unaffected places to areas seeing new economic activity (Tian, 2024).

Beyond China, a positive shock to the Indian information technology (IT) sector due to the dot-com boom resulted in migration away from unaffected areas to places experiencing export-oriented employment gains (Ghose, 2024). Our empirical contribution leverages this shock. Separately, a large external shock to India's textile sector similarly stimulated migration (Helms, 2024). Meanwhile, the entry of labor-intensive production in Brazil generated migration toward places in which global production agglomerated (Hering and Paillacar, 2016).

2.2 Advantaged People Are More Mobile

In short, many people leave unaffected regions and move toward centers of global production. Yet, drawing on theories of migration, we highlight that not all people are equally able to migrate. We argue that those who are socioeconomically advantaged are most geographically mobile, allowing them to more easily seize globalization's new employment opportunities than their less advantaged counterparts.

Classic theories of migration emphasize individuals' economic and non-economic motivations to relocate. Individuals choose to migrate for economic gains like better earning opportunities (Borjas, 1987), better quality of life such as affordable housing (Berger and Blomquist, 1992; Stawarz et al., 2021), and more favorable political environments (Fitzgerald et al., 2014; Maxwell, 2019).

Yet mobility is often not just a choice, but also a privilege. Migration is costly and risky, and individuals can migrate only when they are able to afford the cost of relocation and when expected utility is larger than relocation costs (Borjas, 1987, 1989). For many people, relocation costs are a binding constraint (Caliendo et al., 2017). As a result, workers' mobility can be limited when new opportunities emerge in distant localities (Lim et al., 2023). This suggests that even when opportunities arise, only a fraction of individuals – those who can afford to relocate – are positioned to seize them, unless they are local. The socioeconomically advantaged are most able to undertake the costly and risky action of migration.

Of course, not all individuals from advantaged groups are motivated to relocate. Those with the most resources may stay behind as they lack incentives to pursue further economic opportunity (Dustmann and Okatenko, 2014). However, among individuals with these incentives, those from advantaged groups are better positioned to migrate, as they can afford relocation costs. Thus, we suggest that migrants will be disproportionately from the overlap of advantaged groups and those motivated to move for economic opportunity. This selection pattern is supported by the fact that higher-income and -skilled people are overrepresented in migrant populations (Chiswick, 1999; Chiquiar and Hanson, 2005; Anelli and Peri, 2017; Lim, 2023).

Furthermore, those who belong to advantaged groups are more likely to be accepted by native populations and less likely to face economic, political, and social discrimination upon arrival. The public exhibits a preference for socioeconomically advantaged immigrants (Hainmueller and Hopkins, 2015; Gaikwad and Nellis, 2017), suggesting that they are more likely to be welcomed rather than rejected by natives. For those belonging to disadvantaged groups, even if they can finance relocation costs, anticipation of discrimination can discourage migration (Fitzgerald et al., 2014).

We expect that globalization generates internal migration away from areas left behind and toward areas experiencing labor market benefits. However, we argue that those who migrate are disproportionately from advantaged backgrounds, given their ability to afford relocation costs and higher likelihood of acceptance in destinations. In unexposed localities, this process of migrant selection creates a demographic shift in the population left behind. All else equal, we expect the remaining population is increasingly composed of less advantaged groups.

Our argument suggests that because advantaged groups are more mobile, they more easily benefit from global employment. Recent research instead suggests that because global firms are less discriminatory, disadvantaged groups anticipate liberalization will benefit them, increasing their support for globalization (Gaikwad and Suryanarayan, 2025).[2] We agree that global firms likely have less discriminatory practices, and geographically proximate members of disadvantaged groups should benefit.

[2] See Osgood and Peters (2017) and Li et al. (2024) on similar gender dynamics.

Distant members of disadvantaged groups should also benefit if they can afford migration. Our argument only suggests that migration costs and risks are on average a stronger barrier for geographically distant members of disadvantaged groups, while this barrier is weaker for equally distant members of advantaged groups.

2.3 Selective Out-Migration Drives Political Change

Finally, we argue that globalization-induced out-migration of advantaged groups has political consequences for areas that migrants leave behind. Selective emigration and the absence of certain subpopulations are key channels through which emigration affects home countries (Kapur, 2014; Meseguer and Burgess, 2014). Labor economics primarily views migrants as economic actors and their exit as human capital loss. The departure of the highly educated is framed as *brain drain* (Docquier and Rapoport, 2012) that results in lost skilled labor and entrepreneurs (Anelli et al., 2023), reducing growth (Kapur and McHale, 2009) and affecting income (Mishra, 2007).

A growing literature expands this concept to the loss of *political* actors and examines the effect of emigration on welfare policy (Karadja and Prawitz, 2019), political engagement (Goodman and Hiskey, 2008), autocratic survival (Miller and Peters, 2020), and elections (Anelli and Peri, 2017; Lim, 2023; Dancygier et al., 2022). Depending on migrant attributes, exit creates different demographic shifts and political outcomes. For instance, mass emigration of low-skilled workers strengthens the bargaining power of remaining workers, leading to welfare expansion (Karadja and Prawitz, 2019). On the other hand, the exit of younger and more progressive voters changes the composition of the remaining electorate, benefiting older and traditional candidates (Anelli and Peri, 2017) and far-right parties (Lim, 2023).

These studies indicate that selective emigration and subsequent demographic shifts create political change in origin countries. We argue the same is true of internal migration in emerging economies. We focus on the implications of out-migration of advantaged groups for local public goods provision in left-behind areas.

We argue that the exit of more advantaged groups *weakens* local public goods provision in left-behind localities (Giles and Mu, 2024). Common political dynamics in emerging economies make politicians more responsive to the demands of advantaged groups and their localities (Grossman and Slough, 2022). Central and state governments fund most local public goods (Shah, 2006), but scarce resources and state capacity prevent all localities from receiving sufficient provision (Kyle and Resnick, 2019). This often grants public officials discretion over allocation (Chandra, 2004) and requires citizens to successfully demand that higher-level politicians prioritize the interests of their localities (Kruks-Wisner, 2018a).

In this environment, public officials are typically incentivized to be more responsive to advantaged groups for many reasons. First, advantaged groups are politically powerful and control more economic resources (Tilly, 1998). This creates political incentives to respond to their demands (Kustov and Pardelli, 2018). This is especially so in contexts characterized by clientelism, in which more advantaged groups often fund political machines (Stokes, 2005; Lupu and Warner, 2022). Further, public officials are disproportionately drawn from advantaged groups (Bueno and Dunning, 2017). This allows group members to engage in ethnic favoritism: using discretion over resource allocation to benefit their group (Franck and Rainer, 2012). Advantaged groups also have more powerful social networks on which they can draw (Lee, 2023), making them best able to lobby "extralocal" elites at higher levels of government to supply local public goods (Olson, 1971).

More broadly, advantaged groups tend to be more politically active, meaning that politicians are incentivized to respond to them (Leighley and Vedlitz, 1999). This is not to say that politicians never respond to disadvantaged groups (Keefer and Khemani, 2005). For example, these groups may engage in collective action and create parties that have electoral incentives to respond to them (Banerjee and Somanathan, 2007; Aneja and Ritadhi, 2022). Institutions like ethnic quotas for elected office and public employment increase attention to marginalized groups (Duflo, 2005; Lee, 2021). However, widespread evidence of inequality in responsiveness indicates that advantaged groups typically enjoy greater attention (Lupu and Warner, 2022).

When members of advantaged groups migrate, we argue that politicians are less responsive to the localities they leave behind. Most directly, advantaged groups are more likely to include higher earners; thus, their exit leads to lost tax revenue, impacting the quality of public services in their localities (Dancygier et al., 2022). As advantaged groups disproportionately exit areas left behind by globalization, they also are no longer present to leverage their identity and social networks to attract public goods (Kustov and Pardelli, 2018; Lee, 2018, 2023). Finally, their exit reflects the loss of people who on average are more politically engaged, meaning their absence might substantially reduce local political participation. The result, we argue, is that communities left behind by advantaged groups receive fewer local public goods.

This suggests that globalization, through reshaping internal mobility, leads to declining public goods provision in areas not directly experiencing the positive labor market shock. Other perspectives on globalization and public goods in emerging economies focus on alternative mechanisms, such as the race to the bottom or declining revenue from easy-to-collect taxes (Rudra, 2008; Bastiaens and Rudra, 2018). The logic we present suggests that globalization may not change aggregate public goods provision, but instead *redistribute* public goods, possibly toward localities experiencing both globalization's benefits and migration of advantaged groups.

We note an alternative hypothesis: the exit of advantaged groups *increases* public goods provision through other pathways. For example, the exit of advantaged people may reduce local diversity and make collective action easier, increasing their ability to supply local public goods (Habyarimana et al., 2007). If local elites previously used their power to suppress public goods provision out of fear of taxation, then their exit might free non-elites to pursue greater provision. This hypothesis generates an opposite empirical expectation to our argument.

Another mechanism through which out-migration can affect left-behind areas is the connections migrants maintain with their hometowns (Kapur, 2014). Financial remittances shape the preferences and behavior of recipients by providing an additional source of income that is independent of local economic conditions. Remittances can reduce recipients' political engagement by insulating them from negative shocks (Goodman and Hiskey, 2008; Ahmed, 2017; Tertytchnaya et al., 2018), decreasing their demand for welfare (Doyle, 2015).[3]

[3] Some studies find that remittances increase political engagement, especially in autocracies (Escribà-Folch et al., 2018).

Remittances may also substitute for public goods, reducing demands for and, subsequently, slowing growth in provision in high-out-migration areas. This alternative mechanism would result in observationally similar outcomes. However, while remittance recipients may replace public goods with private alternatives, disadvantaged groups are disproportionately left behind from this substitution due to their lower mobility. This logic also applies to social remittances (Levitt, 1998; Pérez-Armendáriz and Crow, 2010).[4] Given that public goods are more crucial for people who cannot substitute them with private spending, the implications of declining public goods provision remain significant. We empirically investigate this in more detail later.

Similarly, the absence of migrants may not lead to total disengagement from hometown politics. Many migrants maintain connections (Fan, 2007) and could still play a role in demanding public goods in these areas. Migrants' hometown political engagement varies widely depending on accessibility of long-distance participation. However, participation from afar is, on average, costlier than local engagement, leading to lower participation (Kostelka, 2017; Wellman, 2021). Even though migrants may remain engaged in hometown politics, their involvement is likely weaker due to these additional costs. Similarly, Gaikwad and Nellis (2021) find that in India, despite low political participation, (internal) migrants are motivated to engage with their destination's politics regardless of strong ties to their hometown. This, again, suggests migrants' engagement at home is likely weaker, as time and resources are

[4] Unlike most research focused on international migration, expectations for social remittances from internal migration is less clear. Nonetheless, disadvantaged groups tend to be excluded from all remittances given their lower mobility.

divided between destination and hometown.

Finally, we note that our argument focuses on (semi-)permanent rather than circular migration. The mechanisms linking out-migration to reduced public goods provision rely on advantaged groups durably reducing their local presence. The impacts of elite circular migration are less clear and would depend on the extent to which they remain active in their hometown (Lee, 2023). In our context of India, advantaged groups are more likely to permanently relocate, while marginalized groups may be more likely to temporarily migrate (Bhagat, 2011; Tumbe, 2012).

3 Selective Migration and Public Goods in India

We apply our theoretical framework to India, the world's fifth-largest economy and largest electoral democracy. Like many emerging economies, India has substantially liberalized its economy in the last 35 years, reducing tariffs and restrictions on foreign investment (Topalova and Khandelwal, 2011; Li et al., 2024).

