Language Barriers, Internal Migration, and Labor Markets in General Equilibrium[*]

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Abstract

This paper studies how language barriers impact internal migration, inequality between skilled and unskilled workers, and welfare using rich microdata from India applied to a static spatial general equilibrium framework. I document that (1) consistent with lower incentives, workers migrate less often to locations where they face high language barriers, (2) consistent with comparative advantage, migrants with language barriers are employed in speaking-intensive occupations less often, (3) consistent with selection, migrants with language barriers get a wage premium, and (4) these patterns are strongest for unskilled workers. To explain these facts, I develop and estimate a quantitative model. Through the lens of the model, I show that removing language barriers would increase internal migration by 6.2 percentage points, decrease inequality between skilled and unskilled workers by 1.9 percentage points, and increase welfare by 1.2 percent. As economies shift towards services, language barriers increasingly impede aggregate gains due to the rising prevalence of speaking-intensive occupations. In the absence of language barriers—relative to observed changes—structural change would have increased internal migration by 7.2 percentage points, decreased inequality between skilled and unskilled workers by 3.4 percentage points, and increased welfare by 1.9 percent. Finally, I argue that welfare benefits of implementing language programs outweigh costs.

JEL Codes: J24, J31, J61, R23, O15

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1 Introduction

The world is highly multilingual, with over 7,000 languages spoken today. In many countries, there is no *lingua franca*. In these countries, language barriers augment the cost of migration to a degree comparable to, and beyond, geographic barriers.[1] Migrants' decisions on where to move and in which occupations to work depend on the language(s) spoken in the destination. The implications of this manner of sorting may be consequential in labor markets that increasingly reward communication skills.[2] Further, as skilled workers are more likely to be proficient in languages spoken across labor markets (e.g., English, French), language barriers may contribute to inequality between skilled and unskilled workers. This makes language a critical factor in understanding and mitigating economic disparities within multilingual countries.

This paper is the first to study the aggregate effects of language as both a spatial and labor market friction. Specifically, it asks: How do language barriers impact internal migration, inequality between skilled and unskilled workers, and welfare?[3] How do language barriers impact gains from structural change in services, as characterized by a rise in speaking occupations? How could language policy mitigate these effects? I show theoretically and empirically that language barriers significantly obstruct internal migration and labor market outcomes, particularly for unskilled workers. Removing language barriers increases internal migration by 6.2 percentage points, reduces inequality by 1.9 percentage points, and enhances welfare by 1.2 percent. Further, language barriers become particularly significant when economies shift towards services and attenuate gains from structural change. Using India's economic transformation following its 1991 trade liberalization as context, I show that language barriers significantly impeded gains from growing consumer service employment. In the absence of language barriers—and relative to observed changes—rapid growth in retail, hospitality, and other consumer services where occupations are speaking-intensive would have increased internal migration by 7.2 percentage points, decreased inequality between skilled and unskilled workers by 3.4 percentage points, and increased welfare by 1.9 percent. From back-of-the-envelope calculations, I argue that the welfare benefits of implementing language programs outweigh costs, suggesting that these would be a cost-effective policy to mitigate language barriers.

First, I document three descriptive facts on the relationship between language, location, and labor market outcomes. I show that (1) consistent with lower incentives, workers migrate less often to locations where they face high language barriers, (2) consistent with comparative advantage, migrants with language barriers are employed in speaking-intensive occu-

[1] For example, (Kone et al. 2018) empirically demonstrate using a gravity specification that having a common language across districts in India is equivalent to reducing distances by 48%.

[2] Occupations that are intensive in communication skills have been shown to pay 6-11% higher wages across varying degrees of cognitive skills in the context of the United States (Deming 2017).

[3] In this paper, welfare is defined as aggregate real income. This measure does not capture utility from cultural diversity or multilingualism.

pations less often, (3) consistent with selection, migrants with language barriers get a wage premium, and (4) these patterns are less pronounced for skilled (defined as college) workers compared to unskilled (defined as non-college) workers. This highlights the potential role of language barriers in exacerbating inequalities.

To establish these facts, I leverage novel, highly disaggregated data on district-to-district migration from the Census of India (2001, 2011). This dataset provides information on the universe of internal migrants, including their origin, destination, and key demographic characteristics. I complement the census data with other household and administrative datasets to study the impact of language barriers on internal migration, welfare, and inequality.

India's immense linguistic diversity, with 130 languages spoken by significant populations, provides an ideal setting for this research. Proficiency in English is widespread among college-educated workers while workers without college education typically have less exposure to English. Following Fearon (2003), I measure language barriers by constructing a linguistic distance index between district pairs based on shared language branches and speaker populations.[4]

Second, and motivated by the descriptive facts, I build a static quantitative spatial general equilibrium model of migration. In this framework, language is modeled both as a component of migration cost and as a technological friction. Heterogeneous workers (skilled and unskilled) may face language barriers at potential destinations and choose between heterogeneous occupations (speaking and non-speaking) across locations. In addition, I allow for complementarities by skill and occupation type in production, which helps me flexibly uncover the relationship of language to the labor market.

In the model, workers choose destinations and occupations based on their comparative advantage. This sorting mechanism explains why migrants are less likely to move to locations with high language barriers and are less frequently employed in speaking occupations at these locations (descriptive facts 1 and 2). The model also accounts for selection effects: workers who do migrate expect to be highly productive and are able to overcome language migration costs, earning a wage premium where they face a language barrier (descriptive fact 3). I incorporate labor demand considerations by allowing firms to differentiate between workers based on skill and language (descriptive fact 4). This reflects varying linguistic and skill requirements across occupations that contribute to wage adjustments in general equilibrium.

The mechanisms in the model underscore the interplay between sorting and selection mechanisms in general equilibrium: removing language barriers can enhance productivity (increasing wages), and yet simultaneously eliminate the positive selection effect of language and potentially increase labor supply (decreasing wages). These countervailing forces render the net impact on wages theoretically ambiguous, making a structural model essential to

[4] India's linguistic landscape offers a unique opportunity to examine a long-standing puzzle about its persistently low internal mobility. This paper proposes language barriers as a partial explanation for this puzzle.

determine the overall effects. The results suggest that removing the sorting effect of language barriers dominates the effects on wages.

I take the model to microdata from India and estimate novel elasticities of substitution between occupation and worker types. I find high degrees of complementarities between unskilled workers with and without language barriers in speaking occupations, but not so in non-speaking occupations or among skilled workers. I also estimate the average productivity of worker types in speaking occupations. I find that unskilled workers that face language barriers are nearly twice as productive in non-speaking than in speaking occupations, but this is not so for unskilled workers without language barriers or among skilled workers. Thus, the estimates corroborate my hypothesis that language barriers affect unskilled rather than skilled workers, and in speaking rather than non-speaking occupations.

Third, I use the estimated model to conduct three counterfactual exercises. In the first counterfactual, I quantify the impact of language barriers on internal migration, inequality between skilled and unskilled workers, and welfare. To do so, I remove language both as a driver of productivity and component of migration cost. This increases internal migration by 6.2 percentage points, decreases inequality by 1.9 percentage points, and increases welfare by 1.2 percent relative to the estimated model. To contextualize these magnitudes, I target the same aggregate welfare gains and find that removing language barriers is equivalent to (1) proportionally decreasing geographic barriers between every pair of locations by 56 percent or (2) increasing the share of college workers in each location by 34 percent.

In the second counterfactual, I consider the increasing importance of language barriers due to structural change, as characterized by the prevalence of speaking occupations. I quantify the impact of language barriers on internal migration, inequality between skilled and unskilled workers, and welfare when speaking occupations became more prevalent across space. Between 1987 (before India's trade liberalization) and 2011 (the timeline of my analysis), there was rapid growth in particularly consumer services across space (Fan, Peters, and Zilibotti 2023). In other words, there was an increase in the prevalence of speaking occupations across space. This heightened the importance of language skills in the labor market.

To quantify the impact of language on aggregate outcomes when this transformation occurred, I use a structural difference-in-differences approach. I compare the effects of the occupational shift over time in scenarios with and without language barriers. I find that relative to observed changes, and in the absence of language barriers, the increased prevalence of speaking occupations would have caused internal migration to be higher by 7.2 percentage points, inequality between skilled and unskilled workers to be lower by 3.4 percentage points, and welfare to be higher by 1.9 percent.

In the third counterfactual, I consider the cost effectiveness of policies to reduce language barriers.[5] To implement this exercise, I extend the model to allow the government to offer

[5] This is motivated by language programs facilitated by the Federal Office of Migration and Refugees in

language learning opportunities to unskilled migrant workers that face a language barrier. The cost of implementing this program is financed by charging a uniform lump-sum tax to all residents. Unskilled migrants that choose to enroll in the language program weigh the benefit of participating in the labor market without language barriers against the opportunity cost of overcoming them. I calibrate this opportunity cost of learning languages using information on time taken to learn languages and the wages foregone as a consequence. Using the calibrated model, I show that below a threshold cost of language programs, introducing this policy would lead to net welfare gains compared to the benchmark case without programs or costly learning. From back-of-the-envelope calculations, I find that the actual cost of financing such a program is well below the threshold, so language policy should indeed be implemented.

Broadly, this paper leverages India's linguistic diversity and the rise of speaking occupations to investigate the economic impact of language barriers on internal migration, inequality between skilled and unskilled workers, and welfare. It emphasizes the mechanisms through which language barriers shape labor market outcomes and drive aggregate outcomes in diverse, developing economies. The findings in this paper have important implications for understanding sources of inequality and designing policies to promote more inclusive economic growth in multilingual countries.

Related Literature: This paper is related to several strands of literature. First, it contributes to a broad line of work in economic geography and migration that studies aggregate implications of spatial frictions. Similar to Tombe and Zhu (2019), Fan (2019), and Allen, Dobbin, and Morten (2018), the model features multiple regions and sectors (occupations) with costly labor mobility in a static framework. Previous research, including dynamic migration models in Kennan and Walker (2011), Monras (2018), and Caliendo, Dvorkin, and Parro (2019), have emphasized geographic barriers as an impediment to migration but ignored language. In contrast, this paper microfounds and studies the aggregate implications of language, which in part acts as a component of migration cost.

In quantifying aggregate gains from workers following comparative advantage in general equilibrium, this paper is related to Lagakos and Waugh (2013), Bryan and Morten (2019), Hsieh et al. (2019), Burstein, Morales, and Vogel (2019), Burstein et al. (2020), and Bratsberg et al. (2023). Relative to these, I study the impact of language barriers through how they shape internal migration. In this sense, this paper is closest to Wang (2024), who studies language's effect on migration in a quantitative spatial model. In contrast to what I find, Wang (2024) documents that migration increases in ethnolinguistic diversity. They attribute this to amenity value from cultural diversity, which may be offset by communication barriers. In contrast, and consistent with Kone et al. (2018), I find an overall negative relationship

Germany. This aims to help migrants achieve working proficiency in German for the purpose of labor market integration.

between language barriers and internal migration in India. Also unlike in Wang (2024), this paper models language barriers as a technological friction and emphasizes its labor market effects. Thus, it is the first paper in any context to incorporate language as both a spatial and a labor market friction in a quantitative framework.

Second, this paper is related to empirical work that study the role of language in trade, migration, and the labor market. Melitz (2008) introduced linguistic distance to empirical gravity models of trade. Kone et al. (2018) and Imbert and Papp (2020) provide evidence on how Indian migration flows empirically relate to both distance and linguistic differences. Adserà and Pytliková (2015) document the empirical significance of language in shaping international migration patterns. Dustmann and Fabbri (2003) and Chiswick and Miller (2015) study the importance of language proficiency of migrants to the UK in shaping their labor market outcomes. Peri and Sparber (2009) explain the occupation choices of comparably skilled migrants away from communication-language tasks as the imperfect substitutability between migrants and natives in partial equilibrium. This paper borrows insights from this literature to incorporate and study language barriers in general equilibrium.

Third, this paper contributes to the growing literature on macroeconomic development that studies heterogeneous outcomes in developing economies. It is related to Fan, Peters, and Zilibotti (2023), who study the unequal effects of service-led growth in India. Rather than factors that contribute to structural transformation, my focus is on understanding how language barriers shape distributional outcomes against the backdrop of growth in services. It is also related to Ghose (2024), who studies the role of migration cost for education and work in shaping distributional effects of globalization. In contrast, I study the role of language barriers in driving heterogeneous outcomes for workers of different skills and origins.

Road Map: The rest of this paper is structured as follows: Section 2 summarizes context on India's linguistic diversity and structural transformation; Section 3 describes various sources of data on migration, language, and labor market outcomes; Section 4 lays out three descriptive facts that relate language, locations, and the labor market; Section 5 develops a static spatial quantitative general equilibrium model of migration that features language barriers; Section 6 takes the model to the data; Section 7 uses the estimated model to perform counterfactual exercises; Section 8 concludes.

2 Data

A significant challenge for empirical analysis of the impact of language barriers on internal migration and labor market outcomes is the paucity of comprehensive and disaggregated data. To address this, I obtain confidential internal migration data through a special agreement with the Census of India and combine this with data on language and labor market outcomes from various sources. To obtain an occupational ranking of speaking-intensity, I create a concordance between occupations in the Indian household surveys and O*NET.

2.1 Data on Migration

The primary source of data on internal migration is the Census of India (2001, 2011). The publicly available data contains information, at each district, on migrants' education level, age, reasons for migration, the rural/urban nature of their previous residence, and duration of stay in the current residence since migration. However, in order to analyze the effects of language barriers on migration decisions, it is crucial to identify the district of origin jointly with these variables.

I obtained this information, which is available in the more disaggregated district-to-district migration data, through a special agreement with the Census. To the best of my knowledge, this is the first paper to use the 2011 district-to-district migration data, which records migration flows jointly by education level, age, reasons for migration, the rural/urban nature of their previous residence, and duration of stay. This allows for a rich analysis through cross-tabulations that are not possible in the 2001 data. I combine the 2001 and 2011 disaggregated data into a novel district-level panel dataset.[6]

In Table 1, I provide summary statistics on migration flows in India from this data. This shows that in 2001, 11% of migrants moved for work compared to any other reason (education, marriage etc.). Of these, 64% migrated within their own state, to work more than for any other reason. Table 2 shows that in 2011, share of non-college migrants that moved for work was at similar levels, at 10%. The share of college-educated migrants that moved for work was higher, at 24%. The proportion of college and non-college migrants that move within their own state is similar, at approximately 75%. Thus, work is a significant reason for migration, with intra-state moves being more common than inter-state ones for both college and non-college migrants.