While India has experienced rapid economic integration, it has done so highly unevenly. A handful of areas host the overwhelming majority of its global economic activity. More than 75 percent of India's manufacturing exports are produced in just seven of its 28 states (Pradhan and Das, 2012). IT services, one of India's most prominent export sectors and the focus of our analysis, agglomerates primarily in just a few cities (Ghose, 2024). Foreign direct investment inflows are similarly concentrated in six states (Li et al., 2024). While parts of India are intensely integrated with the world economy, the majority of localities have little direct exposure to trade and investment.

Indian society is structured by both stark inequality and a rigid caste hierarchy. Many sources measure India's economic inequality as among the worst in the world (Bharti et al., 2024). "Forward" or "general" castes sit at the top of the social hierarchy and generally enjoy the highest levels of well-being, education, and social status. "Dalit" or "backward" castes sit at the bottom of this hierarchy and face economic, political, and social discrimination; they comprise India's Scheduled Castes (SCs) and Tribes (STs), officially recognized as marginalized by the Constitution. Dalits have historically been excluded from most employment and relegated to work traditionally deemed impure, such as sanitation or processing animal hides (Jaffrelot, 2010). Despite constitutional prohibition and legislation, caste discrimination remains widespread. Muslims, as a religious minority within India, also face marginalization by the dominant Hindu community (Robinson, 2008).

While India is often regarded as having relatively little internal migration, mobility has increased substantially since the turn of the century. Between 2001 and 2011, the number of internal migrants increased from 309 million to 450 million, though most move short distances within their district (62 percent) or across districts within their state (26 percent).[5] Roughly 54 million are interstate migrants as of 2011, around 4 percent of total population; in absolute terms, interstate migration increased by 14 million between 2001 and 2011. Much interstate migration flows from less developed northern states like Bihar, Madhya Pradesh, Rajasthan, and Uttar Pradesh, and into more developed southern and western states and Delhi.

[5] 2011 represents the most recent completed Census.

3.1 Selective Out-Migration in India

We begin by investigating whether migration patterns differ by caste and socioeconomic status using the India Human Development Survey (IHDS), a household-level survey with a nationally representative sample of over 40,000 households. The survey allows us to examine household-level differences between movers and stayers by asking each household if any member has migrated. The IHDS has been used in other studies of out-migration (Sedova and Kalkuhl, 2020; Kumar, 2024).

[INSERT FIGURE 1 HERE]

Figure 1 demonstrates differences in migration rates by caste group, disaggregated by within-state, out-of-state, and international moves (Panel 1a). Brahmins, the most "forward" caste group, demonstrate the highest migration rates. SCs and STs, the most disadvantaged caste groups, show much lower migration rates. The differences are starker when focusing on out-of-state migration (Panel 1b), which involves higher relocation costs and greater geographic and cultural distance. 15.8% of Brahmin households have a member who relocated outside their home state; for SCs and STs, this number is just 7.01%.

This is consistent with our argument and could be due to a few reasons. SCs and STs disproportionately rely on non-portable social welfare benefits tied to their current state, making migration costly. SCs and STs are also much more likely to experience discrimination in potential destinations, reducing incentives to move. Other caste groups have intermediate migration rates consistent with their position in the social hierarchy. This shows the limited mobility of disadvantaged groups.

This pattern is also replicated with the National Sample Survey (NSS), an individual-level survey that captures attributes of movers and stayers by asking respondents their relocation history.[6] Figure S1 in the Supplementary Information (SI) (p. S.2) confirms that SCs and STs are much less mobile than other caste groups, especially when focusing on interstate migration. Figure S2 (p. S.3) further demonstrates this pattern is starkest in less developed, major northern states of origin.

To more systematically analyze attributes of migrants vs. non-migrants, we again use the IHDS, which is a two-wave household-level panel survey, conducted in 2004-2005 and 2011-2012. We use variations of the following model:

$$\begin{aligned}\text{Migrant}_{hw2} &\sim \text{Binomial}(1, p_h)\\ \text{logit}(p_h) &= \alpha + \beta_0\text{SC/ST}_{hw1} + \beta_2\text{Muslim}_{hw1}\\ &\quad + \beta_2\text{No College}_{hw1} + \beta_3\text{Below Poverty Line}_{hw1} + \mathbf{Z}_{hw1}\gamma\end{aligned}$$

where h stands for household and *w1* and *w2* stand for the first and second waves of the survey, respectively. We aim to investigate attributes of households that are more likely to be mobile by comparing households with and without migrants, so we estimate this model using logistic regression.[7]

[INSERT TABLE 1 HERE]

[6]We use the 2007-08 round of the NSS.

[7]We do not include household fixed effects since some of our primary variables of interest (e.g., caste group) are time-invariant. We use a lagged dependent variable to account for the potential lasting effects of migration from previous waves.

The results in Table 1 show patterns consistent with Figure 1. Models (1)-(2) examine whether a household has a member who migrated within or out-of-state, and Models (3)-(4) examine whether the household has a member who migrated out-of-state only. Models (2) and (4) include origin state fixed effects. Across all models, SC and ST households are less likely to be mobile compared to other caste groups. Based on Model (4), the odds of having an interstate migrant among SC/STs are approximately 34% lower than for other caste groups. Education and household financial status are also highly correlated with mobility. A household is less likely to have a migrant if its most educated member has less than a bachelor's degree and the household is below the poverty line.[8] These findings provide support for the selective out-migration argument we make above. Indian internal migrants tend to be from more educated households, less likely to be below the poverty line, and less likely to belong to a Scheduled Caste or Tribe. These patterns are starkest for longer, more costly interstate migration.

3.2 Public Goods Provision in India

In India, central and state governments allocate the vast majority of funds for public goods (Kapur, 2020), which are then distributed to local governments (Bhavnani and Lee, 2018). Like most emerging economies, India faces budget constraints, meaning not all areas receive sufficient resources (Kapur, 2020). Public officials have substantial discretion over the distribution of public goods (Chandra, 2004; Besley et al.,

[8]IHDS constructs Below Poverty Line$_{hw1}$ using consumption per capita along with poverty line provided by India's official planning commission. See IHDS codebook.

2012), even for goods awarded programmatically (Gulzar and Pasquale, 2017). Given scarce resources and official discretion, the distribution of public goods is often driven by individuals and communities making successful claims on higher levels of government. These claims are more likely to succeed when individuals and communities are connected to brokers and gatekeepers of resources (Kruks-Wisner, 2018a,b).

A wealth of evidence demonstrates that Indian politicians are systematically more responsive to claims of advantaged groups and their localities (Banerjee, 2004). Areas with larger upper-caste populations receive more public goods (Banerjee and Somanathan, 2007; Lee, 2018). This is driven, in part, by the fact that higher-level officials are disproportionately upper-caste and display ethnic favoritism (Besley et al., 2004). Advantaged groups are also more effective at lobbying extralocal elites via their powerful social networks (Lee, 2018). For example, wealthy landowning families often use their political power to "divert resources" to their area, which allows for "the successful use of state funds to renovate the access roads, riverbank, and temples" and to "build a new canal to reduce the chronic shortage of drinking water" (Lee, 2023, p. 1844). Localities dominated by lower castes struggle to make successful claims, given discrimination and weak access to officials (Bharathi et al., 2024).

4 Research Design

We now test our argument on the impact of globalization on internal migration and left-behind areas. We leverage a wide range of data on global economic integration, employment, migration, and public goods provision in India. We discuss our identification strategy and data before presenting empirical models.

4.1 Globalization Shock: The Indian IT Boom

To capture variation in the labor market impacts of globalization, we leverage the information technology (IT) boom in India. As one of the largest export-oriented industries in India, the IT sector accounted for 7.5 percent of GDP in 2023 (IBEF, 2024). The growth of the IT sector provides empirical leverage as it was largely driven by exogenous increases in global demand (Shastry, 2012; Khanna and Morales, 2023). While the IT sector saw initial growth in the 1990s, it experienced a sudden surge in the early 2000s due to a sharp increase in global demand for IT services in response to the Y2K bug and the dot-com boom and bust. US and European IT firms began offshoring work to India, attracted by its lower labor costs and expertise in COBOL – a programming language largely obsolete in the US and Europe but still taught in Indian universities, which was essential for resolving Y2K-related issues (Kapur, 2002; Srinivasan and Krueger, 2005; Ghose, 2024). Later, the IT boom and bust further pushed firms to contract with Indian firms to offshore operations, fueled by lower costs and India's favorable time zone for round-the-clock business (Ghose, 2024). Further, US high-skilled visa policy stimulated computer science education in India, but visa caps meant many skilled Indians remained, fostering the boom (Khanna and Morales, 2023).

Like other globalization-induced shocks, the IT boom varied significantly across regions. Growth in IT employment was concentrated in a small set of areas with English-speaking populations, a prerequisite skill for IT services exports. While the size of the local English-speaking population captures variation in labor demand in response to the IT boom, it could potentially be endogenous. To address this, we follow an empirical strategy pioneered by Shastry (2012) and adopted by others (Azam et al., 2013; Ghose, 2024).

Shastry (2012) leverages preexisting local variation in linguistic diversity to capture local exposure to the IT boom. India has significant local linguistic diversity, and individuals must learn a *lingua franca*, either English or Hindi. Historically, people are motivated to learn a language closer to their native tongue. Building on this, Shastry (2012) demonstrates that speakers of native languages more distant from Hindi are more likely to learn English. In consultation with a linguistics expert, she codes native languages on a scale of from zero to five degrees, with zero representing Hindi and five being most distant. Analyzing native languages spoken in all states, Shastry finds that each additional degree of linguistic distance increases the percentage of native speakers who learn English by 7.7 percentage points on average (Shastry, 2012, p. 300). This was even the case in 1961, well before India's liberalization. Therefore, ex ante linguistic distance from Hindi predicts subnational exposure to the IT boom but is plausibly exogenous. We use a version of this approach to identify globalization's impacts on migration and public goods provision.

4.2 Measuring Exposure to the IT Boom

To measure exposure to the IT boom, we use district- and state-level population-weighted linguistic distance from Hindi measured in 1991, following Shastry (2012).[9] We construct a binary indicator where zero represents low linguistic distance and one represents high linguistic distance from Hindi.[10] We dichotomize this measure at the top quartile to address the nonlinear nature of firm location selection with respect to the language environment – firms are highly concentrated in the most attractive districts.[11] We label high-linguistic-distance districts as "treated" in what follows.[12]

[9]Districts are somewhat equivalent to American counties in that they nest within states, but are typically more populous. All analyses use district boundaries set at the 1991 Indian Census; all districts created after 1991 were reassigned to their previous 1991 district status.

[10]Continuous linguistic distance ranges from about 1 (closest to Hindi) to about 5 (most distant from Hindi). See Shastry (2012) for greater detail on construction of the measure.

[11]We use a binary indicator, distinguishing between districts with high and low linguistic distance from Hindi, instead of a continuous measure to capture the geographically concentrated nature of this shock. We also replicate our results using different thresholds, examining whether selection of the cutoff influences the results. See SI Section D (p. S13).

[12]We use the term "treated" as a matter of convention. Our measure may be better interpreted as an encouragement of, or as a proxy for exposure to, treatment.

To validate the extent to which linguistic distance from Hindi is associated with exposure to the IT boom, we first descriptively use the annual number of new IT capital investment projects per district, sourced from CapEx.[13] CapEx reports the annual count of projects in the IT sector by district from 1990 to 2010. These investments include both new IT projects and expansions of existing facilities.

[INSERT FIGURE 2 HERE]

While there were only a handful of IT projects in the 1990s, investment increased dramatically after the onset of the IT boom. Importantly, the magnitude of this increase varied significantly by district linguistic distance from Hindi. Figure 2 confirms our expectation. On average, districts with high linguistic distance (red) attracted significantly more investment projects than districts with low linguistic distance (gray). We replicate these descriptive results using data from three waves of India's Economic Census (1998, 2005, and 2013), which we use to calculate the number of IT workers per capita by district.[14] Using a difference-in-differences regression, we demonstrate a strong relationship between our measure of exposure and the positive impact of the IT boom on employment (SI Section B, Tables S1 (p. S5) and S2 (p. S6)). We also present evidence that linguistic distance from Hindi drives English acquisition (Table S3, p. S7) and that English-speaking populations correlate

[13]CapEx is a dataset from the Center for Monitoring the Indian Economy that tracks capital investments of at least 10 million rupees (about $120,000 in 2024).

[14]Shastry (2012) and Ghose (2024) find similar results using alternative firm-level data on IT presence and employment.

with greater IT employment (Tables S4 (p. S8) and S5 (p. S9)).

4.3 Internal Migration

We measure bilateral internal migration using the 2001 and 2011 rounds of the Indian Population Census. The Census provides migration outflows by state and inflows by district. The Census also asks migrants when they arrived, with options including: less than one year ago, one to four years, five to nine years, 10-19 years, or longer. Based on this information, we create a bilateral migration panel dataset covering six time periods between 1991 and 2011: 1992-1996, 2007-2000, 2001, 2002-2004, 2007-2010, and 2011.[15] The unit of analysis is an origin state-destination district dyad in a given time period.[16] We analyze only interstate migration and exclude within-state movement. We include both male and female migrants. Because most female migration in India is arguably a result of arranged marriage rather than work, we validate our results using only male migration flows. We also estimate supplementary

[15]The duration of time periods in the panel is uneven. To account for this, we include period fixed effects in all specifications. Given the absence of annual migration panel data in India, the use of uneven time periods in the Census has been adopted by other research (e.g., Bhavnani and Lacina, 2015). Including analytic weights to account for different period lengths yields virtually identical estimates.

[16]An obvious limitation of Census migration data is that we can capture migration inflows at the district level but outflows only by state. Ideally, we would capture both at the district level, but this is not possible with publicly available data.

models of monadic district-level migration inflows without regard to origin state.

To examine the relationship between exposure to the IT boom and internal migration, we estimate variations of the following difference-in-differences model:

$$\mathrm{Y}_{od,t} = \beta_0 + \beta_1 \mathrm{CorridorType}_{od} \times \mathrm{Post}_t + \mathbf{Z}_{od,t}\gamma * \kappa_t + \alpha_o + \theta_d + \delta_{od} + \kappa_t + +\sigma_{odt}$$

where $Y_{od,t}$ represents the logged flow of internal migrants from state o into district d in period t. $\mathrm{CorridorType}_{od}$ represents indicator variables for four different types of migration corridors, according to our measure of exposure to the IT boom, using pre-boom information on population-weighted linguistic distance from Hindi in origin states o and destination districts d. These corridor types include $Untreated_o \rightarrow Treated_d$ (our main corridor of interest), $Treated_o \rightarrow Treated_d$, $Treated_o \rightarrow Untreated_d$, and $Untreated_o \rightarrow Untreated_d$. Post_t is a binary indicator equal to one for periods t after the IT boom and zero otherwise. $\mathbf{Z}_{od,t}$ represents a vector of control variables for both origin states o and destination states d including logged population, urbanization rate, employment rate, literacy rate, gender ratio, and population share of SCs and STs, measured at the most recent Census and interacted with period indicators. α_o, θ_d, δ_{od}, and κ_t represent origin state, destination district, dyad, and time period fixed effects, respectively.

We estimate this model using OLS and cluster standard errors by dyad given construction of our treatment.[17] Because we measure bilateral migration and incorporate shocks in origins and destinations, we account for issues identified by Borusyak et al.

[17]Results that follow are consistent using Pseudo-Poisson Maximum Likelihood.

(2023) in models of migration and local shocks. Our design leverages a common-timed shock and does not exploit differential treatment timing.

4.4 Public Goods Provision

We measure district-level *per capita* public goods provision using data from the 1991, 2001, and 2011 Village and Town Directories of the Indian Census. These data capture local public goods decennially; we focus on provision of health centers and primary and secondary schools. Access to health and education is widely used to measure local public goods provision in India (Lee, 2023) as these are important indicators of citizen welfare (Bhattacharjee and Chaudhuri, 2024), and core tasks that are delegated to local administration via central and state governments (Bhavnani and Lee, 2018).[18] Schools and health centers are also most consistent with our theoretical framework, which emphasizes the provision of *local* public goods.[19] Following this approach, we use district-level health centers, primary schools, and secondary schools *per capita* (per 1,000 people). We use these measures to estimate several variations of the following difference-in-differences model:

$$\mathrm{Y}_{it} = \beta_0 + \beta_1 \mathrm{Treated}_i \times \mathrm{Post}_t + \mathbf{Z}_{it}\gamma + \alpha_i + \kappa_t + \sigma_{it}$$

[18] We use physical buildings per capita to proxy access to public goods, though their mere presence may not always improve welfare (Robinson and Torvik, 2005).

[19] We examine this relationship using other local public goods (paved roads and electricity supply) and find similar results (SI Section D (p. S15).

where Y_{it} represents either health centers, primary schools, or secondary schools per capita; $\mathrm{Treated}_i$ represents our indicator of exposure to the IT boom; Post_t is a binary indicator equal to one for periods t after the IT boom and zero otherwise; $\mathbf{Z}_{it}$ represents a vector of district-level control variables identical to those included in our models of migration; and α_i and κ_t represent district and year fixed effects, respectively. We estimate this model using OLS and cluster standard errors by district.

5 Results

5.1 IT Boom and Internal Migration

Table 2 demonstrates how exposure to the IT boom affects bilateral internal migration.[20] In Column (1), we identify the effect of the IT boom on our primary corridor of interest: $Untreated_o \rightarrow Treated_d$. We find that following the IT boom, internal migration substantially increased out of untreated states and into treated destination districts, compared to all other migration corridors. Substantively, internal migration from unexposed to exposed areas was 39 percent higher relative to other corridors.[21] Our results echo similar findings from Ghose (2024).

[INSERT TABLE 2 HERE]

In Columns (2)-(4), we show how the IT boom shaped migration in other types

[20]All results in Table 2 are substantively identical without controls.

[21]Results for are substantively identical if we include indicators for any three corridors in the model and leave only one type of corridor as the reference category.

of corridors: $Treated_o \rightarrow Treated_d$, $Treated_o \rightarrow Untreated_d$, and $Untreated_o \rightarrow Untreated_d$, respectively. We find that migration is also relatively higher between treated origin states and treated destination districts following the boom, while migration decreases between treated origin states and untreated destination districts, as well as between untreated origin states and untreated destination districts. The estimated effects along other corridors are, in percentage terms, smaller in magnitude than for our primary corridor of interest, $Untreated_o \rightarrow Treated_d$. These findings are consistent with our argument that trade shocks reorient internal migration toward exposed localities and away from unexposed localities.[22]

[INSERT FIGURE 3 HERE]

To provide evidence for the plausibility of the parallel trends assumption, and to observe the dynamic effect of the IT boom on migration across corridors, we estimate four separate event studies, one for each type of migration corridor. We present these findings graphically in Figure 3; Period 3 (2001), the first post-boom period, is omitted as the baseline. We include 95% confidence intervals for point estimates. The top-left graph shows the event study for our primary corridor of interest: $Untreated_o \rightarrow Treated_d$. Prior to the IT boom, we observe no clear differences in trends in migration between unexposed origin states and exposed destination districts. Immediately after the boom, migration increases substantially, with the estimated effect growing over time.

[22]In Table S6 (p. S10), we confirm that these findings are not due to inclusion of potentially post-treatment controls.

In the top-right, we observe trends for the $Treated_o \rightarrow Treated_d$ corridor; migration in this corridor was already higher before the IT boom but increases post-boom. The bottom two event studies ($Treated_o \rightarrow Untreated_d$ and $Untreated_o \rightarrow Untreated_d$, respectively) demonstrate that migration into untreated districts concurrently falls. These results suggest that the IT boom specifically increased migration out of unexposed, and toward exposed, localities. In SI Table S7 (p. S11), we estimate simpler models of district migration inflows (without regard to origin) and demonstrate that exposed districts saw substantially more migration.

Finally, we argue that global economic integration generates *selective* migration. Unfortunately, Census data do not allow us to disaggregate migration by caste or other salient characteristics. However, in SI Table S8 (p. S12), we extend Model (1) in Table 2 with a triple interaction between $Untreated_o \rightarrow Treated_d$, $Post_t$, and the percentage of origin state o that belongs to a SC or ST. While the IT boom increased migration from unexposed states to exposed districts, this effect diminishes as the origin state's marginalized population grows. These results are consistent with the proposition that migration generated by the IT boom is caste-selective.

5.2 IT Boom and Public Goods Provision

Now, we turn to how exposure to globalization affects public goods provision. Table 3 presents a positive and statistically significant relationship between exposure to the IT boom and public goods. We estimate each outcome without and with controls. The outcomes of Models (1) and (2) are health centers, Models (3) and (4) primary schools, and Models (5) and (6) secondary schools, all *per capita*. Across different outcomes, we consistently find that districts exposed to the IT boom have higher public goods provision per capita than unexposed districts. In other words, districts with lower exposure to globalization experience relatively lower public goods provision following the boom: about one less health center per 5,000 people, one less primary school per 10,000 people, and 1 less secondary school per 4,000 people, according to our results.[23]

[INSERT TABLE 3 HERE]

Our results so far demonstrate that the IT boom both increased internal migration and created disparities in public goods provision between exposed and unexposed places. We further estimate two-stage least-squares (2SLS) models in which we use exposure to the IT boom to instrument for district in-migration in the first stage, and estimate the effect of instrumented migration on public goods provision in the second stage. We discuss these results in SI Section D (Table S10, p. S14); our results are substantively identical with this alternative strategy.

We caution that these estimates capture only *relative* differences in provision across districts rather than absolute declines in unexposed districts per se. Relative differences in public goods provision can result from either rapid growth in growing areas or declines in left-behind areas. With this caution in mind, the results still highlight disparities in provision between districts, providing important implications for regional and subpopulation inequalities. We also note that while we estimate

[23]In Table S9 (p. S13), we again find that our results are mostly consistent without potentially post-treatment controls.

an event study for internal migration, this is not possible for public goods provision, given just one observation prior to onset of the IT boom. The event study for internal migration, combined with similar results in our 2SLS estimation, suggests that our findings are likely not driven by a violation of the parallel trends assumption.

Combined with Table 2, these results suggest that districts not exposed to a positive globalization-induced labor market shock lost population as their more advantaged residents left for opportunities, and they also experienced relatively slower growth in public goods provision than districts with high exposure to globalization.[24]

We suggest that this disparity in provision is due to selective migration of advantaged groups from unexposed to exposed districts. An observable implication of our argument is that disparities should be wider for unexposed areas that are geographically more distant from the IT boom and narrower for unexposed areas that are closer. Relocation costs, as well as cultural distance and potential for discrimination, grow with physical distance. Indeed, we show in Table 1 and Figure 1 that migration is more selective for longer moves.[25] More distant unexposed districts should experience more intensive selective out-migration as a result, and therefore should experience wider disparities in public goods provision than closer unexposed districts.