2.2 Data on Language

I obtain data on the distribution of languages in India from the Census of India (2001, 2011). This publicly available data contains information on the number of speakers of over 130 languages (each spoken by over 10,000 people each) at home i.e., as a first language, in every district. Using this data and linguistic trees from (Eberhard, Simons, and Fennig 2024), I follow Spolaore and Wacziarg (2009) and construct a measure of language barriers for any region-pair o, d,

$$\text{Linguistic Distance}_{o,d} = \sum_{m}\sum_{n}(s_{o,m} \times s_{d,n} \times \text{dist. b/w languages}_{m,n}),$$

[6] Research on internal migration using 2001 district-to-district data are also relatively scarce. Recent papers that have used the 2001 data to study migration frictions in India are Kone et al. (2018), Rai (2023), Ghose (2024).

where $s_{o,m}$, $s_{d,n}$ denote the share of speakers for any language-pair m, n and the distance between them is inversely related to how many branches they have in common in linguistic trees. This index can be interpreted as the population-weighted likelihood of an average person in origin o being able to communicate with an average person in destination d. A value of 0 indicates absolute convergence in languages, and a value of 1 indicates absolute divergence.

2.3 Data on Labor Market Outcomes

I use monthly data from January 2014 to December 2019 from the Consumer Pyramids Household Surveys (CPHS) to obtain information on individuals' state of origin, occupation choices, wages, education level, and other demographic variables. The state of origin allows me to identify individual migrants that moved to the destination district from outside the state and link them to language barriers. I match occupations to O*NET based on their descriptions to obtain a score of the importance of speaking in each occupation. I define an occupation as speaking-intensive if their rank is above the median. Please see Table 3 for a sample of this match.

2.4 Other Data

I supplement the above data with two others. First, I use the Indian Human Development Survey-II, 2011-12 (Desai, Vanneman, and National Council of Applied Economic Research 2018) to obtain information on English proficiency among college and non-college workers. I use the share of English speakers by education across states of India to build a skill-specific linguistic index for structural estimation. Second, I use microdata from the Employment and Unemployment Rounds of the National Sample Survey (NSS) in 1987 and 2011, before and after India's trade liberalization. I match occupations to O*NET and construct employment shares in speaking and non-speaking occupations across states of India.

2.5 Data Limitations

There are two principal data limitations that constrain my analysis. First, I do not observe languages spoken by individual workers or their degree of proficiency. This is likely to be related to their age and number of years spent at the destination, so I control for these variables in empirical specifications. Second, I do not observe workers over space over time. So, I am unable to track how workers may *change* their occupation when they move to a destination where they face language barriers. I focus on the comparison across groups that differ in language barriers rather than track individuals over time.

3 Background on Linguistic Diversity and Structural Change in India

3.1 Linguistic Diversity in India

India's linguistic diversity is vast, with over 1600 languages in daily use and 22 officially recognized in the Constitution (Government of India 2017). This diversity is geographically structured, with distinct languages predominant within specific provinces. The States Reorganisation Act of 1956 reinforced this structure by redrawing colonial province boundaries to better align with linguistic regions. Consequently, interstate migration often involves crossing linguistic boundaries, with workers entering labor markets that use a different *lingua franca* from their origin state.

This linguistic landscape may significantly impact the labor market, but less so for college-educated workers. English, though not indigenous, has become important in higher education and professional settings. Its importance varies across regions and sectors, often serving as a bridge in multilingual work environments. Workers proficient in English may have access to broader employment opportunities, particularly in sectors with international connections or requiring cross-state collaboration. However, regional language skills remain vital for roles involving local engagement or state-level governance.

3.2 Structural Change and the Rise of Speaking Occupations

In the decades following the 1991 liberalization, India experienced a marked expansion of its service sector. According to Fan, Peters, and Zilibotti (2023), the share of employment in the service sector rose from 19% in 1987 to 28% in 2011, with a particular surge in consumer services. Related to this sectoral shift, there has been a dramatic increase in the prevalence of speaking occupations, which involve a high degree of interpersonal communication, customer interaction, and information exchange. The share of employment in such occupations rose from 2.4% in 1987 to 23% in 2011.

This shift towards speaking occupations occurred against the backdrop of India's significant linguistic diversity. As the economy increasingly rewards communication skills, the ability to speak multiple languages fluently may have been a crucial determinant of labor market prospects. The interplay between the rising demand for communication skills and India's linguistic heterogeneity potentially affects various economic outcomes, including migration patterns, inequality between workers, spatial disparities in economic development, and overall welfare. Understanding these dynamics is crucial for assessing the full impact of India's economic transformation and for informing potential policy responses to address language-related barriers in the labor market.

4 Descriptive Facts

In this section, I present four descriptive facts about the relationship between language barriers, location choices, and labor market outcomes of internal migrant workers in India. I compare three patterns—on migration, occupations, and wages—for college and non-college migrant workers and find that each is attenuated for college relative to non-college workers. This is written up summarily as a fourth fact.

Fact 1 (Migration): *Workers migrate less often to locations with high language barriers, but this is attenuated for college relative to non-college.*

To understand how language barriers are related to the migration of college and non-college workers, I use district-to-district migration data from the 2011 Census jointly with language data from the 2001 Census. This is done to avoid issues of simultaneity, since measures of language barriers are constructed with the distribution of speakers of different languages in each district, which includes contemporaneous migrants. Further, since the 2011 Census contains information on reason for migration jointly with the education level of migrants, I am able to focus my analysis on economic migrants.

I measure bilateral language barriers, $\tau^L_{o,d}$, using the linguistic distance index defined in Section 2.2. For ease of comparison across two dimensions of heterogeneity (language, education), I demarcate migrant workers of each education type into two parts: those with a language barrier relative to their origin and those without, defined by $\mathbb{1}\{\text{Barrier}_{o,d}\} = 1$ if $\tau^L_{o,d} > median$. Doing so enables me to be consistent with the way that I think about workers with and without language barriers in the quantitative model.. I measure bilateral geographic barriers by the geodesic distance between geographic centers of districts o, d.

I estimate the following regression specification, similar to Bryan and Morten (2019) but incorporating language barriers in the specification, by least squares,

$$\begin{aligned}\ln(\pi_{o,d,e}) = \beta_0 + \beta_1 \mathbb{1}\{\text{Barrier}_{o,d}\} + \beta_2 \mathbb{1}\{\text{College}\} + \beta_3 \mathbb{1}\{\text{Barrier}_{o,d}\} \times \mathbb{1}\{\text{College}\} \\ + \beta_4 \ln(\text{Geo. Dist.}_{o,d}) + \beta_5 \ln(\text{Geo. Dist.}_{o,d}) \times \mathbb{1}\{\text{College}\} + \gamma_o + \gamma_d + \varepsilon_{o,d,e},\end{aligned} \tag{1}$$

where $\ln(\pi_{o,d,e}) \equiv \ln(N_{o,d,e}/\sum_d N_{o,d,e})$ is the fraction of workers at origin o with education $e \in \{\text{College, Non-College}\}$ that migrate to destination d, which includes the origin. I add origin and destination fixed-effects, γ_o and γ_d, to control for time-invariant unobserved heterogeneity across districts. In the final specification, I also include an origin state × destination state fixed-effect, to control for any bilateral variation across states, exploiting linguistic and geographic variation across districts *within* states to capture the relationship between language barriers and migration patterns.

Table 5 presents the results of this regression. Columns 1 and 2 report specifications with only language barriers and geographic barriers, respectively. I include these to compare how much additional variation in migration flows is explained by each factor. In the data, linguistic and geographic barriers have a correlation coefficient of 0.35, indicating a moderate positive relationship. This correlation suggests that locations that are geographically distant tend to also have higher language barriers, and vice versa. However, the correlation is not so high as to preclude locations that are geographically close but linguistically distant, and vice versa.

Column 3 presents the most comprehensive specification, incorporating controls for both language barriers and geographic distance, along with their interactions with a college fixed-effect. The coefficient on $\mathbb{1}\{\text{Barrier}_{o,d}\}$ is -0.617 ($p < 0.01$), suggesting a negative association between the presence of a language barrier and migration. This correlation implies that, on average and holding other factors constant, the presence of a language barrier is associated with a decrease in the fraction of migrants by approximately $\exp(-0.617) - 1 = 46\%$. Interestingly, this negative relationship appears to be weaker for college-educated individuals, as indicated by the positive coefficient on the interaction term, $\mathbb{1}\{\text{Barrier}_{o,d}\} \times \mathbb{1}\{\text{College}\}$, which is 0.093 ($p < 0.01$). When considering both coefficients together, the data suggest a $\exp(-0.617 + 0.093) - 1 = 41\%$ lower fraction of migrants in the presence of a language barrier for college-educated workers, a less pronounced difference compared to non-college workers.

It is worth noting two additional patterns that are consistent with the literature. First, college workers are more likely to migrate, as indicated by the positive coefficient on $\mathbb{1}\{\text{College}\}$, which is 0.639 ($p < 0.01$). This suggests that all else equal, college workers have an 89% higher fraction of migrants relative to non-college workers. Second, geographic distance is a significant impediment to internal migration. The coefficient on $\ln(\text{Geo. Dist.}_{o,d})$, which is -1.84 ($p < 0.01$), indicates that a 10% increase in geographic distance is associated with a 18.4% decrease in the fraction of migrants for non-college workers. However, college workers are less deterred by geographic distance, from whom the positive interaction term on $\ln(\text{Geo. Dist.}_{o,d}) \times \mathbb{1}\{\text{College}\}$, which is 0.104 ($p < 0.01$), suggests a 17.4% decrease in the fraction of migrants from the same 10% increase in distance. This indicates that while geographic distance is a significant deterrent for all workers, its effect is less pronounced for those with a college education.

These findings collectively support Fact 1. That is, lower fractions of migrant workers choose locations with high language barriers, but this correlation is less pronounced for college workers relative to non-college workers. This may be because college workers are more likely to speak *lingua franca* like English and have access to occupations that are less dependent on local language proficiency.

Fact 2 (Occupations): *Among migrant workers, those with high language barriers choose occupations that are intensive in speaking less often, but this is attenuated for college relative* *to non-college.*

To understand how language barriers are related to the occupations of college and non-college migrant workers. I use 28 waves (Sep 2017 to Dec 2019) of the CPHS repeated cross-section data jointly with language data from the 2011 Census. The CPHS contains detailed information on labor market outcomes of individual workers, whose observed "state of origin" allows me to link them to language and geographic barriers. I also manually create a concordance between occupations in the CPHS panel and O*NET to obtain an exogenous ranking in intensity of "speaking," defined by O*NET as "talking to others to convey information effectively." I show that among migrant workers, those with high language barriers are less likely than workers with low language barriers to choose occupations that are intensive in "speaking."

In particular, I estimate the following linear probability specification through least squares,

$$\begin{aligned}\Pr\left(\mathbb{1}\{\text{Speaking Occ.}_{i,o,d,j,t}\} = 1 \mid \text{Covariates}_{i,o,d,j,t}\right) &= \beta_0 + \beta_1 \mathbb{1}\{\text{Barrier}_{o,d}\} + \beta_2 \mathbb{1}\{\text{College}_{i,o,d,j,t}\} \\ &+ \beta_3 \mathbb{1}\{\text{Barrier}_{o,d}\} \times \mathbb{1}\{\text{College}_{i,o,d,j,t}\} + \beta_4 \ln(\text{Geo. Dist.}_{o,d}) + \mu \text{Controls}_{i,o,d,j,t} + \gamma_{o,t} + \gamma_{d,t},\end{aligned} \tag{2}$$

where $\text{Controls}_{i,o,d,j,t}$ include gender, age, caste, and lagged wages, which account for the degree to which individuals' demographic characteristics and proxied ability may influence their occupation choice. I add origin-month and destination-month fixed-effects, $\gamma_{o,t}$ and $\gamma_{d,t}$, to control for time-varying factors in the states of origin and destination districts. I include these to minimize, to the extent possible, bias from omitted variables and isolate the relationship between language barriers and occupational choice for college and non-college workers.

The results from these regressions are in Table 6. Column 1 presents the relationship between college education and speaking-intensive occupations for native workers, serving as a point of comparison. Columns 2-4 focus on migrant workers, progressively adding controls aimed at isolating the effects of language barriers and education. The specification in Column 2 adds the indicator for language barrier and its interaction with college education, showing the primary relationships of interest without geographic controls. The specification in Column 3 adds the log of geographic distance to account for spatial factors that might influence occupational choices independent of language.

Column 4 includes all controls and fixed-effects and provides the most comprehensive specification. The coefficient on the language barrier indicator, which is -0.06 ($p < 0.01$) suggests that migrant workers facing a language barrier are 6 percentage points less likely to work in speaking-intensive occupations compared to those without a language barrier. The coefficient on the college indicator, which is 0.11 ($p < 0.01$), suggests that college-educated migrant workers are 11 percentage points more likely to work in speaking-intensive occupations than non-college educated workers. Finally, the interaction term between indicators for language barriers and college education, which is 0.075 ($p < 0.01$), shows that the negative correlation of language barriers on choosing speaking-intensive occupations is reduced by 7.5 percentage points for college-educated workers.

These findings collectively support Fact 2. They show that high language barriers are indeed associated with a lower likelihood of choosing speaking-intensive occupations while college education increases the likelihood of choosing speaking-intensive occupations. Importantly, the interaction supports the second part of Fact 2, showing that the negative correlation of language barriers is indeed muted for college relative to non-college workers.

Fact 3 (Wages): *Among migrant workers, those with high language barriers receive higher wages, but this is attenuateed for college relative to non-college.*

To understand how language barriers are related to the wages of college and non-college migrant workers, once again, I use 28 waves (Sep 2017 to Dec 2019) of the CPHS repeated cross-section data jointly with language data from the 2011 Census. I deflate the nominal wages using the monthly CPI time-series released by the Ministry of Statistics and Programme Implementation, Government of India.

Then, I estimate the following specification by least squares,

$$\begin{aligned}\ln(\text{Wages}_{i,o,d,j,t}) = \beta_0 + \beta_1 \mathbb{1}\{\text{Barrier}_{o,d}\} + \beta_2 \mathbb{1}\{\text{College}_{i,o,d,j,t}\} + \beta_3 \mathbb{1}\{\text{Barrier}_{o,d}\} \times \mathbb{1}\{\text{College}_{i,o,d,j,t}\} \\ + \beta_4 \ln(\text{Geo. Dist.}_{o,d}) + \mu \text{Controls}_{i,o,d,j,t} + \gamma_{j,t} + \gamma_{o,t} + \gamma_{d,t} + \varepsilon_{i,o,d,j,t},\end{aligned} \tag{3}$$

where $\text{Controls}_{i,o,d,j,t}$ are individual i's gender, age, and caste, which account for the degree to which individuals' demographic characteristics may influence their wages. I add origin-month and destination-month fixed-effects, $\gamma_{o,t}$ and $\gamma_{d,t}$, to control for time-varying factors in the origin states and destination districts. Importantly, I include an occupation-month fixed-effect to control for underlying characteristics across occupations that may be contributing to observed differences in wages. I include these to minimize, to the extent possible, bias from omitted variables and isolate the relationship between language barriers and wages for college and non-college workers.