To test this observable implication, we identify districts that are unexposed but directly adjacent to exposed districts.[26] Among neighboring districts, we classify

[24]Our reference to "lost population" refers to out-migration; natural population growth could offset losses from out-migration.

[25]This logic is also consistent with research on migration in India (Tumbe, 2012).

[26]We classify districts as neighboring if they touch or intersect with exposed districts,

only those within the same state as neighboring a treated district, as state borders in India comprise high barriers to mobility, making commuting and migration costly even over shorter distances (Kone et al., 2018).[27] We compare neighboring and non-neighboring unexposed districts in the analyses that follow, with exposed districts as the baseline group of comparison. Our expectation is that the IT boom created the widest disparities between exposed and unexposed, non-neighboring districts.

[INSERT TABLE 4 HERE]

Table 4 shows that the IT boom has no statistically significant differential impact between exposed districts and neighboring unexposed districts. (Treated Neighbor$_i$). However, compared to exposed districts, non-neighboring unexposed districts experienced much lower per capita public goods provision. In other words, our results in Table 3 are largely driven by wider disparities between exposed districts and the more distant unexposed districts. Neighboring districts see, at most, a relative decrease of roughly 1 health center per 30,000, no decline in primary schools, and roughly 1 secondary school per 25,000. More distant districts see relative decreases of roughly 1 health center per 5,000, 1 primary school per 10,000, and 1 secondary school per 3,500 – a significantly greater disparity. This evidence is consistent with our proposed

using open-source GIS libraries in Python.

[27]In the SI, we present separate results that distinguish between neighboring (same state), neighboring (different state), and non-neighboring districts (Table S12, p. S17). We find that neighboring districts in different states show no significant difference in public goods provision compared to non-neighboring districts.

mechanism. We again caution that our findings focus on relative differences between exposed and unexposed places. However, relative differences are important as they may deepen existing inequalities by widening gaps in opportunities for economic mobility. This is particularly true for less advantaged, less mobile groups.

5.3 Exploring Mechanisms

How does out-migration of advantaged groups affect public goods provision? Our proposed mechanism lies in the connections advantaged groups possess, which makes them best positioned to attract public goods. This is due, in part, to their shared identity with extralocal elites and powerful social networks.

To test this mechanism, we again use data from the IHDS, which asks respondents if they have an acquaintance in government. Figure 4 illustrates that political connections strongly vary along India's caste hierarchy. Compared to marginalized SCs and STs, members of forward and general caste groups are more than doubly likely to have a political connection. Given our finding that marginalized groups are the least mobile, this pattern suggests that they are also the least politically connected.

[INSERT FIGURE 4 HERE]

Table 5 more robustly demonstrates that mobile people tend to have better political connections. Models (1)-(2) show that the odds of having acquaintances in government are approximately 30 percent higher for migrant households. This pattern is consistent in Models (3)-(4), where we compare households with interstate migrants to all others. The results also indicate that those who belong to a marginalized caste, lack a college education, and are in poverty are less likely to have government connections. We note that these cross-sectional findings provide only an indirect test of our mechanism.[28] However, they demonstrate that mobile people are also more politically connected and hence better positioned to attract public goods.

[INSERT TABLE 5 HERE]

An additional observable implication of our argument is that individuals in left-behind areas should have lower perceptions of the quality of local public goods. The second wave of the IHDS asks respondents about their confidence in public hospitals and schools. We demonstrate that individuals in states with high out-migration rates or low exposure to the IT boom report lower confidence in the quality of public goods, particularly public schools (Table S15, p. S19). Again, we caution that these cross-sectional results provide only illustrative evidence of our proposed mechanism.

Areas with high out-migration may also experience lower public goods provision due to remittances, which recipients may use to substitute public goods with private ones. Although remittance recipients may do so, disadvantaged groups are still left out of this substitution due to their low mobility. In Table S16 (p. S20), we demonstrate that lower-caste households are less likely to receive remittances. This finding is unsurprising, given they are also less likely to have migrant family members (Table 1). While we cannot rule out the role of remittances, it does not substantively alter the impact that lower public goods provision has for marginalized groups.

[28] Both IHDS waves come after the start of the IT boom; comparable survey data before the IT boom are not available.

5.4 Generalizability Beyond India

Finally, we discuss generalizability of our theory and findings. First, the IT boom may be atypical of other global labor market shocks due to its "skill-biased" nature. While our findings are most directly relevant for higher-skilled labor demand shocks, we expect similar dynamics for other geographically concentrated shocks that are less skilled, since relocation costs likely remain a barrier to access. Such conditions are widespread (World Bank, 2009). Additionally, recent research indicates that even "lower-skill" labor shocks from globalization benefit relatively higher-skilled workers in emerging economies (Menéndez González et al., 2023). However, more geographically diffuse shocks may not have the same consequences.

India's unique caste hierarchy may raise additional generalizability concerns. Caste influences both migration decisions and political power, potentially amplifying the impact of labor market shocks on left-behind areas. While caste is perhaps among the most rigid social hierarchies, ranked ethnic systems are prevalent in many emerging economies (Gaikwad and Suryanarayan, 2025). In addition, while the exact selection process may vary, migrants are systematically different from non-migrants in many other contexts, including Western (Anelli and Peri, 2017; Anelli et al., 2023; Maxwell, 2019) and Central Eastern Europe (Lim, 2023; Auer and Schaub, 2024), and the Middle East/North Africa (Docquier et al., 2020). Migrant attributes differ across contexts, as do their resulting impacts. Nonetheless, this article offers an important implication: selective out-migration can influence left-behind areas by driving demographic shifts that influence public goods provision.

Finally, the impact of global economic shocks on local public goods provision may vary depending on the role of local connections in securing resources from higher levels of government. In India, the hierarchical nature of public goods provision means that shared ethnicity and social networks shape resource allocation. Intergovernmental transfers to fund local public goods provision are common, so we expect our argument generalizes beyond India (Shah, 2006). However, in programmatic systems that limit the influence of advantaged groups, we might expect more muted effects.

6 Conclusion

We conclude by discussing key implications. Our study helps better understand how globalization shapes politics in emerging economies. Previous research primarily focuses on advanced economies, emphasizing backlash in localities hit by negative shocks. We show that positive shocks in emerging economies also engender relative globalization "losers", leading to political shifts in left-behind areas. Our findings also highlight the role of internal migration as a key mechanism affecting the distribution of globalization's benefits. While it is well-documented that globalization shocks are spatially concentrated, the role of mobility as a channel of accessing opportunity is understudied (Bonifai et al., 2024). Our findings suggest a complementary mechanism to identify globalization's winners and losers and its political consequences.

We note potential future research. Public goods provision is only one potential outcome of globalization and selective out-migration. The demographic shifts we identify could, for example, influence electoral outcomes (Lim, 2023) or descriptive representation (Smith et al., 2012), which we plan to explore in further research.

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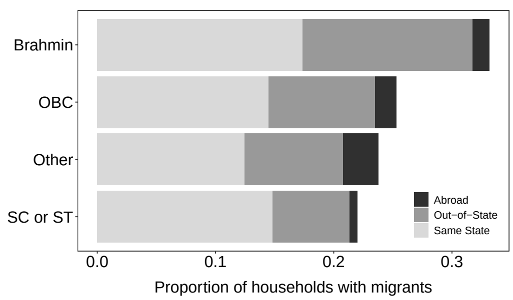
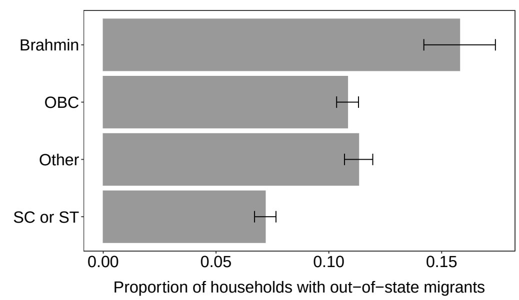
Figure 1: Proportion of Households with Migrants by Caste Group



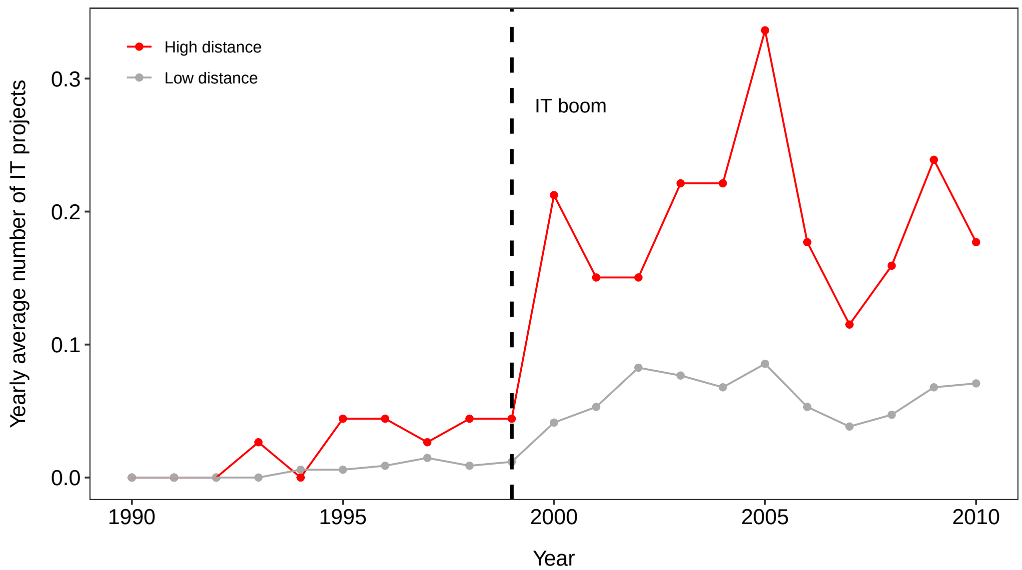
(a) All migrants



(b) Out-of-state migrants

Note: 1a: disaggregated by migration distance. 1b: out-of-state migration only. OBC: Other Backward Caste. SC/ST: Scheduled Caste/Scheduled Tribe. Source: IHDS-II (2011-12).

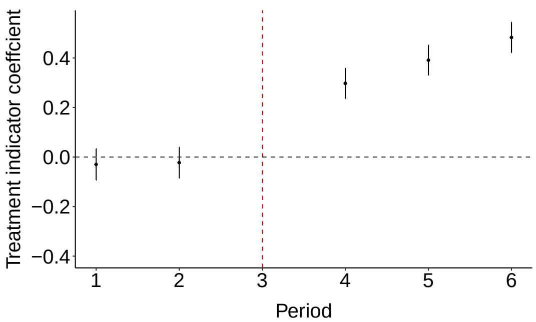
Figure 2: Linguistic Distance and Exposure to IT Boom, 1990-2010



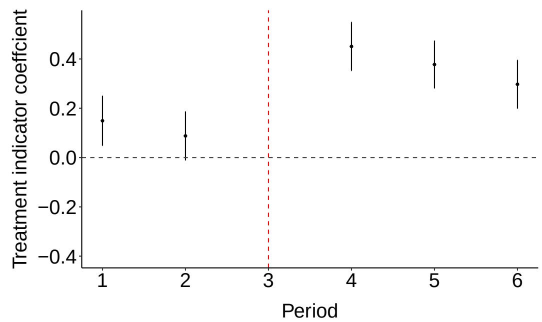
Note: districts with high (red) and low (gray) linguistic distance from Hindi. IT: information technology. Source: CapEx.