The results from these regressions are in Table 7. Once again, Column 1 showing the baseline relationship for native workers and Columns 2-4 focus on migrant workers. As before, the specification in Column 2 adds the indicator for language barrier and its interaction with college education, showing the primary relationships of interest without geographic controls. The specification in Column 3 adds the log of geographic distance to account for spatial factors that might influence occupational choices independent of language.

Column 4, which includes all controls and fixed-effects, provides the most comprehensive specification. The coefficient on the language barrier indicator, which is 0.055 ($p < 0.01$), suggests that migrant workers facing a language barrier earn approximately 5.5% higher wages compared to those without a language barrier. The coefficient on the college indicator, which is 0.134 ($p < 0.01$), suggests that migrant workers with a college education earn about 13.4% higher wages relative to migrant workers without a college education. The coefficient on the interaction term between language barriers and college education, which is -0.062 ($p < 0.01$), suggests that the positive correlation of language barriers on wages is reduced by approximately 6.2 percentage points for college-educated workers. Finally, it is worth noting that the coefficient on geographic distance between origin and destination, which is 0.034 ($p < 0.01$), suggests that migrants who travel farther earn a wage premium. This is consistent with the migration literature that has suggested that geographic barriers have a selection effect (Bryan and Morten 2019).

These findings collectively support Fact 3. They suggest that high language barriers are indeed associated with higher wages among migrant workers. Importantly, the wage premium associated with language barriers is muted for college relative to non-college workers. This may be due to a selection effect of language barriers, which is attenuated for college workers. That is, workers who face language barriers may need higher idiosyncratic productivity to be able to overcome the barriers.

Fact 4 (College vs. Non-College): *Each of the patterns in Facts 1, 2, and 3 is attenuated for college relative to non-college.*

Summary: This section presents four descriptive facts about the relationship between language barriers, location choices, and labor market outcomes for internal migrant workers in India, comparing patterns for college and non-college-educated individuals. First, workers are less likely to migrate to locations with high language barriers. Second, among migrants, those facing high language barriers are less likely to choose occupations intensive in speaking skills. Third, migrant workers facing high language barriers tend to receive higher wages. Fourth, each of these patterns is attenuated for college relative to non-college workers.

These patterns persist even when controlling for geographic distance and other relevant factors. College-educated workers are generally more mobile, more likely to choose speaking-intensive occupations, and earn higher wages than their non-college counterparts. The observed patterns suggest complex interactions between language barriers, education levels, and labor market outcomes. In the following section, I show how these facts can be explained in a spatial equilibrium model with multiple locations, multiple occupations, and heterogeneous workers that differ by skill, education, and language barriers.

5 A Quantitative Spatial Model

In this section, I develop a static Roy-Fréchet quantitative spatial general equilibrium model of migration in the presence of language barriers. First, I describe preferences and derive sorting and selection equations. Second, I explain the production structure, where heterogeneous occupations (speaking and non-speaking) in each region use heterogeneous labor (skilled and unskilled, and further, with and without language barriers) as imperfect substitutes in a nested CES structure. Third, I impose market clearing conditions and define general equilibrium.

Building on standard spatial models, I incorporate language barriers as both a productivity effect and a movement friction. In particular, I model language as a technological friction that affects the average productivity of workers, and more so in speaking-intensive occupations. That is, in any region and conditional on their education, workers with language barriers are less productive on average, and more so, in occupations that are speaking-intensive. I also model language as a component of migration cost. This is to capture how language barriers, beyond affecting workers' productivity, can impede their decision to move to regions where they cannot speak the language. Finally, I allow each occupation to imperfectly substitute between workers with and without language barriers, conditional on their skill. The Appendix contains detailed derivations of the main equations of the model.

Environment: Let there be R regions in the economy, which represent the states of India. I denote the origin region by o and the destination region by d. Workers may be skilled or unskilled. This is defined by their education e, that is, by whether they have a college degree (c) or not (nc). I assume that each region o is endowed with $N_{o,c}$ units of skilled workers and $N_{o,nc}$ units of unskilled workers. At any potential destination d, a worker may face a language barrier (b) or not (nb). I formally define language barrier as a mapping, $\mathscr{L} : \{(o,d)\} \longrightarrow \{b, nb\}$, that specifies whether a worker born in o faces a barrier at d (or not), depending on the language at the destination relative to the origin. Notice that since language barrier is a function of both origin and destination, whether a worker faces a language barrier in the labor market is determined in equilibrium.

Further, let there be $J = 2$ types of occupations in each region, defined by whether they are speaking-intensive (e.g., salesperson, professor, waiter) or not (e.g., computer programmer, construction worker, cable operator). This is to capture that language at the destination may be more important while working in some occupations than others. A firm in each region uses a nested CES production structure with three layers: the outer nest aggregates over speaking and non-speaking occupations, the middle nest aggregates over skilled and unskilled workers, and finally, the inner nest aggregates over skilled and unskilled workers with and without language barriers. This form allows the degree of substitution between labor inputs to be flexible. But we may expect, for instance, that skilled workers with and without language barriers are more substitutable than unskilled workers with and without language barriers. This is because skilled workers often have access to a common language (e.g., English in India) used across different labor markets, while unskilled workers typically require local language proficiency.

I assume that workers, who differ by skill and anticipate facing different language barriers in equilibrium, make idiosyncratic productivity draws for each occupation $j \in J$ and destination $d \in R$ from a Fréchet distribution. This form allows the mean productivity of skilled and unskilled workers to be different, and moreover, to depend on whether they face a language barrier at the destination, and whether occupations are speaking-intensive. Formally, the distribution is,

$$z^i_{j,e,\mathscr{L}(o,d)} \sim^{i.i.d} G_{j,e,\mathscr{L}(o,d)}(z^i) = \exp(-A_{j,e,\mathscr{L}(o,d)}(z^i)^{-\theta}),$$

where the location parameter, $A_{j,e,\mathscr{L}(o,d)}$, governs absolute advantage and determines the average productivity of workers with education e with language barrier $\mathscr{L}(o,d)$ in occupation j. The dispersion parameter, θ, reflects the importance of comparative advantage. As θ decreases, there is a greater difference between the productivity draws of workers with different education and language barriers in speaking vs. non-speaking occupations. This specification does not impose any restrictions on the relative magnitudes of the mean productivity draws for different groups. But we may expect, for instance, that the draws for unskilled workers have a lower mean if they face a language barrier, and that the mean is even lower when the occupation is speaking-intensive, that is, $A_{spk,nc,b} < A_{spk,nc,nb}$.

Preferences: I assume that workers' preferences are linear in consumption and amenities, which are discounted by geographic and language barriers at the destination relative to their origin. Workers supply one unit of labor inelastically. They take wages per unit of productivity, $w_{d,j,e,\mathscr{L}(o,d)}$, as given and maximize their utility subject to a budget constraint. They spend their entire income on the consumption good, which is priced at P. Thus, the indirect utility of worker i with education e from origin $o \in R$ who works at occupation $j \in J$ at destination $d \in R$ is given by

$$U^i_{o,d,j,e} = \underbrace{(1-\tau^G_{o,d})(1-\tau^L_{o,d,e})\ \alpha_d\ (w_{d,j,e,\mathscr{L}(o,d)}/P)}_{\equiv \Lambda_{o,d,j,e}}\ \underbrace{z^i_{j,e,\mathscr{L}(o,d)}}_{\text{Fréchet draw}},$$

where $\tau^G_{o,d}$ is the geographic barrier, $\tau^L_{o,d,e}$ is the language barrier (measured separately for college and non-college workers), and α_d are region-specific amenities. They choose (d,j) s.t. $U^i_{o,d,j,e} \geq U^i_{o,d',j',e}\ \forall (d',j') \neq (d,j)$. From the properties of the Fréchet distribution, the probability that workers from origin o with education e choose occupation j and destination d is given by

$$\pi_{o,d,j,e} = \frac{A_{j,e,\mathscr{L}(o,d)} \left(\Lambda_{o,d,j,e}\right)^{\theta}}{\Phi_{o,e}},$$

where $\Phi_{o,e} \equiv \sum_{(d',j')} A_{j',e,\mathscr{L}(o,d')} \left(\Lambda_{o,d',j',e}\right)^{\theta}$. This is the key sorting equation, which captures the idea that workers sort based on relative productivities, income, migration costs, and amenities. From the law of large numbers, it follows that the number of workers from origin o with education e choose occupation j at destination d is $N_{o,d,j,e} = \pi_{o,d,j,e} N_{o,e}$. [This is consistent with Facts 1 and 2.]

Further exploiting properties of the Fréchet distribution, the average productivity of worker from origin o with education e in occupation j at destination d is given by

$$E\left[z^{i}_{j,e,\mathscr{L}(o,d)} \mid U^{i}_{o,d,j,e} \geq U^{i}_{o,d',j',e} \;\; \forall (d',j') \neq (d,j)\right] = \tilde{\Gamma}(\pi_{o,d,j,e}/A_{j,e,\mathscr{L}(o,d)})^{-1/\theta},$$

where $\tilde{\Gamma} \equiv \Gamma(1-1/\theta)$ and $\Gamma(\cdot)$ is the gamma function. This equation implies that as more workers from origin o with education e migrate to work at occupation j at destination d, their average productivity decreases because the marginal migrant is drawn from further down the left tail of the productivity distribution. The expression for the average wage of worker from origin o with education e in occupation j at destination d,

$$\bar{w}_{o,d,j,e} = \tilde{\Gamma}(\pi_{o,d,j,e}/A_{j,e,\mathscr{L}(o,d)})^{-1/\theta} w_{d,j,e,\mathscr{L}(o,d)} = \frac{\tilde{\Gamma}\;\Phi_{o,e}}{(1-\tau^{G}_{od})(1-\tau^{L}_{o,d,e})\alpha_d},$$

embeds this mechanism. This is the key selection equation and captures the idea that when few workers from origin o with education e choose occupation j at destination d, their average productivity is higher, and so their average wages are higher. [This is consistent with Fact 3.]

Regional Production: In each region $d \in R$, a representative firm uses a triple-nested CES production function to produce y_d units of a good, which has price p_d. The outer nest combines labor inputs from speaking and non-speaking occupations in the region using a CES function with elasticity of substitution κ and share parameter, $\phi_{d,j}$,

$$y_d = \left[\sum_{j \in J} (\phi_{d,j})^{\frac{1}{\kappa}} (\ell_{d,j})^{\frac{\kappa-1}{\kappa}}\right]^{\frac{\kappa}{\kappa-1}},$$

where college and non-college labor in each occupation are combined in the middle nest using a CES function with elasticity of substitution ρ,

$$\ell_{d,j} = \left[(\ell_{d,j,c})^{\frac{\rho-1}{\rho}} + (\ell_{d,j,nc})^{\frac{\rho-1}{\rho}}\right]^{\frac{\rho}{\rho-1}},$$

where college and non-college workers with and without language barriers in each occupation are combined in the inner nest using a CES function with elasticity of substitution $\nu_{j,e}$,

$$\ell_{d,j,e} = \left[(\ell_{d,j,e,b})^{\frac{\nu_{j,e}-1}{\nu_{j,e}}} + (\ell_{d,j,e,nb})^{\frac{\nu_{j,e}-1}{\nu_{j,e}}} \right]^{\frac{\nu_{j,e}}{\nu_{j,e}-1}}, \text{ where } e \in \{c, nc\}.$$

The regional firm takes wages and prices as given and maximizes profit. This is given by $p_d y_d - \sum_{j \in J} \sum_{e \in \{c,nc\}} \sum_{\mathscr{L}(o,d) \in \{b,nb\}} w_{d,j,e,\mathscr{L}(o,d)} \ell_{d,j,e,\mathscr{L}(o,d)}$. The first-order conditions determine labor demand,

$$\ell_{d,j,e,\mathscr{L}(o,d)} = \left(MP_{d,j} \cdot MP_{d,j,e} \cdot w_{d,j,e,\mathscr{L}(o,d)} \right)^{\frac{\nu_{j,e}-1}{\nu_{j,e}}}$$

where $MP_{d,j} = p_d (y_d)^{\frac{1}{\kappa-1}} (\phi_{d,j})^{\frac{1}{\kappa}} (\ell_{d,j})^{\frac{\rho}{\rho-1}\frac{\kappa-1}{\kappa}-1}$ is the marginal product of labor for occupation j at region d, and $MP_{d,j,e} = (\ell_{d,j,e})^{\frac{\nu_{j,e}}{\nu_{j,e}-1}\frac{\rho-1}{\rho}-1}$ is the marginal product of labor for workers with education e in occupation j at region d. I assume that markets are perfectly competitive, so prices are equal to marginal cost functions,

$$p_d = \left[\sum_{j \in J} \phi_{d,j} (w_{d,j})^{1-\kappa} \right]^{\frac{1}{1-\kappa}},$$

where

$$w_{d,j} = \left[(w_{d,j,c})^{1-\rho} + (w_{d,j,nc})^{1-\rho} \right]^{\frac{1}{1-\rho}},$$

and

$$w_{d,j,e} = \left[(w_{d,j,e,b})^{1-\nu_{j,e}} + (w_{d,j,e,nb})^{1-\nu_{j,e}} \right]^{\frac{1}{1-\nu_{j,e}}}, \text{ where } e \in \{c, nc\}.$$

The ordering of the nests reflects the hierarchical nature of production decisions and substitution patterns in labor markets. I place the speaking versus non-speaking occupational distinction in the outer nest because it represents the most fundamental technological choice firms face: how to allocate production between occupations that require different speaking intensities. The college versus non-college distinction appears in the middle nest since skill-based substitution occurs within each occupational category, with potentially different patterns between speaking and non-speaking tasks. Language barriers enter the innermost nest because they represent a friction that modifies worker productivity within skill groups, rather than a fundamental technological distinction.

This ordering allows for occupation-specific elasticities between workers with and without language barriers ($\nu_{j,e}$). This captures that the substitutability of workers with language barriers likely varies by both occupation type and education level. This key feature would be harder to capture with alternative nesting structures. Importantly, if the innermost elasticities ($\nu_{j,e}$) turn out to be large, this nesting structure naturally collapses to more conventional production functions that distinguish only between skilled and unskilled labor, nesting my model within the broader literature on education-based labor market sorting.

Aggregate Production: I assume that an aggregate firm combines the regional goods into a single consumption good, Y, with price P, using a CES function,

$$Y = \left[\sum_{d \in R} (y_d)^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}},$$

where σ is the elasticity of substitution between regional goods and determines the degree to which price differences across regions affect the overall price index. That is, higher values of σ indicate greater substitutability (so, less sensitivity) of the aggregate price index to regional price variations. The firm takes prices as given and maximizes profit, which is given by $PY - \sum_{r \in R} p_d y_d$. The first-order condition determines regional good demand,

$$y_d = (p_d/P)^{-\sigma} Y,$$

where the consumption good is assumed to be traded costlessly across regions and there is no international trade. This implies that all regions face the same price index, which is defined by $\left[\sum_{d \in R} (p_d)^{1-\sigma} \right]^{\frac{1}{1-\sigma}}$. Under perfect competition, the price P equals the marginal cost, which in this case, is identical to the expression for the price index. I assume that the consumption good is numeraire i.e., $P = 1$.

Market Clearing Conditions and Equilibrium: The labor market clearing condition equates labor supply from workers at region d and occupation j from worker with education e and language barrier $\mathscr{L}(o,d)$ with demand from regional firms,

$$\sum_{o:(o,d) \in \{b,nb\}} \underbrace{\tilde{\Gamma} \Big(\pi_{o,d,j,e} / A_{j,e,\mathscr{L}(o,d)} \Big)^{-\frac{1}{\theta}}}_{\text{avg. productivity}} \underbrace{\pi_{o,d,j,e} \, N_{o,e}}_{\text{no. of workers}} = \ell_{d,j,e,\mathscr{L}(o,d)}.$$

The regional goods market clearing condition equates the supply of regional good in region d with demand from the aggregate firm,

$$y_d = (p_d/P)^{-\sigma} Y.$$

The aggregate goods market clearing condition equates the supply of the consumption good from the aggregate firm with the total demand from workers,

$$Y = \sum_{d \in R} \sum_{j \in J} \sum_{e \in \{c,nc\}} \sum_{\mathscr{L}(o,d) \in \{b,nb\}} (w_{d,j,e,\mathscr{L}(o,d)} \ \ell_{d,j,e,\mathscr{L}(o,d)})/P.$$

The equilibrium in this model is defined as follows. Given fundamentals, $\Theta \equiv \{A_{j,e,\mathscr{L}(o,d)}, \theta, \sigma, \phi_{d,j}, \kappa, \rho, \nu_{j,e}, N_{d,e}, \tau^G_{o,d}, \tau^L_{o,d,e}, \ \alpha_d\}_{o,d \in R, j \in J, e \in \{c,nc\}, \mathscr{L}(o,d) \in \{b,nb\}}$, an equilibrium is a set of wages and prices, $\{w_{d,j,e,\mathscr{L}(o,d)}, p_d, P\}_{o,d \in R, j \in J, e \in \{c,nc\}, \mathscr{L}(o,d) \in \{b,nb\}}$, that solves the optimization problems of consumers, regional firms, and the aggregate firm, as well as market clearing conditions for labor, regional goods, and the aggregate good.

6 Taking the Model to the Data

In this section, I outline the procedure by which I discipline the model parameters.[7] I proceed in two steps. First, I estimate the Fréchet dispersion parameter, θ, from a regression of migration flows against migration costs. Second, I jointly estimate the Fréchet location parameter, $A_{j,e,\mathscr{L}(o,d)}$, amenities, α_d, and CES elasticities from the outer, middle, and inner nests, κ, ρ, and $\nu_{j,e}$ in a GMM procedure. For this, I use moment conditions derived from the sorting equation and labor demand equations.

I use the CPHS data to construct migration flows between states of India, disaggregated by occupations and skill.[8] Using the origin and destination states, I match this data to geodesic distance and linguistic index. Since the data is a repeated cross-section, I use time periods as an additional source of variation. These are defined at a frequency of four months on monthly waves from January 2014 to December 2019. This definition results in $T+1 = 18$ time periods, of which the first is defined as the initial period ($t = 0$). I denote each subsequent period by $t = 1, ..., 17$.

In the first step, to estimate the Fréchet dispersion parameter, θ, I compute the Head-Reis index to derive a relationship between migration flows and migration costs (see the Appendix for the derivation). I parameterize the geographic component of migration cost, $\tau^G_{o,d}$, using geodesic distance between states of India. Similarly, I parameterize the linguistic component of migration cost, $\tau^L_{o,d,e}$, using linguistic distance between states of India. For this mapping, I build a skill-specific linguistic index, which assumes that different populations of college and non-college workers across states may speak English as a second language.

Using parameterizations of migration costs, I fit the relationship between migration flows and migration costs by least squares. For identification of θ, the specification allows for a constant and an error term that is assumed to be uncorrelated with migration costs in expec-

[7] See the Appendix for a summary of model parameters and their identification.

[8] The CPHS contains information on destination districts and origin states, so the estimation could be done at this level. However, the concern with that is that when disaggregated migration flows by occupation and skill at the district level drastically reduces the number of observations.

tation. That is, I estimate θ from the following,

$$\ln\Big(\sqrt{\frac{N_{o,d,j,e,t}}{N_{d,d,j,e,t}}\frac{N_{d,o,j,e,t}}{N_{o,o,j,e,t}}}\Big) = \text{Constant} + \theta\ln\Big[(1-\tau^{G}_{o,d})(1-\tau^{L}_{o,d,e})\Big] + \varepsilon_{o,d,j,e,t},$$

where the source of identifying variation is over state-pairs, occupations, and time periods. Table 8 contains the regression results and my preferred specification estimates $\hat{\theta} = 5.4$.

In the second step, I jointly estimate the Fréchet location parameter, $A_{j,e,\mathscr{L}(o,d)}$, amenities, α_d, and CES elasticities from the outer, middle, and inner nests, κ, ρ, and $\nu_{j,e}$ in a two-step GMM procedure with instrumental variables. For the identification of these parameters, I need to take a stand on the migration costs, $\tau^{G}_{o,d}$ and $\tau^{L}_{o,d,e}$, the CES elasticity from the aggregate nest, σ, and the CES share parameters from the outer nest, $\phi_{r,j}$.

As described above, I parameterize migration costs by geodesic distance and linguistic index between states. Additionally, I take the CES elasticity parameter of the aggregate nest, σ, from Bryan and Morten (2019) and follow them in presenting results for a value of $\sigma = 8$. I proxy for CES share parameters from the outer nest, $\phi_{r,j}$, from employment shares in speaking and non-speaking occupations.

The GMM objective function uses four sets of moment conditions to jointly estimate the Fréchet location parameter, $A_{j,e,\mathscr{L}(o,d)}$, amenities, α_d, and CES elasticities from the outer, middle, and inner nests, κ, ρ, and $\nu_{j,e}$. The first is the log-linearized sorting equation to identify $A_{j,e,\mathscr{L}(o,d)}$ and α_d,

$$\Big(\frac{1}{T}\Big)\Big(\frac{1}{|o:(o,d)\in\mathscr{L}(o,d)|}\Big)\sum_{t=1}^{T}\sum_{(o,d)\in\mathscr{L}(o,d)}\Bigg(\ln(\pi_{o,d,j,e,t})$$

$$-\Big(\ln(A_{j,e,\mathscr{L}(o,d)}) + \theta\Big[\ln(1-\tau^{G}_{od}) + \ln(1-\tau^{L}_{o,d,e}) + \ln(w_{d,j,e,\mathscr{L}(o,d),t}) + \ln(\alpha_d) + \ln(\Phi_{o,e,t})\Big]\Big)\Bigg),$$

where these parameters are over-identified, with $8+R$ unknowns and $8R$ moment conditions. The sources of identifying variation are origin states with or without a language barrier to destination state d. Time periods are an additional source of variation.

The GMM objective function nests the model solution. That is, in each iteration, the model solution is computed using data, known parameters, and guess values for the parameters being estimated. The model solution for the particular iteration gives equilibrium values of $w_{d,j,e,\mathscr{L}(o,d)}$, which ensures that all components of the sorting equation are known, except for $A_{j,e,\mathscr{L}(o,d)}$ and α_d, which are being estimated.

The next three sets of moment conditions correspond to the outer, middle, and inner CES nests and identify the CES elasticities, κ, ρ, and $\nu_{j,e}$. Derived from taking ratios of labor demand equations, the moment conditions can be expressed as linear relationships between relative labor quantities and relative wages at three levels of aggregation.

Taking time differences, the moment conditions corresponding to the outer, middle, and inner CES nests are, respectively,

$$\left(\frac{1}{T-1}\right)\left(\frac{1}{R}\right)\sum_{t=1}^{T-1}\sum_{d=1}^{R}\left(\Delta_t \ln\left(\frac{w_{d,j,t}}{w_{d,j',t}}\right)-\left(\frac{1-\kappa}{\kappa}\right)\cdot\Delta_t \ln\left(\frac{\ell_{d,j,t}}{\ell_{d,j',t}}\right)\right),$$

$$\left(\frac{1}{T-1}\right)\left(\frac{1}{R}\right)\sum_{t=1}^{T-1}\sum_{d=1}^{R}\left(\Delta_t \ln\left(\frac{w_{d,j,c,t}}{w_{d,j,nc,t}}\right)-\left(\frac{1-\rho}{\rho}\right)\Delta_t \ln\left(\frac{\ell_{d,j,c,t}}{\ell_{d,j,nc,t}}\right)\right)\cdot\Delta_t \ln\left(\frac{\ell_{d,j,c,t}}{\ell_{d,j,nc,t}}\right)\Bigg),$$

$$\left(\frac{1}{T-1}\right)\left(\frac{1}{R}\right)\sum_{t=1}^{T-1}\sum_{d=1}^{R}\left(\Delta_t \ln\left(\frac{w_{d,j,e,b,t}}{w_{d,j,e,nb,t}}\right)-\left(\frac{1-\nu_{j,e}}{\nu_{j,e}}\right)\Delta_t \ln\left(\frac{\ell_{d,j,e,b,t}}{\ell_{d,j,e,nb,t}}\right)\right)\cdot\Delta_t \ln\left(\frac{\ell_{d,j,e,b,t}}{\ell^{d,j,e,nb,t}}\right)\Bigg),$$

where I substitute for $w_{d,j,e,\mathscr{L}(o,d),t}$ from the selection equation and $\ell_{d,j,e,\mathscr{L}(o,d),t}$ from labor market clearing condition,

$$w_{d,j,e,\mathscr{L}(o,d),t}=\sum_{o:(o,d)\in\mathscr{L}(o,d)}\bar{w}_{o,d,j,e,t}\cdot\tilde{\Gamma}(\pi_{o,d,j,e,t}/A_{j,e,\mathscr{L}(o,d)})^{-\frac{1}{\theta}},$$

$$\ell_{d,j,e,\mathscr{L}(o,d),t}=\sum_{o:(o,d)\in\mathscr{L}(o,d)}\pi_{o,d,j,e,t}\,N_{o,e,t}\cdot\tilde{\Gamma}\Big(\pi_{o,d,j,e,t}/A_{j,e,\mathscr{L}(o,d)}\Big)^{-\frac{1}{\theta}},$$

so that $w_{d,j,e,\mathscr{L}(o,d),t}$ and $\ell_{d,j,e,\mathscr{L}(o,d),t}$ are written in terms of data, known parameters, and the unknown parameters being estimated, $\nu_{j,e}$, ρ, κ, and $A_{j,e,\mathscr{L}(o,d)}$. These parameters are exactly identified, with 6 unknown parameters and 6 moment conditions. The source of identifying variation are regions for the inner and outer nests and regions and occupations for the middle nest. Time periods, as before, are an additional source of variation.

For the identification of the CES elasticity parameters, there is reason to be concerned about simultaneity between wages and the dependent variable in each of the moment conditions. That is, higher relative wages may increase the influx of migrants at a location, but an increase in the relative supply of workers may depress wages. Further, wages of workers might be influenced by unobserved skills or by existing migrant networks at the destination, that also affect their propensity to migrate, resulting in omitted variable bias. Amenities at the destination may be endogenous, as they might improve due to the influx of migrants.

To allay these concerns, and based on arguments in the literature on migrant networks, e.g., Munshi (2003), I use data on past migration shares and relative labor quantities to build shift-share instrumental variables following Altonji and Card (1991) and Card (2001). The instrumental variables for the CES moment conditions are, respectively,

$$\frac{z_{d,j,t}}{z_{d,j',t}} = \frac{\sum_{o\in R}\left(\frac{N_{o,d,j,t=0}}{N_{d,j,t=0}}\ \Delta_t N_{o,-d,-j}\right)}{\sum_{o\in R}\left(\frac{N_{o,d,j',t=0}}{N_{d,j',t=0}}\ \Delta_t N_{o,-d,-j'}\right)},$$

$$\frac{z_{d,j,c,t}}{z_{d,j,nc,t}} = \frac{\sum_{o\in R}\left(\frac{N_{o,d,j,c,t=0}}{N_{d,j,c,t=0}}\ \Delta_t N_{o,-d,-j,c}\right)}{\sum_{o\in R}\left(\frac{N_{o,d,j,nc,t=0}}{N_{d,j,nc,t=0}}\ \Delta_t N_{o,-d,-j,nc}\right)},$$

$$\frac{z_{d,j,e,b,t}}{z_{d,j,e,nb,t}} = \frac{\sum_{o\in R}\left(\frac{N_{o,d,j,e,b,t=0}}{N_{d,j,e,b,t=0}}\ \Delta_t N_{o,-d,-j,e,b}\right)}{\sum_{o\in R}\left(\frac{N_{o,d,j,e,nb,t=0}}{N_{d,j,e,nb,t=0}}\ \Delta_t N_{o,-d,-j,e,nb}\right)}.$$

In the first stage, I regress these instruments on potentially endogenous regressors (relative labor quantities) and compute residuals. In the second stage, I implement the GMM procedure described above with residuals entering multiplicatively in the moment conditions. These instruments meet the exclusion restriction if past migration flows are uncorrelated with current labor demand conditions. Further, residuals from the first-stage regressions mitigate bias from omitted variables.

I conduct various validation exercises to ensure that the estimates are robust. First, I compare targeted and untargeted moments from the estimated model and data. Second, I replicate the descriptive facts using the estimated model. Third, I compute CES shares using estimated CES elasticities and labor demand conditions and compare them to the corresponding shares computed from data. I find that their correlation is 0.7.

The estimates of Fréchet location parameters and CES elasticities from the GMM procedure validate my hypothesis that language barriers affect unskilled rather than skilled workers, and in speaking rather than non-speaking occupations. I normalize the Fréchet location parameter estimate of non-college workers with language barriers in speaking occupations, $\hat{A}_{spk,b,nc}$ to be 1. I find that $\hat{A}_{spk,b,nc} = 1.9$, so non-college workers without language barriers are nearly twice as productive on average in speaking occupations than those with language barriers.