Figure 3: Bilateral Migration Event Studies

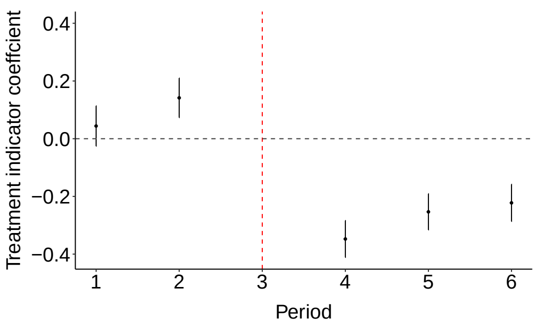
(a) Untreated to treated



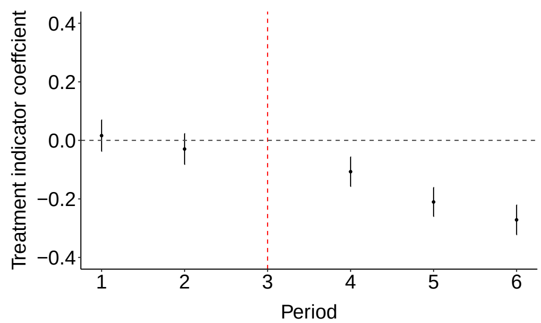
(b) Treated to treated



(c) Treated to untreated

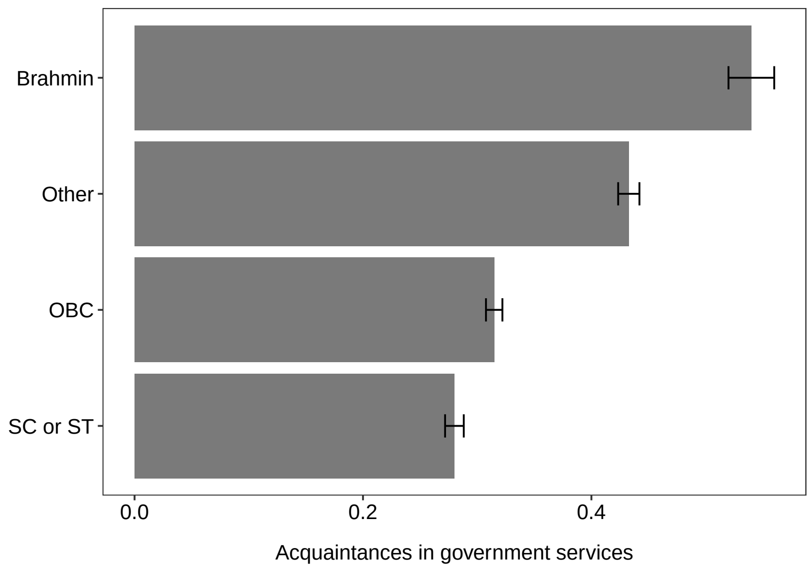


(d) Untreated to untreated



Note: yearly coefficient of treatment indicator from event study model with 95% confidence intervals. Period 3 (2001) omitted as reference period. All models include fixed effects and controls listed in Table 2.

Figure 4: Government Connection by Caste Group



Note: share of respondents with acquaintance in government by caste group. OBC: Other Backward Caste. SC/ST: Scheduled Caste/Scheduled Tribe. Source: IHDS-I (2004-05).

Table 1: Attributes of Migrant Households in India

	Migrant$_{hw2}$		Interstate migrant$_{hw2}$	
	(1)	(2)	(3)	(4)
SC/ST$_{hw1}$	-0.178^{**}	-0.190^{**}	-0.409^{**}	-0.388^{**}
	(0.028)	(0.029)	(0.044)	(0.045)
No college$_{hw1}$	-0.158^{**}	-0.165^{**}	-0.172^{**}	-0.140^{**}
	(0.036)	(0.037)	(0.049)	(0.052)
Below poverty line$_{hw1}$	-0.028	-0.128^{**}	-0.090^{*}	-0.097^{*}
	(0.030)	(0.033)	(0.044)	(0.048)
Muslim$_{hw1}$	-0.145^{**}	-0.168^{**}	0.243^{**}	0.038
	(0.039)	(0.042)	(0.050)	(0.055)
HH size$_{hw1}$	0.033^{**}	0.016^{**}	0.031^{**}	0.0004
	(0.004)	(0.004)	(0.005)	(0.006)
Age$_{hw1}$	0.002^{**}	0.001^{*}	0.0003	$0.001^{\dagger}$
	(0.0005)	(0.0005)	(0.001)	(0.001)
Observations	38,850	38,850	38,850	38,850
State FE	X	✓	X	✓
Control for $Migrant_{w1}$	✓	✓	✓	✓
Akaike inf. crit.	42,094.400	40,177.060	24,464.840	22,325.920

Note: †p<0.1; *p<0.05; **p<0.01. All models estimated using logistic regression. Robust standard errors in parentheses. Covariates and outcomes measured in Wave 1 (2004-05) and 2 (2011-12), respectively. HH: household. SC/ST: Scheduled Caste/Scheduled Tribe.

Table 2: Exposure to IT Boom and Bilateral Internal Migration

	log(Migrants$_{odt}$)			
	(1)	(2)	(3)	(4)
Untreated$_o$ $\rightarrow$ Treated$_d$ $\times$ Post$_t$	0.329**			
	(0.022)			
Treated$_o$ $\rightarrow$ Treated$_d$ $\times$ Post$_t$		0.177**		
		(0.033)		
Treated$_o$ $\rightarrow$ Untreated$_d$ $\times$ Post$_t$			-0.308**	
			(0.027)	
Untreated$_o$ $\rightarrow$ Untreated$_d$ $\times$ Post$_t$				-0.145**
				(0.021)
Observations	60,246	60,246	60,246	60,246
Controls	✓	✓	✓	✓
R^2	0.925	0.925	0.925	0.925

Note: †p<0.1; *p<0.05; **p<0.01. All models estimated with OLS and include origin state, destination district, dyad, and period fixed effects. Standard errors clustered by dyad in parentheses. Control variables measured at most recent Census and interacted with period indicators. Control variables include: logged population, literacy rate, employment rate, urbanization rate, gender ratio, and Scheduled Caste/Scheduled Tribe population share.

Table 3: Exposure to IT Boom and Public Goods Provision

	Health centers$_{it}$ (per capita)		Primary schools$_{it}$ (per capita)		Secondary schools$_{it}$ (per capita)	
	(1)	(2)	(3)	(4)	(5)	(6)
Treated$_i$ × Post$_t$	0.153**	0.188**	0.092*	0.090*	0.212**	0.253**
	(0.017)	(0.022)	(0.046)	(0.038)	(0.026)	(0.034)
Observations	1,356	1,356	1,356	1,356	1,344	1,344
Controls	X	✓	X	✓	X	✓
R^2	0.445	0.458	0.887	0.905	0.481	0.491

Note: †p<0.1; *p<0.05; **p<0.01. All models estimated with OLS with district and year fixed effects. Standard errors clustered by district in parentheses. Control variables include: logged population, literacy rate, employment rate, urbanization rate, gender ratio, and Scheduled Caste/Scheduled Tribe population share.

Table 4: Exposure to IT Boom and Public Goods Provision – Neighbors vs. Non-Neighbors

	Health centers$_{it}$ (per capita)		Primary schools$_{it}$ (per capita)		Secondary schools$_{it}$ (per capita)	
	(1)	(2)	(3)	(4)	(5)	(6)
Treated neighbor$_i$ × Post$_t$	-0.005	-0.030*	0.035	0.069	-0.018	-0.038†
	(0.004)	(0.012)	(0.069)	(0.058)	(0.015)	(0.023)
No treated neighbor$_i$ × Post$_t$	-0.168**	-0.205**	-0.106*	-0.107**	-0.233**	-0.276**
	(0.018)	(0.023)	(0.047)	(0.038)	(0.028)	(0.035)
Observations	1,356	1,356	1,356	1,356	1,344	1,344
Controls	X	✓	X	✓	X	✓
R^2	0.458	0.473	0.888	0.906	0.491	0.503

Note: †p<0.1; *p<0.05; **p<0.01. All models estimated with OLS with district and year fixed effects. Standard errors clustered by district in parentheses. Control variables include: logged population, literacy rate, employment rate, urbanization rate, gender ratio, and Scheduled Caste/Scheduled Tribe population share.

Table 5: Migrant Households and Government Connections

	Government acquaintance$_{hw1}$			
	(1)	(2)	(3)	(4)
Migrant$_{hw1}$	0.258**	0.272**		
	(0.035)	(0.038)		
Interstate migrant$_{hw1}$			0.191**	0.183**
			(0.052)	(0.055)
SC/ST$_{hw1}$	−0.205**	−0.282**	−0.204**	−0.282**
	(0.026)	(0.028)	(0.026)	(0.028)
No college$_{hw1}$	−1.080**	−1.155**	−1.081**	−1.155**
	(0.029)	(0.030)	(0.029)	(0.030)
Below poverty line$_{hw1}$	−1.267**	−1.057**	−1.269**	−1.062**
	(0.036)	(0.038)	(0.036)	(0.038)
Muslim$_{hw1}$	−0.344**	−0.369**	−0.344**	−0.369**
	(0.037)	(0.040)	(0.037)	(0.040)
Age$_{hw1}$	−0.005**	−0.004**	−0.005**	−0.004**
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Observations	40,737	40,737	40,737	40,737
State FE	×	✓	×	✓
Akaike inf. crit.	48,254.190	45,549.640	48,292.950	45,590.610

Note: †p<0.1; *p<0.05; **p<0.01. All models estimated using logistic regression. Robust standard errors in parentheses. SC/ST: Scheduled Caste/Scheduled Tribe.

Supplementary Information

Globalization, Internal Migration, and Public Goods Provision in Emerging Economies

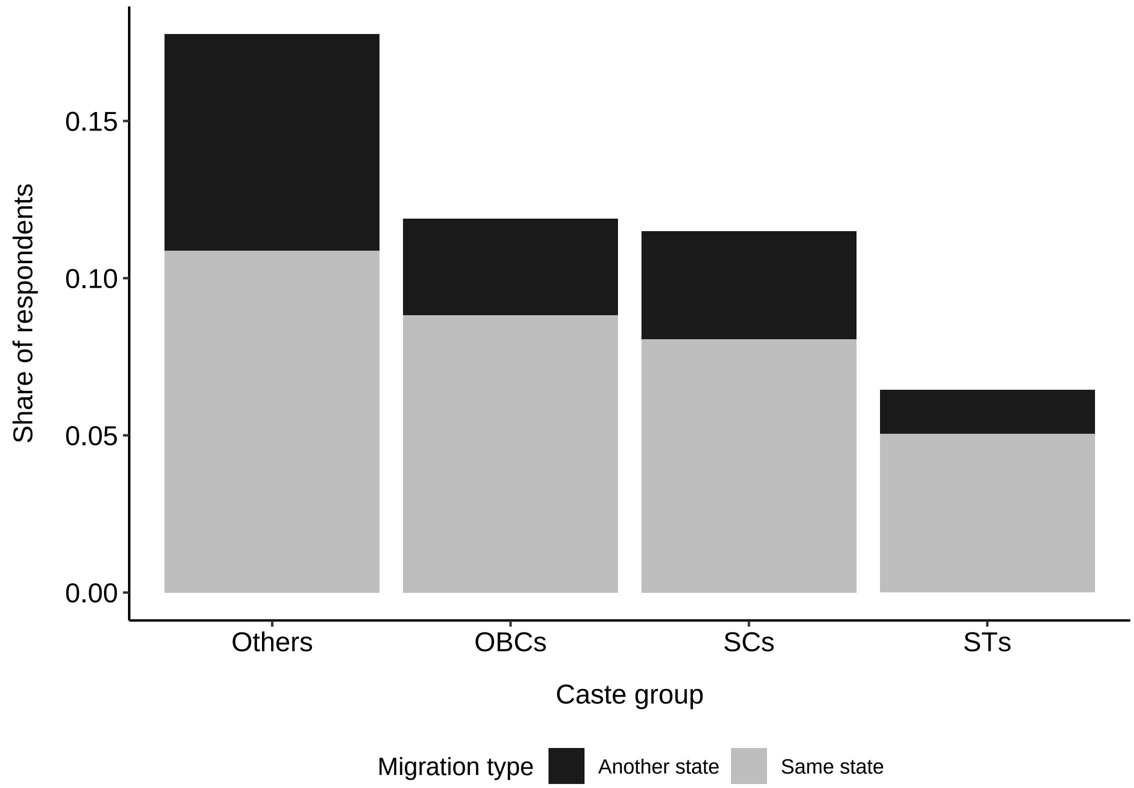
This material is intended for online publication only.