For college workers in speaking occupations, the ratio between the average productivity of workers without language barriers and those with language barriers is more even, at 1.1. Similarly, this ratio is close to 1 for both college and non-college workers in non-speaking occupations. Thus, productivity differences between workers with and without language barriers are more pronounced for non-college workers in speaking occupations.

The estimates of CES elasticities corroborate this story. For the outer nest, I find that the elasticity of substitution between labor in speaking and non-speaking occupations is $\hat{\kappa} = 2.65$. This is a novel estimate with no benchmark in the literature. It has an intuitive interpretation. In this context, both front-office occupations that involve interaction with customers and back-office occupations that involve less interaction with the customers complement each other in production. For example, both a waiter, who interacts with the customer, and a chef, who provides the food, complement each other in producing the restaurant service.

For the middle nest, I find that the elasticity of substitution between college and non-college workers is $\hat{\rho} = 1.58$ across occupations and regions. Reassuringly, it is close to benchmark values in the literature. For example, Katz and Murphy (1992) find an estimate of 1.4 in the context of the US and Khanna and Morales (2023) find an estimate of 1.7 in the context of the India.

For the inner nest, I find varying elasticities of substitution between workers with and without language barriers ($\nu_{j,c}$, $\nu_{j,nc}$) across different occupations and skills. These are also novel elasticities with no benchmark for comparison in the literature. In non-speaking occupations, the elasticity of substitution is relatively high for both college ($\nu_{\text{non-spk},c} = 18.4$) and non-college workers ($\nu_{\text{non-spk},nc} = 19.8$), indicating that workers with and without language barriers are quite substitutable in these roles. For speaking occupations, college-educated workers still show a high degree of substitutability ($\nu_{\text{spk},c} = 15.6$). However, there is a notable difference for non-college workers in speaking occupations, where the elasticity of substitution is substantially lower ($\nu_{\text{spk},nc} = 4.6$). This suggests that in speaking occupations, non-college workers with and without language barriers are much less substitutable, highlighting the importance of language skills in these roles for workers without college education.

7 Counterfactuals

In this section, I use the estimated model to conduct three counterfactual exercises. First, I quantify the impact of language barriers on internal migration, inequality between skilled and unskilled workers, and welfare. Second, I quantify the impact of language barriers on the same aggregate outcomes when the spatial distribution of speaking occupations changed across space between 1987 and 2011. Third, I introduce language programs for unskilled migrants and weigh the cost of the policy against the benefit, as defined in terms of aggregate welfare.

7.1 Quantifying the Effect of Language Barriers on Internal Migration, Welfare, and Inequality

In the first counterfactual, I quantify the scope of the aggregate effects of language barriers through the lens of the model. To do this, I shut down language barriers both as a component of migration cost ($\tau^L_{o,d,e} = 0$) and as a driver of productivity ($A_{j,b,e} = A_{j,nb,e}$ if $j =$ speaking-intensive), holding other estimated parameters and model fundamentals constant. I then compare internal migration, inequality between skilled and unskilled workers, and welfare relative to the benchmark from the estimated model.

The results are in Table 11. The first panel shows the effect of removing language barriers. Internal migration is defined as the percent share of the population that migrated outside their origin state. Inequality between skilled and unskilled workers is defined as the percent difference in aggregate real income across the two groups. Welfare is defined as aggregate real income in the economy, which is equal to Y in the model. When language barriers are shut down, internal migration increases by 6.2 percentage points, inequality decreases by 1.9 percentage points, and welfare increases by 1.3 percent.

To contextualize these magnitudes, I target the same welfare gains and quantify the extent to which bilateral geographic barriers, $\tau^G_{o,d}$, need to decrease or the spatial distribution of college workers, $N_{r,c}$, need to increase to achieve this. The second panel shows that removing language barriers is equivalent, in terms of welfare gains, to proportionally decreasing geographic barriers between each pair of regions by 56 percent. By doing so, internal migration increases by 6.9 percentage points and inequality decreases by 1.6 percentage points. This is more than what is achieved by removing language barriers alone.

The third panel shows that removing language barriers is equivalent, in terms of welfare gains, to proportionally increasing the share of college workers across regions by 34 percent. By doing so, internal migration increases by 6.7 percentage points and inequality decreases by 2.1 percentage points. This is also more than what is achieved by removing language barriers alone.

7.2 Quantifying the Effect of Language Barriers on Gains from Structural Change

In the second counterfactual, I use the estimated model to understand how language barriers may attenuate gains from structural change, as characterized by a rise in the prevalence of speaking occupations. Since trade liberalization in India in 1991, the service sector in both rural and urban areas has seen substantial growth. Employment share in the service sector rose from 19% in 1987 to 28% in 2011. This was particularly concentrated in consumer services such as restaurants, retail, healthcare, and IT (Fan, Peters, and Zilibotti 2023). Since occupations in these sectors are likely to involve significant communication, I examine the prevalence of speaking occupations in the same time frame. Employment share in speaking occupations rose from 2.4% in 1987 to 23% in 2011, which points to the growing importance of language skills in India's evolving labor market.

In this exercise, I explore how language barriers may have impacted gains from structural growth in services, as characterized by a prevalence of speaking occupations across space. I quantify the impact of language barriers internal migration, inequality between skilled and unskilled workers, and welfare when speaking occupations became more prevalent across space.

To implement this, I use the estimated model to conduct a structural difference-in-differences exercise. The first difference is between aggregate outcomes from the benchmark estimated model and from setting speaking occupations across space to their prevalence in 1987. I proxy for the prevalence of speaking occupations using employment shares and set the share parameters of the CES function, $\phi_{r,spk}$, to levels in 1987. The second difference is between this change occurring with language barriers present and one without. Let $\mathbb{Y}$ denote the outcomes: internal migration, inequality between skilled and unskilled workers, and welfare. The impact of language barriers is given by,

$$\mathbb{Y}_{DID} = (\mathbb{Y}_{2011,\ barriers} - \mathbb{Y}_{1987,\ barriers}) - (\mathbb{Y}_{2011,\ no\ barriers} - \mathbb{Y}_{1987,\ no\ barriers}),$$

where $\mathbb{Y}_{2011,\ barriers}$ is computed from the estimated model, $\mathbb{Y}_{1987,\ barriers}$ is computed from setting the spatial distribution of occupations in the estimated model to levels in 1987, $\mathbb{Y}_{2011,\ no\ barriers}$ is computed from removing language barriers from the estimated model, and $\mathbb{Y}_{1987,\ no\ barriers}$ is computed from setting the spatial distribution of speaking occupations in the estimated model to levels in 1987 and also removing language barriers. Language barriers decreased internal migration by 7.6 percentage points, increased inequality by 3.4 percentage points, and decreased welfare by 1.9 percent.

The comparison is between the estimated model and a world without language barriers, but where speaking occupations increased in the same way across space between 1987 and 2011. The latter is not likely to have occurred as firms and workers probably made their location and human capital acquisition choices, respectively, to access opportunities from globalization. As Shastry (2012) shows, some Indian districts have a more elastic supply of English language human capital, which is particularly relevant for service exports. These districts attracted more export oriented skilled jobs, specifically in information technology, and experienced greater growth in schooling.

Though the parallel trends assumption in this difference-in-differences exercise is possibly violated, had language barriers not existed, firms are likely to have sorted across space according to their comparative advantage. In other words, the effects I find are likely lower bounds on what the impact of language barriers may be if we allow spatial sorting of firms and endogenous human capital acquisition for workers. In any case, this exercise shows that language barriers became more salient for labor market success when structural change and growth in services led to a higher prevalence of speaking occupations.

7.3 Language Policy

In this section, I weigh the costs and benefits of a language policy. The policy is motivated by cultural integration courses for foreign nationals in Germany, of which a major component is a language program. The program aims to bring migrants to working proficiency in German so that they can participate in the labor market without language barriers.

In a similar vein, I introduce a simple extension to the model whereby non-college migrant workers may enrol in language programs to overcome language barriers. To evaluate the potential benefits from this policy, I introduce two kinds of costs to the model. The first cost is faced by migrant workers: an opportunity cost of learning languages for migrant workers, $c_{o,d}$, which they incur if they choose to enrol in the program. If they choose to enrol in the program and incur the opportunity cost of learning, they may participate in the labor market without language barriers. The second cost is faced by the government: the expense of implementing language programs, which is ultimately borne by all workers in the economy in the form of a uniform lump-sum tax.

The language programs and associated costs introduce several changes to the model, which are focused on region-pairs (o,d) that have a language barrier between them. When making the choice to migrate between any region-pair (o,d) that has a language barrier, non-college workers now make an additional choice of whether to enrol in the program. In other words, when language programs are made available to non-college workers, language barrier becomes a function of whether or not they choose to enrol i.e., $\mathscr{L}(o,d,\mathbb{1}\{\text{enrol}\})$. In particular, $\mathscr{L}(o,d,\mathbb{1}\{\text{enrol}\}) = b$ if $\mathbb{1}\{\text{enrol}\} = 0$ and $\mathscr{L}(o,d,\mathbb{1}\{\text{enrol}\}) = nb$ if $\mathbb{1}\{\text{enrol}\} = 1$. That is, language barriers remain for the worker if they choose not to enrol, but they are removed if they do.

For some migrants, it is optimal to migrate to a location where they face language barriers and incur the opportunity cost of learning. For them, the benefit of participating in the labor market without language barriers outweighs the opportunity cost of overcoming them. The fraction of non-college workers that choose to migrate from origin o to destination d to work in occupation j and learn the language is given by

$$\pi_{o,d,j,nc}(\mathbb{1}\{\text{enrol}\} = 1) = \frac{A_{j,nc,nb}\left[(1-\tau^{G}_{o,d})\ \alpha_d\ (w_{d,j,e,nb})\right]^{\theta}\ (c_{o,d})^{-\theta}}{\Phi_{o,nc}},$$

where $\Phi_{o,nc} = \sum_{(d',j',\mathbb{1}\{\text{enrol}\})} A_{j',nc,\mathscr{L}(o,d',\mathbb{1}\{\text{enrol}\})}\ (\Lambda_{o,d',j',nc,\mathbb{1}\{\text{enrol}\}})^{\theta}$. The numerator captures that workers that would have previously had barrier productivity, $A_{j,nc,b}$ and incurred a language migration cost ($\tau^{L}_{o,d,nc} > 0$) now have non-barrier productivity, $A_{j,nc,nb}$, and do not incur a language migration cost ($\tau^L_{o,d,nc} = 0$). They do, however, incur the opportunity cost of learning, $c_{o,d}$.

However, for other migrants, it is optimal to a location where they face language barriers but choose *not* to participate in the language program. For them, the opportunity cost of overcoming language barriers overcomes the benefit of participating in the labor market without them. The fraction of non-college workers that choose to migrate from origin o to destination d to work in occupation j and do *not* learn the language is given by

$$\pi_{o,d,j,nc}(\mathbb{1}\{\text{enrol}\} = 0) = \frac{A_{j,nc,b}\left[(1-\tau^G_{o,d})(1-\tau^L_{o,d,e})\ \alpha_d\ (w_{d,j,e,b})\right]^\theta}{\Phi_{o,nc}},$$

where $\Phi_{o,nc} = \sum_{(d',j',\mathbb{1}\{\text{enrol}\})} A_{j',nc,\mathscr{L}(o,d',\mathbb{1}\{\text{enrol}\})}\ (\Lambda_{o,d',j',nc,\mathbb{1}\{\text{enrol}\}})^\theta$. Notice that workers that would have previously had barrier productivity, $A_{j,nc,b}$ and incurred a language migration cost ($\tau^L_{o,d} > 0$) continue to do so. Since they opt not to participate in the language program, they do not incur the opportunity cost of learning, $c_{o,d}$.

To incorporate the cost of implementing language programs, I assume that the government finances the program by charging a uniform lump-sum tax to all workers in the economy. The tax is charged to every worker i in the economy,

$$\text{Language Tax}^i = \frac{\sum_{r\in R}\text{Cost of Language Programs}_r}{\sum_{r\in R}\sum_{e\in\{c,nc\}} N_{r,e}},$$

where the the numerator is the total cost of implementing language programs across states of India and the denominator is the total number of workers in the economy. Since the tax is equally borne by each worker in the economy, it not affect bilateral migration shares. However, it does discount aggregate welfare. In particular, I subtract the total cost of language programs from the aggregate nominal income in the economy, which is divided by the aggregate price index, P, to obtain Y^{Policy}.

Calibration of Costs: In this section, I describe how I calibrate costs in the model. First, I calibrate $c_{o,d}$ using information on the time taken to learn languages and wages foregone as a consequence. To do so, I compute bilateral time costs using data from the United States State Department on the number of hours required for native English speakers to master 66 foreign languages up to "General Working Proficiency." Next, I compute the genealogical distance between English and each foreign language from Ethnologue language trees. Then, I estimate the following specification by least squares,

$$\text{Hours}_{\text{English, Foreign}} = \alpha \cdot \text{Distance}_{\text{English, Foreign}} + \varepsilon_{\text{English, Foreign}},$$

where $\text{Distance}_{\text{English, Foreign}}$ is the genealogical distance between English and each foreign language from Ethnologue language trees. I fit the regression without a constant to be consistent with the fact that a native speaker of any language would need 0 hours to learn that language. The slope coefficient, $\hat{\alpha} = 1148$ hours, is the average time taken to learn languages. Then, I predict bilateral time costs by multiplying the coefficient from this regression, $\hat{\alpha}$ with the linguistic distance index between region-pairs,

$$\text{Time Cost}_{o,d} = \hat{\alpha} \cdot \text{Linguistic Distance}_{o,d},$$

which measures the average number of hours that a person at origin o needs to overcome language barriers to destination d. Finally, I multiply this by the average wage per hour[9] of workers to obtain the opportunity cost of learning language i.e., $c_{o,d} = \text{Time Cost}_{o,d} \cdot \bar{w}_{o,d}$.

Second, I calibrate the cost of language programs using budget and expenditure reports from the Center Institute of Indian Languages (CIIL), a subsidiary of the Ministry of Education, Government of India. This was setup in 1970 to promote linguistic harmony by teaching 20 Indian languages to non-native learners. The CIIL, along with seven Regional Language Centers (RLCs), currently implements various language training programs in 22 languages.