List of Figures

List of Tables

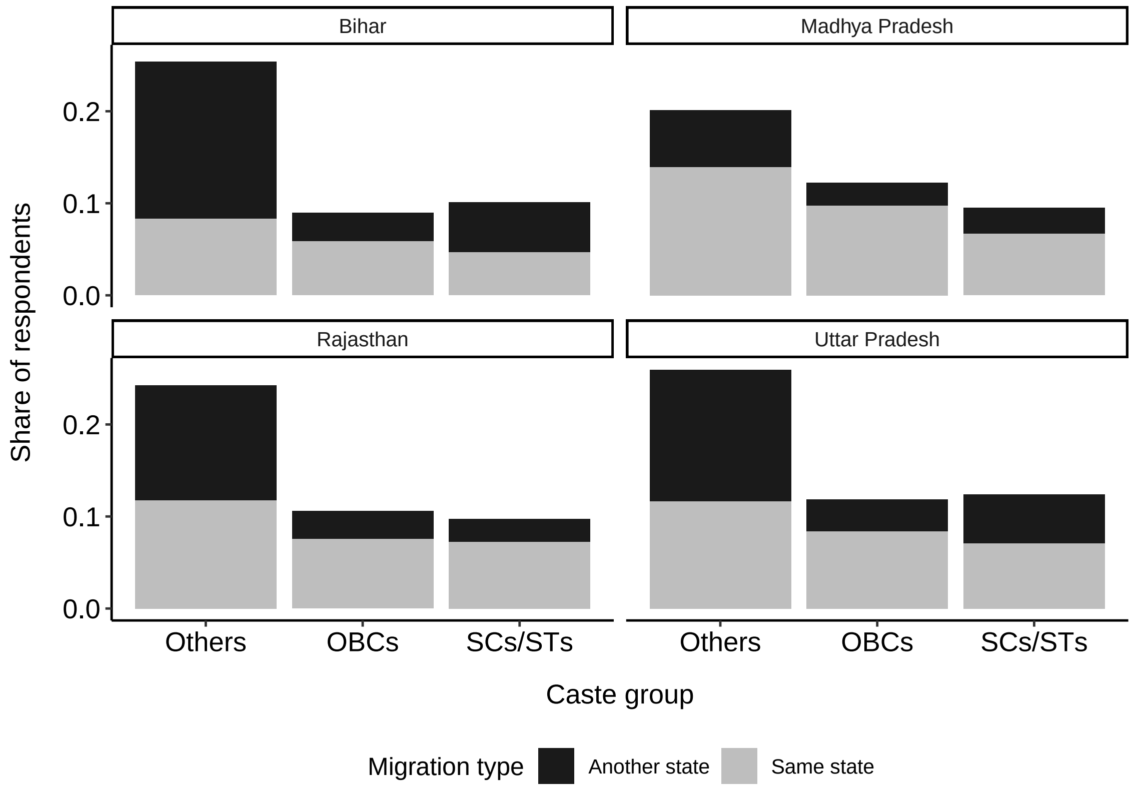
A: Individual-Level Migration Patterns

Figure S1: Internal Migration by Caste and Migration Type



Note: OBC: Other Backward Caste. SC/ST: Scheduled Caste/Scheduled Tribe. Source: National Sample Survey, 64th round (2007-08).

Figure S2: Internal Migration by Caste and Migration Type – Major Origin States



Note: OBC: Other Backward Caste. SC/ST: Scheduled Caste/Scheduled Tribe. Source: National Sample Survey, 64th round (2007-08).

B: Linguistic Distance, English Acquisition, and the IT Boom

Identifying the causal impact of the IT boom on internal migration and public goods provision requires a plausibly exogenous measure of exposure to new IT employment opportunities. Our measurement strategy builds on Shastry (2012), who uses district-level population-weighted linguistic distance from Hindi in 1991 to proxy for exposure to the IT boom. Here, we demonstrate that post-boom growth in Indian IT employment was indeed concentrated in districts with high linguistic distance from Hindi. We use data from the 1998, 2005, and 2013 rounds of India's Economic Census to estimate variations of following difference-in-differences model:

$$\text{IT Employment}_{i,t} = \beta_o + \beta_1 \text{Treated}_i \times \text{Post}_{it} + \mathbf{Z}_{i,t}\gamma + \theta_i + \kappa_t + \sigma_{it}$$

where IT Employment$_{it}$ represents IT employment per capita in district i at time t. All other notation is the same as our primary difference-in-differences model. Control variables are measured at the most recent Population Census. Table S1 reports results in which the outcome is IT employment per capita. Columns (1) and (3) present results with and without controls, respectively, for our primary dichotomized measure of exposure. The coefficient for Treated$_i \times$ Post$_t$ is positive and significant across these models, indicating that districts with high linguistic distance from Hindi experienced strong growth in IT employment following the boom. These results confirm the pattern that the IT sector is agglomerated only among the most linguistically distant districts. In Columns (2) and (4), we instead use the continuous measure of linguistic distance standardized to a 0-1 scale. Using this measure assumes a linear relationship between linguistic distance and the IT boom. Using this continuous measure, the estimated impact is still positive but our estimate is noisier and not significant at conventional levels. As we note, we prefer the dichotomized measure as it better reflects the highly agglomerated nature of the IT boom in India.

We also use an alternative outcome, IT employment as a share of total employment, in Table S2 and find substantively identical results. These models confirm that high linguistic distance from Hindi is strongly related to exposure to the IT boom.

Table S1: Exposure to IT Boom and IT Employment Per Capita

	ITES employment per capita$_{it}$			
	(1)	(2)	(3)	(4)
Treated$_i$ × Post$_t$	0.387*		0.398*	
	(0.158)		(0.163)	
Continuous$_i$ × Post$_t$		0.229		0.201
		(0.173)		(0.177)
log(population)$_{it}$			-0.104	-0.240
			(0.550)	(0.558)
Employment rate$_{it}$			0.015†	0.012
			(0.008)	(0.008)
Urbanization$_{it}$			0.001	0.003
			(0.010)	(0.010)
Female$_{it}$			0.077	0.071
			(0.055)	(0.058)
SC/ST$_{it}$			-0.013	-0.009
			(0.010)	(0.009)
Observations	1,354	1,354	1,354	1,354
R^2	0.595	0.592	0.597	0.594

Note: †p<0.1; *p<0.05; **p<0.01. All models estimated with OLS and include district and year fixed effects. IT employment per capita calculated from three waves of Economic Census (1998, 2005, 2013). Control variables measured at most recent Population Census. SC/ST: Scheduled Caste/Scheduled Tribe. Standard errors clustered by district in parentheses.

Our strategy assumes that linguistic distance from Hindi increases exposure to the IT boom because it encourages English acquisition, which attracts the IT sector. We discuss existing evidence that supports this assumption in the main text, but provide additional original analysis here. First, Shastry (2012) demonstrates a robust, positive, and statistically significant relationship between linguistic distance from Hindi and English-language acquisition at the state × native-language level. She finds this in 1991 and even in 1961, well before India's liberalization. This is the most disaggregated level of analysis possible because district-level data on multilingualism is not available. This evidence is key to our underlying identification strategy.

To complement this analysis, we estimate a model of English acquisition for the 113 native languages in the 1991 Census. Our two primary outcomes are: the

Table S2: Exposure to IT Boom and IT Employment Share

	ITES employment share$_{it}$			
	(1)	(2)	(3)	(4)
Treated$_i$ × Post$_t$	0.197†		0.221*	
	(0.113)		(0.108)	
Continuous$_i$ × Post$_t$		0.124		0.124
		(0.115)		(0.106)
log(population)$_{it}$			-0.040	-0.112
			(0.526)	(0.538)
Employment rate$_{it}$			0.011*	0.010†
			(0.005)	(0.005)
Urbanization$_{it}$			-0.005	-0.004
			(0.010)	(0.010)
Female$_{it}$			0.044	0.040
			(0.032)	(0.034)
SC/ST$_{it}$			-0.005	-0.003
			(0.007)	(0.007)
Observations	1,354	1,354	1,354	1,354
R^2	0.531	0.529	0.534	0.531

Note: †p<0.1; *p<0.05; **p<0.01. All models estimated with OLS and include district and year fixed effects. IT employment share calculated from three waves of Economic Census (1998, 2005, 2013). Control variables measured at most recent Population Census. SC/ST: Scheduled Caste/Scheduled Tribe. Standard errors clustered by district in parentheses.

percentage of *all* speakers, and the percentage of *multilingual* speakers, of language l who had acquired English as a second language in 1991. The primary independent variable is language l's linguistic distance from Hindi on a scale from 0 (Hindi itself) to 5 (most distant from Hindi) based on Shastry (2012). We include an indicator for Hindi, estimate this model using OLS, and weight observations by the number of speakers, all consistent with Shastry's approach.[1]

Table S3 displays our results. In Column (1), we analyze the percentage of language speakers who know English. In Column (2), we analyze the percentage of

[1]As Shastry notes, including an indicator for Hindi accounts for the fact that those whose native language is Hindi (already a lingua franca) and who choose to be multilingual may be more likely to acquire English as their second language.

Table S3: Linguistic Distance and English Acquisition

	English percent$_l$	English multilingual percent$_l$
	(1)	(2)
Distance$_l$	2.221**	10.062**
	(0.680)	(2.922)
Constant	0.260	3.883
	(2.014)	(11.310)
Observations	113	113
R^2	0.357	0.433

Note: †p<0.1; *p<0.05; **p<0.01. Models estimated with OLS, weighted by number of speakers, and include indicator for Hindi. Robust standard errors in parentheses.

multilingual language speakers who know English, consistent with Shastry's analysis. For both outcomes, linguistic distance from Hindi is strongly and positively related to English acquisition. Each additional degree of distance from Hindi leads to a 2.22 percentage point increase in the share of language speakers who know English. The outcome mean is 5.77, so the most distant languages ($Distance_l = 5$) have about double the national average of English speakers. In Column (2) each additional degree of distance from Hindi leads to a 10-percentage-point increase in the percentage of multilingual language speakers who know English. The outcome mean is 18.44, which means that the most distant languages have nearly three times the national average of English speakers among their multilinguals. This evidence, combined with that in Shastry (2012), robustly demonstrates that linguistic distance from Hindi drives English acquisition.

Second, we provide descriptive evidence that a larger English-speaking population is associated with greater IT presence. We first note data limitations in demonstrating this correlative relationship. The Indian Census provides data only on native languages at the district level. Data on second language acquisition is only available at the more aggregated state and national levels. As a result, we cannot observe the total number of English speakers at the district level.