In calibrating the cost of implementing language programs, I account for non-recurring infrastructure costs and recurring costs of teacher training and curriculum design, salaries for teachers, admin, and support staff, and maintenance. Each language center trains approximately 66 students per year and, on average, students need 1200 hours to learn a language. Assuming that capital depreciates in 10 years, I distribute the non-recurring infrastructure costs across 10 years' worth of students. Thus, I compute the cost per student to be \$3.6 per hour. As a sanity check, I compare this to the average cost of private English lessons in India, which is approximately \$5.6 per hour. This appears reasonable, as private lessons in English are likely to be more expensive than language programs. This is because English teachers not as widely available as teachers in local languages and private tutors seek to make profit, whereas language programs instituted by the government seeks only to cover costs.

Cost vs. Benefit of Language Programs: To evaluate how the cost of language programs weigh against the benefit, I consider a range of values of the language program to meet the demand computed from the calibrated model. Using the model, I predict how many workers would incur $c_{o,d}$ and enrol in the program at each region. I take a weighted sum of cost per student to account for how many hours workers from different origins would need to learn language of a given destination (Time Cost$_{o,d}$).

For each value of the cost of the program, I compute aggregate welfare, Y^{Policy}. To do so, I add up the costs in each region and subtract the total cost of language programs from the aggregate income in the economy. The cost of language programs for each region is borne equally by all workers in that region through a uniform lump-sum tax. I define benefit from the program as the percent gap between Y^{Policy} and the welfare in the baseline estimated

[9] I compute this from data on monthly wages, which is available in the CPHS waves, and data on the average number of hours worked by occupation, which is available in the NSS.

model without language policy, Y.

Figure 3 plots cost against benefit of language policy. The point at which the difference goes below 0 can be considered the threshold cost of the program. Above this threshold, costs outweigh the benefits, and it is not worth implementing such a policy. However, my back-of-the-envelope calculation of the cost of the language program ($3.6 per hour) lies well below the threshold. So, I argue that language policy should indeed be implemented.

8 Conclusion

This paper is the first to quantify aggregate impact of language barriers as a spatial and a labor market friction. To do so, it leverages India's linguistic diversity and the rise of speaking-intensive occupations to uncover the economic consequences of language barriers on internal migration, inequality between skilled and unskilled workers, and welfare.

The analysis reveals that removing language barriers would increase internal migration by 6.2 percentage points, enhance welfare by 1.2 percent, and reduce inequality by 1.9 percentage points. These effects are particularly pronounced in the context of structural change towards service-oriented economies. As speaking occupations became more prevalent across India, language barriers caused internal migration to be lower by 7.2 percentage points, welfare to be lower by 1.9 percent, and inequality to be higher by 3.4 percentage points.

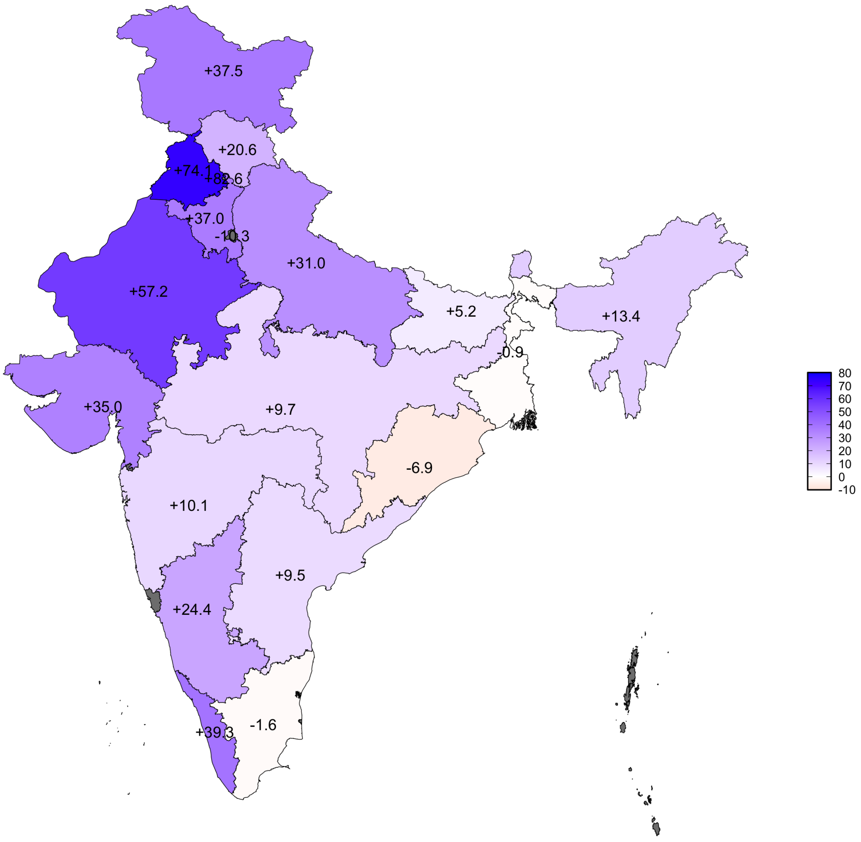
The quantitative model developed in this paper captures the interplay between sorting and selection mechanisms in general equilibrium. It demonstrates how language barriers affect workers' migration decisions, occupational choices, and productivity, with differential impacts on skilled and unskilled workers. This framework provides insight into the role of language in shaping labor market outcomes and driving aggregate economic patterns. Importantly, the findings suggest that language-based interventions could be effective policy tools. Back-of-the-envelope calculations indicate that implementing language programs for unskilled migrant workers could mitigate the negative impacts of language barriers, potentially leading to net welfare gains.

This research underscores the critical role of language in economic development and inequality. The implications of language barriers may extend to other crucial domains, particularly education. Future research could explore how language shapes migration for education and access to college across regions. For example, the medium of instruction in schools may significantly influence students' educational trajectories and subsequent college choices. Considering language as a factor in educational outcomes and endogenous college choice can offer a more comprehensive understanding of how linguistic diversity impacts economic inequality across generations.

Studying such language policies could provide insights into the long-term effects of language on human capital accumulation and socioeconomic mobility. As countries navigate multilingualism and structural economic changes, addressing language barriers in both labor markets and educational systems will be crucial for promoting inclusive growth and reducing disparities in diverse societies.

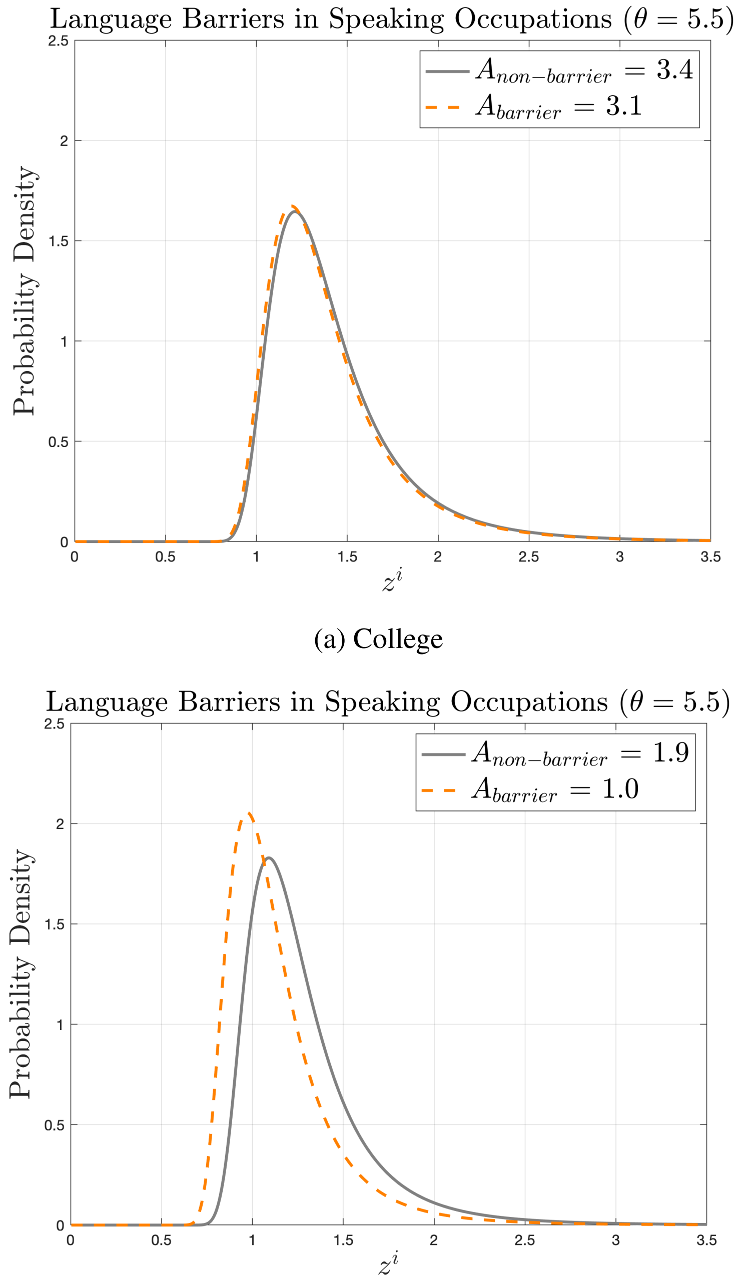
Figures and Tables

Figure 1: Changes in Employment Shares of Speaking Occupations between 1987 and 2011



Notes: Data is from the Employment-Unemployment Rounds of the National Sample Survey 1987 and 2011. The NCO codes are matched by description to O*NET to obtain a ranking of speaking-intensity. Change is computed as the percentage point difference in employment in each state. State boundaries are from 1987. The northeastern states and Sikkim are pooled together.

Figure 2: Estimates of $A_{j,e,\mathscr{L}(o,d)}$ for College and Non-College in Speaking Occupations

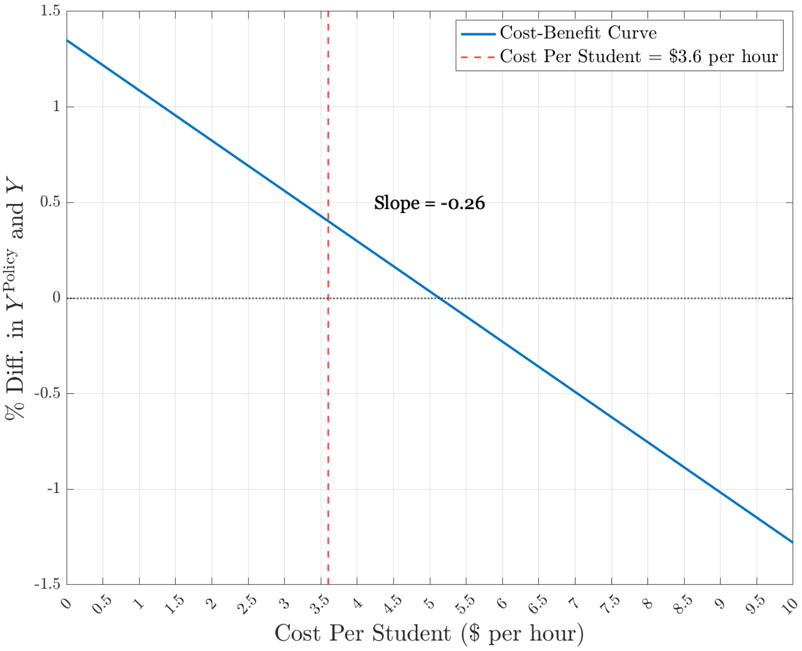


(a) College

(b) Non-College

Notes: Using estimates of $A_{j,e,\mathscr{L}(o,d)}$ and θ, I simulate the probability density functions by taking draws of z^i for college and non-college workers with and without language barriers in speaking occupations. The figure shows that $A_{spk,nb,c} = 1.1 \cdot A_{spk,b,c}$ whereas $A_{spk,nb,nc} = 1.9 \cdot A_{spk,b,nc}$.

Figure 3: Cost vs. Benefit of Language Policy



Notes: Cost is defined as the expense per student ($ per hour) of instituting language programs. The expense per student is aggregated using information on how many workers that face language barriers will enrol in the program in each state and the number of hours it would take them to overcome the language barrier they face. Benefit is defined as the percent difference in Y^{Policy}, which is welfare under the policy (computed by subtracting the aggregate real income by the cost of implementing language programs), and Y, which is welfare under the estimated model.

Table 1: Within-State vs. Out-of-State Migration by Reason (2001)

Reason for Migration	*Share*	*Within-State*	*Out-of-State*
Work, Business	0.11	0.64	0.36
Education	0.01	0.83	0.17
Marriage	0.50	0.92	0.08
Other	0.38	0.86	0.14

Notes: Data sourced from the 2001 Census of India. "Share" represents the proportion of total migrants for each reason. "Within-State" and "Out-of-State" columns show the proportion of migrants for each reason who moved within their state or to another state, respectively.

Table 2: Within-State vs. Out-of-State Migration by Reason and Education (2011)

Reason for Migration	*College*			*Non-College*		
	Share	*Within-State*	*Out-of-State*	*Share*	*Within-State*	*Out-of-State*
Work, Business	0.24	0.76	0.24	0.10	0.73	0.27
Education	0.03	0.79	0.21	0.01	0.90	0.10
Marriage	0.26	0.83	0.17	0.45	0.93	0.07
Other	0.47	0.84	0.16	0.44	0.90	0.10

Notes: Data sourced from the 2011 Census of India. "Share" represents the proportion of total migrants for each reason, separated by education level. "Within-State" and "Out-of-State" columns show the proportion of migrants for each reason and education level who moved within their state or to another state, respectively. College refers to individuals with "degree or higher" education.

Table 3: Occupations Categorized by O*NET Speaking Importance Levels

	Occupation	*O*NET Speaking Importance Level*
Speaking	Lawyers	91
	Teachers (School, University)	78
	Nurses	78
	Human Resources Managers	78
	Call Center Operators	78
	Sales Representatives	75
	Customer Service Representatives	72
	Receptionists	72
	Child Care Maids	69
	Journalists	63
Non-Speaking	Electricians	60
	Software Developers	56
	Carpenters	53
	Agricultural Laborers	50
	Masons, Brick Layers	50
	Truck, Bus Drivers	50
	Textile Workers (e.g., Weavers)	47
	Data Entry Operators	47
	Domestic Helpers, Cleaners	44
	Plumbers	38

Notes: Data sourced from the monthly individual income tables from the Consumer Pyramids Household Surveys. The occupation descriptions are matched to those in the O*NET database and ranked in ordinal fashion using a measure of the importance of speaking. The median rank is used to create two groups of occupations: speaking and non-speaking. The sample of 10 occupations in each group includes examples close to the median. The total number of occupations in the full sample is over 200.

Table 4: Wage and Employment in Speaking and Non-Speaking Occupations

	Wage Ratio		*Employment Share*	
	College	*Non-College*	*College*	*Non-College*
Speaking	1.30	1.16	0.07	0.14
Non-Speaking			0.05	0.74

Notes: Data sourced from the monthly individual income tables from the Consumer Pyramids Household Surveys. Wages are deflated using monthly state-level CPI from the Reserve Bank of India. Wage ratio is defined as the population-weighted mean wages in speaking vs. non-speaking occupations. College workers are paid 30% higher in speaking occupations than in non-speaking occupations. Non-college workers are paid 16% higher wages in speaking occupations than in non-speaking occupations. Employment share is defined as the number of college and non-college in each occupation type as a fraction of the total number of workers in the economy.

Table 5: Language and Migration of College vs. Non-College

Dependent Variable: $\ln(\pi_{o,d,e})$	(1)	(2)	(3)
$\mathbb{1}\{\text{Barrier}_{o,d}\}$	-2.21***		-.617***
	(.021)		(.020)
$\mathbb{1}\{\text{Barrier}_{o,d}\} \times \mathbb{1}\{\text{College}\}$	.074***		.093***
	(.024)		(.022)
$\mathbb{1}\{\text{College}\}$	.892***	.685***	.639***
	(.015)	(.030)	(.014)
$\ln(\text{Geo. Dist.}_{o,d})$		-1.97***	-1.84***
		(.009)	(.008)
$\ln(\text{Geo. Dist.}_{o,d}) \times \mathbb{1}\{\text{College}\}$		.116***	.104***
		(.013)	(.014)
Origin District FE	Yes	Yes	Yes
Dest. District FE	Yes	Yes	Yes
Origin State × Dest. State FE	Yes	Yes	Yes
R^2	0.180	0.314	0.316
Observations	277,379	277,379	277,379

Notes: Data on migration is sourced from the Census of India 2011. Data on languages is sourced from Census of India 2001. Standard errors are in parentheses and clustered at the destination district. *** means $p < 0.01$.

Table 6: Language and Occupation Choice of College vs. Non-College

	Natives	*Migrants*		
Dependent Variable: $\mathbb{1}\{\text{Speaking Occ.}_{i,o,d,j,t}\}$	(1)	(2)	(3)	(4)
$\mathbb{1}\{\text{Barrier}_{o,d}\}$		-.066***		-.057***
		(.007)		(.007)
$\mathbb{1}\{\text{Barrier}_{o,d}\} \times \mathbb{1}\{\text{College}_{i,o,d,j,t}\}$		.078***		.075***
		(.012)		(.012)
$\mathbb{1}\{\text{College}_{i,o,d,j,t}\}$	.248***	.296***	.121***	.114***
	(.0006)	(.004)	(.036)	(.040)
$\ln(\text{Geo. Dist.}_{o,d})$			-.005	.002
			(.005)	(.005)
$\ln(\text{Wages}_{i,o,d,j,t-1})$	Yes	Yes	Yes	Yes
$\text{Controls}_{i,o,d,j,t}$	Yes	Yes	Yes	Yes
Origin State × Month FE	No	Yes	Yes	Yes
Dest. District × Month FE	Yes	Yes	Yes	Yes
R^2	0.246	0.274	0.273	0.292
Observations	4,457,316	109,591	109,591	109,591

Notes: Data sourced from the monthly individual income tables from the Consumer Pyramids Household Surveys. Wages are deflated using monthly state-level CPI from the Reserve Bank of India. Data on languages sourced from the Census of India 2011. Standard errors are in parentheses and clustered at the destination district × month. *** means $p < 0.01$.

Table 7: Language and Wages of College vs. Non-College

	Natives	*Migrants*		
Dependent Variable: $\ln(\text{Wages}_{i,o,d,j,t})$	(1)	(2)	(3)	(4)
$\mathbb{1}\{\text{Barrier}_{o,d}\}$		.063*** (.013)		.055*** (.013)
$\mathbb{1}\{\text{Barrier}_{o,d}\} \times \mathbb{1}\{\text{College}_{i,o,d,j,t}\}$		-.063*** (.014)		-.062*** (.014)
$\mathbb{1}\{\text{College}_{i,o,d,j,t}\}$	.196*** (.001)	.279*** (.006)	.128*** (.048)	.134*** (.048)
$\ln(\text{Geo. Dist.}_{o,d})$			.036*** (.007)	.034*** (.007)
$\text{Controls}_{i,o,d,j,t}$	Yes	Yes	Yes	Yes
Occupation × Month FE	Yes	Yes	Yes	Yes
Origin State × Month FE	No	Yes	Yes	Yes
Dest. District × Month FE	Yes	Yes	Yes	Yes
R^2	0.607	0.676	0.673	0.676
Observations	4,105,305	103,442	103,442	103,442

Notes: Data sourced from the monthly individual income tables from the Consumer Pyramids Household Surveys. Wages are deflated using monthly state-level CPI from the Reserve Bank of India. Data on languages sourced from the Census of India 2011. Standard errors are in parentheses and clustered at the destination district × month. *** means $p < 0.01$.

Table 8: Estimation of θ

	(1)	(2)
$\ln\left[(1-\tau^G_{o,d})(1-\tau^L_{o,d,e})\right]$	5.35^{***}	5.47^{***}
	(.200)	(.170)
Destination × Occupation FE	N	Y
Observations	1,433	1,433

Notes: Data on migration flows sourced from the monthly individual income tables from the Consumer Pyramids Household Surveys. Data on language sourced from Census 2011 and IHDS-II.

Table 9: Estimates of CES Elasticities

Description		*Sub. Elasticity (x)*	*Point Estimate ($\frac{1-x}{x}$)*	*Standard Error*
Occupation	$\hat{\kappa}$	2.65	-0.623^{**}	(0.308)
Skill	$\hat{\rho}$	1.71	-0.415^{**}	(0.211)
Language Barrier	$\hat{v}_{non\text{-}spk,c}$	18.4	-0.946^{**}	(0.473)
	$\hat{v}_{spk,c}$	15.6	-0.936^{**}	(0.468)
	$\hat{v}_{non\text{-}spk,nc}$	19.8	-0.949^{**}	(0.478)
	$\hat{v}_{spk,nc}$	4.6	-0.783^{**}	(0.389)

Notes: Data on migration flows sourced from the monthly individual income tables from the Consumer Pyramids Household Surveys. Data on language sourced from Census 2011 and IHDS-II. ** means $p < 0.05$.

Table 10: Correlation of Targeted and Untargeted Moments from Data and Estimated Model

	Moment	*Correlation of Model vs. Data*
Targeted	$\pi_{o,d,j,c}$	0.94
	$\pi_{o,d,j,nc}$	0.97
Untargeted	$\bar{w}_{o,d,j,c}$	0.88
	$\bar{w}_{o,d,j,nc}$	0.83
	$N_{o,d,j,c}$	0.93
	$N_{o,d,j,nc}$	0.96

Notes: Data on migration flows sourced from the monthly individual income tables from the Consumer Pyramids Household Surveys. Wages are deflated using monthly state-level CPI from the Reserve Bank of India. Data on language sourced from Census 2011 and IHDS-II.

Table 11: Effect of Removing Language Barriers

	Internal Migration	*Inequality*	*Welfare*
Remove Language Barriers ($\tau^L_{o,d,e} = 0$, $A_{j,e,b} = A_{j,e,nb}$ if $j = spk$)	+6.2 p.p.	-1.9 p.p.	+1.3%
↓ *Geographic Barriers* (prop. ↓ $\tau^G_{o,d}$ by 56%)	+6.9 p.p.	-1.6 p.p.	+1.3%
↑ *College Share* (prop. ↑ $N_{r,c}$ by 34%)	+6.7 p.p.	-2.1 p.p.	+1.3%

Notes: This table contains three panels with change in internal migration, inequality between skilled and unskilled workers, and welfare relative to the benchmark from the estimated model. Internal migration is defined as the share of the population that migrated outside their origin state. Inequality between skilled and unskilled workers is defined as the percent difference in the real income of the two groups. Welfare is defined as the real income in the economy. The first panel shows results from removing language barriers. The second and third panel show results from targeting the same welfare gains as in the first panel. However, this is achieved by decreasing $\tau^G_{o,d}$, geographic barriers between region-pairs o,d, and increasing $N_{r,c}$, share of college workers in each region r, respectively, with no change to language barriers.

Table 12: Structural Difference-in-Differences

	Language Barriers ✓	*Language Barriers* ×
Speaking Occupations in 2011 ($\phi_{r,spk,2011}$)	$Y_{2011,\ est.\ model}$	$Y_{2011,\ cf}$
Speaking Occupations in 1987 ($\phi_{r,spk,1987}$)	$Y_{1987,\ cf}$	$Y_{1987,\ cf}$

Notes: This table outlines the two margins of difference in this exercise. The first is between 1987 and 2011, which are periods before and after trade liberalization in India. The CES share parameter in the outer nest is proxied from NSS data by employment shares in speaking and non-speaking occupations across states of India. The second margin of difference simulates this difference after removing language barriers.

Table 13: Effect of Language Barriers on Gains from Structural Change

	Internal Migration	*Inequality*	*Welfare*
Y_{DID}	-7.6 p.p.	+3.4 p.p.	-1.9%

Notes: Internal migration is defined as the share of the population that migrated outside their origin state. Inequality between skilled and unskilled workers is defined as the percent difference in the real income of the two groups. Welfare is defined as the real income in the economy.

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Appendix: Model Derivations

This appendix presents the derivation of main equations of the model. First, I explain the notation used in the paper and list the model parameters for reference. Second, I derive the sorting and selection equations from the workers' utility maximization problem. Third, I derive the price equations and demand conditions from the optimization problems of the regional and aggregate firms.

Notation: In the table below, I describe the notation used in the paper to denote regions, occupations, and workers.

Regions ($r \in R$)	Origin	$o \in R$
	Destination	$d \in R$
Occupations ($j \in J$)	$j \in \{$Speaking, Non-Speaking$\}$	$j \in \{$spk, non-spk$\}$
Workers (i)	Education $\in \{$College, Non-College$\}$	$e \in \{c, nc\}$
	Language Barrier $\in \{$Barrier, Non-Barrier$\}$	$\mathscr{L}(o,d) \in b, nb$

Model Parameters: In the table below, I list the model parameters and describe what they mean.

Parameter	Description	Dimensions
$\tau^G_{o,d}$	geographic barriers	$R \times R$
$\tau^L_{o,d,e}$	language barriers	$R \times R \times 2$
α_r	amenities	$R \times 1$
$A_{j,e,\mathscr{L}(o,d)}$	Fréchet, location	$J \times 2 \times 2$
θ	Fréchet, dispersion	1×1
σ	elasticity parameter, aggregate nest	1×1
κ	elasticity parameter, outer nest	1×1
$\phi_{r,j}$	share parameter, outer nest	$R \times J$
ρ	elasticity parameter, middle nest	1×1
$\nu_{j,e}$	elasticity parameter, inner nest	$J \times 1$

Utility and Sorting: The key sorting equation is derived from the probability that worker i from origin o with education e chooses occupation j at location d. Let $z^i_{j,e,\mathscr{L}(o,d)} \equiv z$ and $z^i_{j',e,\mathscr{L}(o,d')} \equiv z'$. From the properties of the Fréchet distribution,

$$
\begin{aligned}
\pi_{o,d,j,e} &= \Pr\Big(\Lambda_{o,d,j,e}\, z \geq \Lambda_{o,d',j',e}\, z' \ \ \forall (d',j') \neq (d,j)\Big) \\
&= \Pr\Big(z' \leq \frac{\Lambda_{o,d,j,e}}{\Lambda_{o,d',j',e}} z \ \ (d',j') \neq (d,j)\Big) \\
&= \int_0^\infty \prod_{(d',j')\neq(d,j)} G_{j',e,\mathscr{L}(o,d')}\Big(\frac{\Lambda_{o,d,j,e}}{\Lambda_{o,d',j',e}} z\Big)\, dG_{j,e,\mathscr{L}(o,d)}(z) \\
&= \int_0^\infty \prod_{(d',j')\neq(d,j)} \exp\Big[-A_{j',\mathscr{L}(o,d'),e}\Big(\frac{\Lambda_{o,d,j,e}}{\Lambda_{o,d',j',e}} z\Big)^{-\theta}\Big]\, dG_{j,e,\mathscr{L}(o,d)}(z) \\
&= \int_0^\infty \exp\Big[-(\Lambda_{o,d,j,e} z)^{-\theta} \sum_{(d',j')\neq(d,j)} A_{j',e,\mathscr{L}(o,d')}(\Lambda_{o,d',j',e})^{\theta}\Big)\Big] A_{j,e,\mathscr{L}(o,d)}\theta z^{-\theta-1} \\
&\quad \cdot \exp\Big(-A_{j,e,\mathscr{L}(o,d)} z^{-\theta}(\Lambda_{o,d,j,e})^{-\theta}(\Lambda_{o,d,j,e})^{\theta}\Big) dz \\
&= \int_0^\infty \exp\Big[-(\Lambda_{o,d,j,e} z)^{-\theta} \sum_{(d',j')\neq(d,j)} A_{j',e,\mathscr{L}(o,d')}(\Lambda_{o,d',j'e})^{\theta} - \\
&\quad \cdot (\Lambda_{o,d,j,e} z)^{-\theta} A_{j,e,\mathscr{L}(o,d)}(\Lambda_{o,d,j,e})^{\theta}\Big] A_{j,e,\mathscr{L}(o,d)}\theta z^{-\theta-1} dz \\
&= \int_0^\infty \exp\Big[-(\Lambda_{o,d,j,e} z)^{-\theta} \underbrace{\sum_{(d',j')} A_{j',e,\mathscr{L}(o,d')}(\Lambda_{o,d',j',e})^{\theta}}_{\equiv(\Phi_{o,e})^{\theta}}\Big] A_{j,e,\mathscr{L}(o,d)}\theta z^{-\theta-1} dz \\
&= \frac{A_{j,e,\mathscr{L}(o,d)}}{(\Lambda_{o,d,j,e})^{-\theta}(\Phi_{o,e})^{\theta}} \int_0^\infty (\Lambda_{o,d,j,e})^{-\theta}(\Phi_{o,e})^{\theta}\theta z^{-\theta-1} \exp\Big(-(\Lambda_{o,d,j,e})^{-\theta}(\Phi_{o,e})^{\theta} z^{-\theta}\Big) dz \\
&= \frac{A_{j,e,\mathscr{L}(o,d)}(\Lambda_{o,d,j,e})^{\theta}}{(\Phi_{o,e})^{\theta}}
\end{aligned}
$$