Table S4: Pre-IT Boom Native English Speakers and IT Employment Per Capita

	ITES employment per capita$_{it}$			
	(1)	(2)	(3)	(4)
Native English$_i$ $\times$ Post$_t$	7.040**	7.034**	7.030**	7.146**
	(2.131)	(2.157)	(2.156)	(2.160)
log(population)$_{it}$		-0.353	-0.350	-0.269
		(0.529)	(0.523)	(0.548)
Employment rate$_{it}$			0.007	0.012†
			(0.006)	(0.007)
Urbanization$_{it}$			0.001	0.001
			(0.010)	(0.010)
Female$_{it}$				0.104*
				(0.051)
SC/ST$_{it}$				-0.009
				(0.009)
Observations	1,354	1,354	1,354	1,354
R^2	0.611	0.612	0.612	0.614

Note: $^{\dagger}p<0.1$; $^{*}p<0.05$; $^{**}p<0.01$. All models estimated with OLS and include district and year fixed effects. IT employment per capita calculated from three waves of Economic Census (1998, 2005, 2013). Control variables measured at most recent Population Census. SC/ST: Scheduled Caste/Scheduled Tribe. Standard errors clustered by district in parentheses.

With this limitation in mind, we conduct two descriptive analyses. First, we estimate models in which we replace our measure of exposure to the IT boom with the percentage of people who speak English as their native language in 1991. Natively speaking English is extremely rare in India: the maximum value of this measure is roughly 0.7%. As a result, this is a very conservative measure of English speaker presence, though it is likely positively correlated with acquisition of English as a second language. We present these results in Table S4. There is a strong, positive, and statistically significant correlation between pre-IT boom native English speaker presence and post-boom IT employment.

Table S5: Pre-IT Boom State English Speakers and IT Employment Per Capita

	ITES employment per capita$_{it}$			
	(1)	(2)	(3)	(4)
English speakers$_j$ × Post$_t$	0.040*	0.039*	0.039*	0.041*
	(0.018)	(0.019)	(0.019)	(0.019)
log(population)$_{it}$		-0.224	-0.224	-0.133
		(0.546)	(0.537)	(0.569)
Employment rate$_{it}$			0.004	0.009
			(0.006)	(0.007)
Urbanization$_{it}$			0.001	0.001
			(0.009)	(0.009)
Female$_{it}$				0.095
				(0.062)
SC/ST$_{it}$				-0.013
				(0.011)
Observations	1,354	1,354	1,354	1,354
R^2	0.599	0.599	0.599	0.601

Note: $^\dagger p<0.1$; $^* p<0.05$; $^{**} p<0.01$. All models estimated with OLS and include district and year fixed effects. IT employment per capita calculated from three waves of Economic Census (1998, 2005, 2013). Control variables measured at most recent Population Census. SC/ST: Scheduled Caste/Scheduled Tribe. Standard errors clustered by district in parentheses.

Second, we replace our measure of exposure to the IT boom with the percentage of people who have acquired English in district i's state j in 1991. This allows us to leverage state-level data on English acquisition. The disadvantage is that we must employ a state-level indicator to analyze a district-level outcome. We must assume that there is no systematic heterogeneous distribution of English speakers within states that biases our results. With this in mind, our results in Table S5 show a strong, positive, and significant correlation between pre-IT boom state-level English presence and post-boom IT employment. While imperfect, these analyses provide additional support for the conjecture that linguistic distance from Hindi is causally

Table S6: Exposure to IT Boom and Bilateral Internal Migration – Using Only Pre-Treatment Controls

	log(Migrants_{odt})			
	(1)	(2)	(3)	(4)
$\text{Untreated}_o \rightarrow \text{Treated}_d \times \text{Post}_t$	0.279**			
	(0.021)			
$\text{Treated}_o \rightarrow \text{Treated}_d \times \text{Post}_t$		0.088**		
		(0.031)		
$\text{Treated}_o \rightarrow \text{Untreated}_d \times \text{Post}_t$			-0.275**	
			(0.025)	
$\text{Untreated}_o \rightarrow \text{Untreated}_d \times \text{Post}_t$				-0.051**
				(0.019)
Observations	60,246	60,246	60,246	60,246
Controls	✓	✓	✓	✓
R^2	0.925	0.925	0.925	0.925

Note: †p<0.1; *p<0.05; **p<0.01. All models estimated with OLS and include origin state, destination district, dyad, and period fixed effects. Standard errors clustered by dyad in parentheses. Control variables measured in 1991 and interacted with period indicators. Control variables include: logged population, literacy rate, employment rate, urbanization rate, gender ratio, and Scheduled Caste/Scheduled Tribe population share.

related to presence of the IT sector via its impacts on English acquisition.

C: Exposure to IT Boom and Internal Migration

We show that following the IT boom, internal migration inflows increase from unexposed states to exposed districts. We estimate additional models of internal migration to ensure robustness and extend our findings. First, our control variables are measured both well before the IT boom (in 1991) and immediately after its onset (in 2001). We note that our baseline results are similar with and without the inclusion of control variables. However, to further ensure that our results are not due to inclusion of post-treatment control variables, we estimate the impact of exposure to the IT boom on migration with control variables measured in 1991 and interacted with period indicators. Table S6 presents the results, which are substantively very similar.

We also estimate a simpler, monadic model of district migration inflows without

Table S7: Exposure to IT Boom and District Internal Migration

	$\log(\text{Migrants}_{it})$			
	(1)	(2)	(3)	(4)
$\text{Treated}_i \times \text{Post}_t$	0.112^{*}	0.128^{**}	0.165^{**}	0.182^{**}
	(0.047)	(0.044)	(0.043)	(0.043)
Observations	2,712	2,712	2,712	2,712
Control for population	X	✓	✓	✓
Control for local econ. characteristics	X	X	✓	✓
Control for local demographics	X	X	X	✓
R^2	0.928	0.929	0.937	0.938

Note: †p<0.1; *p<0.05; **p<0.01. All models estimated with OLS and include district and year fixed effects. Standard errors clustered by district in parentheses. Control variables measured at most recent Census and interacted with period indicators. Control variables include: logged population, literacy rate, employment rate, urbanization rate, gender ratio, and Scheduled Caste/Scheduled Tribe population share.

regard to origin state. Table S7 shows that internal migration inflows are concentrated in exposed districts.

We also extend our bilateral migration results to explore if the IT boom generated selective out-migration. We re-estimate Model (1) in Table 2 but include a triple interaction between our $Untreated_o \rightarrow Treated_d$ corridor indicator, $Post_t$, and $PercentSCST_{ot}$, the percentage of population in origin state o at time t that SCs and STs represent. In Table S8, we show the results. The triple interaction is negative and statistically significant, while the double interaction remains positive. This indicates that while the IT boom increased interstate migration from unexposed states to exposed districts, this effect declines as the origin state's SC/ST share increases. These results are consistent with the proposition that the interstate migration generated by the IT boom is selective in ways consistent with our argument.

Table S8: Selective Out-Migration in Response to the IT Boom

	log(Migrants_{it})
	(1)
$\text{Untreated}_o \rightarrow \text{Treated}_d \times \text{Post}_t \times \text{Percent SC/ST}_{ot}$	-0.003**
	(0.001)
$\text{Untreated}_o \rightarrow \text{Treated}_d \times \text{Post}_t$	0.434**
	(0.039)
$\text{Untreated}_o \rightarrow \text{Treated}_d \times \text{Percent SC/ST}_{ot}$	0.006
	(0.015)
Observations	60,246
Controls	✓

Note: †p<0.1; *p<0.05; **p<0.01. Model estimated with OLS and includes origin state, destination district, dyad, and period fixed effects. Standard errors clustered by dyad in parentheses. Control variables measured at most recent Census and interacted with period indicators. All constituent interaction terms included in model but suppressed in table. Control variables include: logged population, literacy rate, employment rate, urbanization rate, gender ratio, and Scheduled Caste/Scheduled Tribe population share.

D: Exposure to IT Boom and Public Goods Provision

Alternative Specifications

We estimate additional alternative specifications to probe the robustness of our findings with respect to public goods provision. First, our control variables are measured both well before the IT boom (in 1991) and immediately after its onset (in 2001). We note that our baseline results are very similar both with and without the inclusion of control variables. However, to further ensure that our results are not due to inclusion of post-treatment control variables, we estimate the impact of exposure to the IT boom on public goods provision with control variables measured in 1991 and interacted with year indicators. Table S9 presents the results. The results are mostly consistent in terms of estimated magnitude and statistical significance. The estimate for primary schools is no longer statistically significant at conventional levels

Table S9: Exposure to IT Boom and Public Goods Provision – Using Only Pre-Treatment Controls

	Hospitals$_{it}$ (per capita)	Primary schools$_{it}$ (per capita)	Secondary schools$_{it}$ (per capita)
	(1)	(2)	(3)
Treated$_i$ × Post$_t$	0.276**	0.083	0.364**
	(0.032)	(0.051)	(0.050)
Observations	1,356	1,356	1,344
R^2	0.514	0.895	0.526
1991 Controls × Year	✓	✓	✓

Note: †p<0.1; *p<0.05; **p<0.01. Control variables are all measured in pre-treatment period, then interacted with binary indicators of each wave to account for potential time varying effects of these variables. Control variables include: logged population, literacy rate, employment rate, urbanization rate, gender ratio, and Scheduled Caste/Scheduled Tribe population share measured in 1991. All models estimated with OLS and include district and year fixed effects. Standard errors clustered by district in parentheses.

(p=.104). These additional results provide little indication that our baseline results are driven by the inclusion of post-treatment control variables.

Second, our reduced-form difference-in-differences analysis demonstrates that the IT boom increased internal migration and created disparities in public goods provision between exposed and unexposed places. However, our difference-in-differences analysis does not allow us to directly demonstrate the underlying causal chain: that the IT boom increases internal migration, which then shapes public goods provision. To provide more evidence for our underlying mechanism, we estimate a set of two-stage least-squares (2SLS) instrumental variables models. In the first stage, we use exposure to the IT boom to instrument for district-level interstate migration in the preceding decade. In the second stage, we estimate the impact of instrumented district interstate migration in the preceding decade on public goods provision. We present the results in Table S10, in which we show 2SLS models without and with controls for each public goods outcome. Our results are consistent with our argument and reduced-form estimates in Table 3. We also display first-stage results and con-

Table S10: Exposure to IT Boom and Public Goods Provision – Two-Stage Least-Squares Estimation

	Health centers$_{it}$ (per capita)		Primary schools$_{it}$ (per capita)		Secondary schools$_{it}$ (per capita)	
	(1)	(2)	(3)	(4)	(5)	(6)
$\log(\widehat{\text{Migrants}_{it}})$	0.474**	0.606**	0.286†	0.289*	0.653**	0.822**
	(0.093)	(0.130)	(0.147)	(0.127)	(0.126)	(0.180)
	First stage regression					
	$\log(\text{Migrants}_{it})$					
Treated$_i$ × Post$_t$	0.323**	0.308**	0.323**	0.308**	0.325**	0.306**
	(0.052)	(0.053)	(0.052)	(0.053)	(0.052)	(0.054)
First-stage F-statistic	70.0	60.0	70.0	60.0	69.9	57.5
Observations	1,356	1,356	1,356	1,356	1,344	1,344
Controls	X	✓	X	✓	X	✓

Note: †p<0.1; *p<0.05; **p<0.01. All models estimated with 2SLS regression and include district and year fixed effects. Standard errors clustered by district in parentheses. Control variables include: logged population, literacy rate, employment rate, urbanization rate, gender ratio, and Scheduled Caste/Scheduled Tribe population share.

firm that the IT boom is a strong instrument for interstate migration. These results provide additional support for our underlying causal argument.