Expected Productivity and Selection: The key selection equation is derived from the expected productivity of worker i of from origin o and education e conditional on having chosen destination d and occupation j. Let $z^i_{j,e,\mathscr{L}(o,d)} \equiv z$ and $z^i_{j',e,\mathscr{L}(o,d')} \equiv z'$. From the properties of the Fréchet distribution,

$$
E\Big[z \mid z' \leq \frac{\Lambda_{o,d,j,e}}{\Lambda_{o,d',j',e}} z \ \ \text{s.t. } (d',j') \neq (d,j)\Big]
$$

$$
\begin{aligned}
&= \frac{1}{\pi_{o,d,j,e}} \int_{z=0}^{\infty} \int_{z'=0}^{\frac{\Lambda_{o,d,j,e}}{\Lambda_{o,d',j',e}} z} z \, g_{j,e,\mathscr{L}(o,d)}(z) \; g_{j',e,\mathscr{L}(o,d')}(z') \, dz \, dz' \\
&= \frac{1}{\pi_{o,d,j,e}} \int_{z=0}^{\infty} z \, g_{j,e,\mathscr{L}(o,d)}(z) \, \Big(\int_{z'=0}^{\frac{\Lambda_{o,d,j,e}}{\Lambda_{o,d',j',e}} z} g_{j',e,\mathscr{L}(o,d')}(z') \, dz' \Big) \, dz \\
&= \frac{1}{\pi_{o,d,j,e}} \int_{z=0}^{\infty} z \, g_{j,e,\mathscr{L}(o,d)}(z) \; g_{j',e,\mathscr{L}(o,d')} \Big(\frac{\Lambda_{o,d,j,e}}{\Lambda_{o,d',j',e}} z \Big) \, dz \\
&= \frac{1}{\pi_{o,d,j,e}} \int_{z=0}^{\infty} z \theta A_{j,e,\mathscr{L}(o,d)} z^{-\theta-1} \exp \Big(A_{j,e,\mathscr{L}(o,d)} z^{-\theta} \Big) \; \exp \Big(A_{j',e,\mathscr{L}(o,d')} (\frac{\Lambda_{o,d,j,e}}{\Lambda_{o,d',j',e}} z)^{-\theta} \Big) \, dz \\
&= \frac{1}{\pi_{o,d,j,e}} \int_{z=0}^{\infty} z \theta A_{j,e,\mathscr{L}(o,d)} z^{-\theta-1} \exp \Big(-(\frac{\Phi^{oe}}{\Lambda_{o,d,j,e}})^{\theta} z^{-\theta} \Big) \, dz \\
&= \frac{1}{\pi_{o,d,j,e}} \int_{z=0}^{\infty} z \theta A_{j,e,\mathscr{L}(o,d)} z^{-\theta-1} \exp \Big(- \frac{A_{j,e,\mathscr{L}(o,d)}}{\pi_{o,d,j,e}} z^{-\theta} \Big) \, dz \\
&= \int_{z=0}^{\infty} z \theta \frac{A_{j,e,\mathscr{L}(o,d)}}{\pi_{o,d,j,e}} z^{-\theta-1} \exp \Big(- \frac{A_{j,e,\mathscr{L}(o,d)}}{\pi_{o,d,j,e}} z^{-\theta} \Big) \, dz \\
&= \Gamma(1 - 1/\theta) (\pi_{o,d,j,e} / A_{j,e,\mathscr{L}(o,d)})^{-1/\theta}
\end{aligned}
$$

Expected Utility: The expected utility of worker i from origin o with education e is derived across all possible destinations d and occupations j. Let $z^{i}_{j,e,\mathscr{L}(o,d)} \equiv z$. Given the properties of the Fréchet distribution and the multiplicative nature of the utility function,

$$
\begin{aligned}
E\Big[U^{i}_{o,d,j,e} \Big] &= E\Big[\max_{(d,j)} \Lambda_{o,d,j,e} \, z \Big] \\
&= \int_{0}^{\infty} \Big[1 - \prod_{(d,j)} \Pr \Big(\Lambda_{o,d,j,e} \, z \leq t \Big) \Big] dt \\
&= \int_{0}^{\infty} \Big[1 - \prod_{(d,j)} \Pr \Big(z \leq \frac{t}{\Lambda_{o,d,j,e}} \Big) \Big] dt \\
&= \int_{0}^{\infty} \Big[1 - \prod_{(d,j)} \exp \Big(- A_{j,e,\mathscr{L}(o,d)} (\frac{t}{\Lambda_{o,d,j,e}})^{-\theta} \Big) \Big] dt \\
&= \int_{0}^{\infty} \Big[1 - \exp \Big(- \sum_{(d,j)} A_{j,e,\mathscr{L}(o,d)} (\frac{t}{\Lambda_{o,d,j,e}})^{-\theta} \Big) \Big] dt \\
&= \int_{0}^{\infty} \Big[1 - \exp \Big(- t^{-\theta} \sum_{(d,j)} A_{j,e,\mathscr{L}(o,d)} (\Lambda_{o,d,j,e})^{\theta} \Big) \Big] dt \\
&= \int_{0}^{\infty} \Big[1 - \exp \Big(- \underbrace{\sum_{(d,j)} A_{j,e,\mathscr{L}(o,d)} (\Lambda_{o,d,j,e})^{\theta}}_{\equiv (\Phi_{o,e})^{\theta}} t^{-\theta} \Big) \Big] dt
\end{aligned}
$$

$$
\begin{aligned}
&= \int_0^\infty \left[1 - \exp\left([1/\Phi_{o,e}]^{-\theta} t^{-\theta}\right)\right] dt \\
&= \frac{\Gamma(1-1/\theta)}{1/\Phi_{o,e}} \\
&= \Gamma(1-1/\theta)\ \Phi_{o,e}.
\end{aligned}
$$

Wages: Wages are pinned down by the labor demand conditions, which are derived from the first order conditions of the profit maximization problem of the firm in region d,

$$
\max_{\{\ell_{d,j,e,\mathscr{L}(o,d)}\}} p_d y_d - \sum_{j \in J, e \in \{c,nc\}, \mathscr{L}(o,d) \in \{b,nb\}} w_{d,j,e,\mathscr{L}(o,d)} \ell_{d,j,e,\mathscr{L}(o,d)},
$$

where the firm takes wages, $w_{d,j,e,\mathscr{L}(o,d)}$, as given and chooses labor inputs, $\ell_{d,j,e,\mathscr{L}(o,d)}$. From the first order conditions of this problem,

$$
w_{d,j,e,\mathscr{L}(o,d)} = MP_{d,j} \cdot MP_j^{d,e} \cdot (\ell_j^{d,e,\mathscr{L}(o,d)})^{\frac{v_{j,e}}{v_{j,e}-1}},
$$

where $MP_{d,j} = p_d(y_d)^{\frac{1}{\kappa-1}} (\phi_{d,j})^{\frac{1}{\kappa}} (\ell_{d,j})^{\frac{\rho}{\rho-1}\frac{\kappa-1}{\kappa}-1}$ is the marginal product of labor for occupation j at region d and $MP_{d,j,c} = (\ell_{d,j,c})^{\frac{v_j^c}{v_j^c-1}\frac{\rho-1}{\rho}-1}$ is the marginal product of labor for college workers in occupation j at region d.

Regional Prices: Prices are pinned down by the marginal cost function, which are derived from the first order conditions of the cost minimization problem of the firm in region d,

$$
\min_{\{\ell_{d,j,e,\mathscr{L}(o,d)}\}} \sum_{j \in J, e \in \{c,nc\}, \mathscr{L}(o,d) \in \{b,nb\}} w_{d,j,e,\mathscr{L}(o,d)} \ell_{d,j,e,\mathscr{L}(o,d)}
$$

$$
\text{s.t. } y_d = \left[\sum_{j \in J} (\phi_{d,j})^{\frac{1}{\kappa}} (\ell_{d,j})^{\frac{\kappa-1}{\kappa}}\right]^{\frac{\kappa}{\kappa-1}}.
$$

First, the cost minimization problem of the inner nest is,

$$
\min_{\ell_{d,j,e,b}, \ell_{d,j,e,nb}} w_{d,j,e,b}\ell_{d,j,e,b} + w_{d,j,e,nb}\ell_{d,j,e,nb} \text{ s.t. } \ell_j^{d,e} = \left[(\ell_{d,j,e,b})^{\frac{v_{j,e}-1}{v_{j,e}}} + (\ell_{d,j,e,nb})^{\frac{v_{j,e}-1}{v_{j,e}}}\right]^{\frac{v_{j,e}}{v_{j,e}-1}},
$$

which allows us to solve for the cost of $\ell_j^{d,e}$,

$$w_{d,j,e}=\Big[(w_{d,j,e,b})^{1-\nu_{j,e}}+(w_{d,j,e,nb})^{1-\nu_{j,e}}\Big]^{\frac{1}{1-\nu_{j,e}}}.$$

Second, the cost minimization problem of the middle nest is,

$$\min_{\ell_{d,j,c},\ell_{d,j,nc}} w_{d,j,c}\ell_{d,j,c}+w_{d,j,nc}\ell_{d,j,nc} \text{ s.t. } \ell_{d,j}=\Big[(\ell_{d,j,c})^{\frac{\rho-1}{\rho}}+(\ell_{d,j,nc})^{\frac{\rho-1}{\rho}}\Big]^{\frac{\rho}{\rho-1}}$$

which allows us to solve for the cost of $\ell_{d,j}$,

$$w_{d,j}=\Big[(w_{d,j,c})^{1-\rho}+(w_{d,j,nc})^{1-\rho}\Big]^{\frac{1}{1-\rho}}.$$

Finally, the cost minimization problem of the outer nest is,

$$\min_{\{\ell_{d,j}\}}\sum_{j\in J} w_{d,j}\ell_{d,j} \text{ s.t. } y_d=\Big[\sum_{j\in J}(\phi_{d,j})^{\frac{1}{\kappa}}(\ell_{d,j})^{\frac{\kappa-1}{\kappa}}\Big]^{\frac{\kappa}{\kappa-1}},$$

which allows us to solve for the cost of y_d, the final cost function,

$$C(y_d)=y_d\Big[\sum_{j\in J}\phi_{d,j}(c_{d,j})^{1-\kappa}\Big]^{\frac{1}{1-\kappa}}.$$

Thus, price equals the marginal cost function,

$$p_d=\frac{\partial C(y_d)}{\partial y_d}=\Big[\sum_{j\in J}\phi_{d,j}(w_{d,j})^{1-\kappa}\Big]^{\frac{1}{1-\kappa}},$$

where

$$w_{d,j}=\Big[(w_{d,j,c})^{1-\rho}+(w_{d,j,nc})^{1-\rho}\Big]^{\frac{1}{1-\rho}},$$

and

$$w_{d,j,e}=\Big[(w_{d,j,e,b})^{1-\nu_{j,e}}+(w_{d,j,e,nb})^{1-\nu_{j,e}}\Big]^{\frac{1}{1-\nu_{j,e}}}, \text{ where } e\in\{c,nc\}.$$

Aggregate Price: The assumption that the aggregate good is traded costlessly across regions implies that each region faces the same price index. This follows from the profit maximization problem of the aggregate firm,

$$\max_{\{y_d\}} PY-\sum_{d\in R} p_d y_d.$$

The first-order condition yields the demand for regional goods,

$$y_d = (p_d/P)^{-\sigma} Y,$$

which can be substituted back into the production function to get that $P = \left[\sum_{d \in R}(p_d)^{1-\sigma}\right]^{\frac{1}{1-\sigma}}$. This is a natural price index and represents the cost of producing one unit of the aggregate good Y given the prices of the regional goods p_d. Further, the expression for the price index is equivalent to the derivative of the cost function of the aggregate firm, which is also equal to P due to perfect competition. To see this, consider the aggregate firm's cost minimization problem,

$$\min_{\{y_d\}} \sum_{d \in R} p_d y_d$$

$$\text{s.t. } Y = \Big[\sum_{d \in R} (y_d)^{\frac{\sigma-1}{\sigma}}\Big]^{\frac{\sigma}{\sigma-1}},$$

which allows us to solve for the cost of Y,

$$C(Y) = Y \cdot \Big[\sum_{d \in R} (p_d)^{1-\sigma}\Big]^{\frac{1}{1-\sigma}}.$$

Thus, the price equals the marginal cost function,

$$P = \Big[\sum_{d \in R} (p_d)^{1-\sigma}\Big]^{\frac{1}{1-\sigma}},$$

which is normalized to 1 by assumption that the aggregate good is numeraire.

Estimation of θ: I infer the migration elasticity, θ, from the relationship between cross-migration flows and migration costs. In particular, I derive the Head-Reis index,

$$\frac{N_{o,d,j,e}}{N_{d,d,j,e}} \frac{N_{d,o,j,e}}{N_{o,o,j,e}} = \frac{\pi_{o,d,j,e}}{\pi_{d,d,j,e}} \frac{N_{o,e}}{N_{d,e}} \frac{\pi_{d,o,j,e}}{\pi_{o,o,j,e}} \frac{N_{d,e}}{N_{o,e}}$$

$$= \Big(\frac{\Lambda_{o,d,j,e}}{\Lambda_{d,d,j,e}} \frac{\Lambda_{d,o,j,e}}{\Lambda_{o,o,j,e}}\Big)^{\theta}$$

$$= \Big[\frac{(1-\tau^G_{o,d})(1-\tau^L_{o,d,e})}{(1-\tau^L_{d,d})(1-\tau^L_{d,d,e})} \frac{(1-\tau^G_{d,o})(1-\tau^L_{d,o,e})}{(1-\tau^G_{o,o})(1-\tau^L_{o,o,e})}\Big]^{\theta}$$

$$= \Big[(1-\tau^G_{o,d})(1-\tau^L_{o,d,e})\Big]^{\theta},$$

where the final step follows from the symmetry in geographic and language barriers, $\tau^G_{o,d} =$

$\tau^G_{d,o}$, $\tau^L_{o,d,e} = \tau^L_{d,o,e}$, and from the absence of barriers for workers that do not migrate, $\tau^G_{d,d} = \tau^L_{d,d,e} = \tau^G_{o,o} = \tau_{o,o,e} = 0$. For identification of θ, the specification allows for a constant and an error term that is assumed to be uncorrelated with migration costs in expectation. That is, I estimate θ from the following,

$$\ln\left(\sqrt{\frac{N_{o,d,j,e,t}}{N_{d,d,j,e,t}}\frac{N_{d,o,j,e,t}}{N_{o,o,j,e,t}}}\right) = \text{Constant} + \theta \ln\left[(1-\tau^G_{o,d})(1-\tau^L_{o,d,e})\right] + \varepsilon_{o,d,j,e,t},$$

where the source of identifying variation is over state-pairs, occupations, and time periods. Table 8 contains the regression results.