Experimenting with Different Linguistic Distance Thresholds

Our main analysis uses a binary indicator, Treated$_i$, for districts in the top quartile of linguistic distance from Hindi. We explore the sensitivity of this threshold by replicating the analyses from Table 3 (Models (2), (4), and (6)) using binary indicators with increasingly lower linguistic distance thresholds: top 30%, 35%, 40%, and so on to 60%. Figure S3 presents the coefficient of Treated$_i$ × Post$_t$ across these different thresholds. For all measures of public goods provision, the coefficient estimate declines as the cutoff increases. As the threshold changes from the top quartile to the top 40% and 50%, the coefficient is no longer statistically significant at the 95%

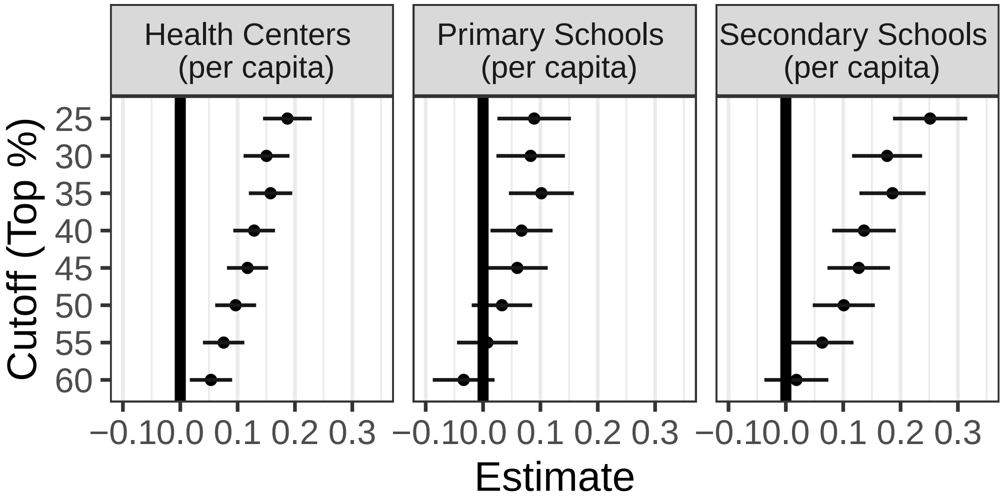


Figure S3: Impact of Different Thresholds of Linguistic Distance from Hindi.

level for primary and secondary schools per capita, respectively. The coefficient for health centers per capita remains statistically significant but substantially declines in magnitude with increasingly lower thresholds.

Exploring the Effects of Neighbors

In the article, we demonstrate that disparities in public goods provision are primarily driven by comparisons between treated districts and the most geographically distant untreated districts. We suggest this is consistent with our proposed mechanism of selective out-migration. Here, we provide additional results consistent with this approach. First, we identify districts that are not directly exposed to the IT boom but that neighbor exposed districts in the same state. Treated $(\text{alternative})_i$ is an alternative binary indicator of exposure to the IT boom: 1 indicates that a district is either directly exposed to the IT boom or, if not directly exposed, is located in a neighboring district that is exposed. A value of 0 indicates that a district is neither directly exposed nor located in a neighboring district that is exposed. Table S11 replicates Table 3 with this alternative measure of treatment, accounting for neighboring effects. Table S12 disaggregates neighboring districts by whether they are in

Table S11: Exposure to IT Boom and Public Goods Provision – Alternative Treatment

	Health centers$_{it}$ (per capita)		Primary schools$_{it}$ (per capita)		Secondary schools$_{it}$ (per capita)	
	(1)	(2)	(3)	(4)	(5)	(6)
Treated (alternative)$_i$ × Post$_t$	0.167**	0.197**	0.113**	0.124**	0.229**	0.266**
	(0.018)	(0.022)	(0.040)	(0.033)	(0.027)	(0.033)
Observations	1,356	1,356	1,356	1,356	1,344	1,344
Controls	X	✓	X	✓	X	✓
R^2	0.458	0.473	0.888	0.906	0.491	0.503

Note: †p<0.1; *p<0.05; **p<0.01. All models estimated with OLS and include district and year fixed effects. Standard errors clustered by district in parentheses. Control variables include: logged population, literacy rate, employment rate, urbanization rate, gender ratio, and Scheduled Caste/Scheduled Tribe population share.

the same or different state as the neighboring treated district.

Other Types of Public Goods Provision

In the main text, we focus on health centers and schools per capita when examining the effects of the IT boom on public goods provision. We extend our results with two other local public goods: share of villages with paved roads and electricity supply. Data are again from the decennial Population Census. While health centers and schools are measured across both urban (town) and rural areas (villages) within district, paved roads and electricity focuses on rural areas (villages) only. Table S13 demonstrates that districts exposed to the IT boom tend to have a higher share of paved roads and access to electricity. We demonstrate similar heterogeneity by neighboring status in Table S14.

E: Alternative Mechanisms

Table S15 demonstrates that IHDS respondents who live in high-out-migration and low-IT-boom exposure areas report lower confidence in public hospitals and schools.

Table S16 replicates our model specification from Table 1 using the IHDS, demonstrating that SC/ST households are less likely to receive remittances. This is unsurprising given they are less likely to have a migrant household member (Table 1). This highlights that although remittances recipients may substitute public goods with private ones, the most disadvantaged groups are left behind from this substitution and are most affected by lower public goods provision.

Table S12: Exposure to IT Boom and Public Goods Provision - Neighbor Effects by State

	Health centers$_{it}$ (per capita)		Primary schools$_{it}$ (per capita)		Secondary schools$_{it}$ (per capita)	
	(1)	(2)	(3)	(4)	(5)	(6)
Treated neighbor (same state)$_i$ × Post$_t$	-0.005	-0.024*	0.035	0.072	-0.018	-0.030
	(0.004)	(0.010)	(0.069)	(0.058)	(0.015)	(0.020)
Treated neighbor (diff. state)$_i$ × Post$_t$	-0.575**	-0.599**	-0.276**	-0.304**	-0.804**	-0.833**
	(0.093)	(0.091)	(0.089)	(0.082)	(0.149)	(0.151)
No treated neighbor × Post$_t$	-0.123**	-0.154**	-0.086†	-0.081*	-0.168**	-0.203**
	(0.015)	(0.019)	(0.047)	(0.037)	(0.022)	(0.025)
Observations	1,356	1,356	1,356	1,356	1,344	1,344
Controls	X	✓	X	✓	X	✓
R^2	0.558	0.570	0.889	0.908	0.575	0.585

Note: $^{\dagger}p<0.1$; $^{*}p<0.05$; $^{**}p<0.01$. All models estimated with OLS and include district and year fixed effects. Standard errors clustered by district in parentheses. Control variables include: logged population, literacy rate, employment rate, urbanization rate, gender ratio, and Scheduled Caste/Scheduled Tribe population share.

Table S13: Exposure to IT Boom and Provision of Other Public Goods

	Paved road (village)		Power supply (village)	
	(1)	(2)	(3)	(4)
Treated$_i$ × Post$_t$	0.118**	0.184**	0.089**	0.131**
	(0.020)	(0.024)	(0.034)	(0.038)
Controls	X	✓	X	✓
Observations	1,344	1,344	1,324	1,324
R^2	0.756	0.773	0.674	0.683

Note: $^{\dagger}p<0.1$; $^{*}p<0.05$; $^{**}p<0.01$. All models estimated with OLS and include district and year fixed effects. Standard errors clustered by district in parentheses. Dependent variables measured as district share of villages with paved road or electricity. Control variables include: logged population, literacy rate, employment rate, urbanization rate, gender ratio, and Scheduled Caste/Scheduled Tribe population share.

Table S14: Exposure to IT Boom and Provision of Other Public Goods – Neighbors vs. Non-Neighbors

	Paved road (village)		Power supply (village)	
	(1)	(2)	(3)	(4)
No treated neighbor$_i$× Post$_t$	-0.138**	-0.207**	-0.110**	-0.153**
	(0.021)	(0.024)	(0.034)	(0.039)
Treated neighbor$_i$× Post$_t$	0.070*	0.021	0.115*	0.075
	(0.027)	(0.029)	(0.052)	(0.050)
Controls	X	✓	X	✓
Observations	1,344	1,344	1,324	1,324
R^2	0.763	0.782	0.679	0.688

Note: $^{\dagger}p<0.1$; $^{*}p<0.05$; $^{**}p<0.01$. All models estimated with OLS and include district and year fixed effects. Standard errors clustered by district in parentheses. Dependent variables measured as district share of villages with paved road or electricity. Control variables include: logged population, literacy rate, employment rate, urbanization rate, gender ratio, and Scheduled Caste/Scheduled Tribe population share.

Table S15: Out-Migration and Attitudes toward Public Goods

	Confidence in public			
	Hospitals$_{hw2}$	Schools$_{hw2}$	Hospitals$_{hw2}$	Schools$_{hw2}$
	(1)	(2)	(3)	(4)
Out-migrant share$_{st}$	−0.061	−0.166**		
	(0.037)	(0.043)		
Low exposure$_{it}$			−0.023	−0.073*
			(0.035)	(0.031)
Receive remittances$_{hw2}$	0.026	0.015	0.015	−0.002
	(0.017)	(0.018)	(0.018)	(0.018)
SC/ST$_{hw2}$	0.041**	0.050**	0.036**	0.042**
	(0.014)	(0.012)	(0.014)	(0.012)
No college$_{hw2}$	0.040*	0.028	0.040*	0.032†
	(0.018)	(0.017)	(0.017)	(0.017)
Below poverty line$_{hw2}$	−0.007	−0.017	−0.012	0.004
	(0.018)	(0.017)	(0.017)	(0.016)
Muslim$_{hw2}$	0.009	−0.004	0.007	−0.019
	(0.029)	(0.027)	(0.029)	(0.026)
Observations	31,501	31,318	37,112	36,915
R^2	0.004	0.016	0.002	0.007

Note: $^{\dagger}p<0.1$; $^{*}p<0.05$; $^{**}p<0.01$. All models estimated using OLS. Clustered standard errors by district in parentheses. Out-migration rate calculated for 2007–2011. Models also include service attitudes in Wave 1. IHDS does not distinguish between public and private services in Wave 1, but attitudes account for general satisfaction. SC/ST: Scheduled Caste/Scheduled Tribe.

Table S16: Recipients of Remittances

	Receive remittances$_{w2}$		
	(1)	(2)	(3)
SC/ST$_{w1}$	-0.032^{**}	-0.029^{**}	-0.011^{**}
	(0.004)	(0.004)	(0.003)
No college$_{w1}$	0.002	0.001	0.019^{**}
	(0.005)	(0.005)	(0.004)
Below poverty line$_{w1}$	-0.007	-0.003	0.010^{**}
	(0.005)	(0.005)	(0.003)
Muslim$_{w1}$	-0.001	-0.003	0.014^{**}
	(0.006)	(0.006)	(0.004)
HH size$_{w1}$	-0.001^{*}	-0.001	-0.002^{**}
	(0.001)	(0.001)	(0.0005)
Age$_{w1}$	0.0005^{**}	0.0004^{**}	0.0003^{**}
	(0.0001)	(0.0001)	(0.00005)
Receive remittances$_{w1}$		✓	✓
Migrant household			✓
Observations	38,850	38,849	38,849
Akaike inf. crit.	26,178.770	25,180.530	-245.338

Note: †p<0.1; *p<0.05; **p<0.01. All models estimated with logistic regression and include state fixed effects. Robust standard errors in parentheses. SC/ST: Scheduled Caste/Scheduled Tribe. HH: household.