Drivers of Concentration: The Roles of Trade Access, Structural Transformation, and Local Fundamentals

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Abstract

What factors determine the degree of spatial concentration of a country's population? I investigate the drivers of concentration by adding non-homothetic preferences to a modern quantitative spatial model, obtaining a two-sector spatial model in which concentration depends on trade networks, structural transformation, and location-specific fundamentals (i.e. productivities and amenities). The model delivers an analytical expression decomposing changes in spatial concentration into separate terms that reflect the roles of these three forces. I then bring the model to the data in two steps: first, estimate trade gravity equations to recover year- and sector-specific trade-cost matrices; then calibrate the model to the 2005 global economy (featuring 1611 locations across 192 countries) by finding local fundamentals that rationalize population and income data given the equilibrium equations. I use this calibrated model for counterfactual exercises that clarify the role of trade access on spatial concentration. Results indicate that increasing access to foreign markets reduces concentration in most countries. Finally, I use the model-implied decomposition equation to disentangle the roles of structural transformation, differential trade access, and local fundamentals in accounting for the observed 1990-2015 changes in concentration for 44 countries. The bulk of the variation is explained by local fundamentals, with only 1% accounted for by differential trade access and structural transformation.

1 Introduction

Which factors determine the degree of spatial concentration of a country's domestic population? The concentration of people in space is an important aspect of the

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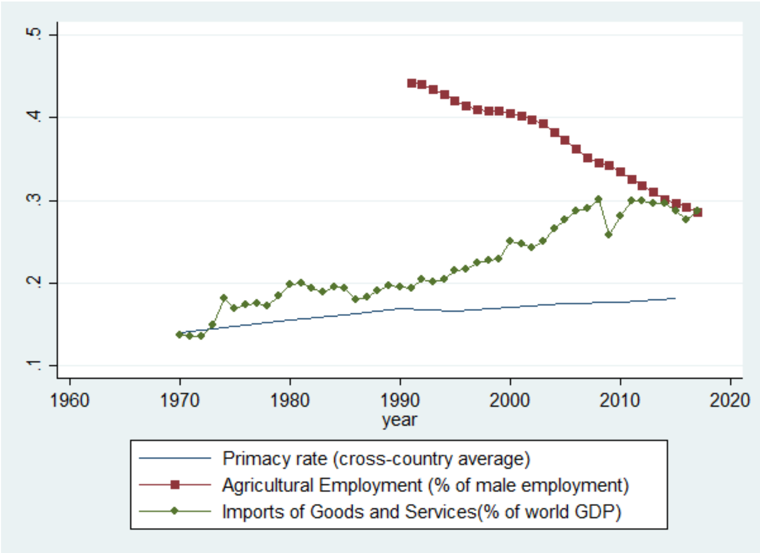
modern global economy, especially because it is associated with higher incomes, social mobility, and general economic development (see e.g. Glaeser (2011)), which makes it important to understand its drivers. Moreover, if spatial concentration is influenced by other economic variables (such as trade costs), then a full account of the welfare effects of changes in these variables may require explicit recognition of their effects on concentration. A better understanding of the causes of concentration may also help us predict the effects on the world's economic geography of potential future events such as a retreat from globalization (e.g. due to geopolitical tensions, trade wars, pandemics) or the continued transition of the global economy away from agriculture.

A traditional literature within urban economics (see e.g. Roback (1982)) states that the relative attractiveness of different locations for firms and workers depends on location-specific fundamentals such as local productivity and local amenities, which therefore affect the distribution of population across locations and, by consequence, the degree of spatial concentration. Thus, any attempt to understand the drivers of concentration should include these fundamentals. On the other hand, recent empirical evidence has shown that both access to trade networks and the economy's structural transformation away from agriculture can have effects that vary across space. This observation suggests that these two forces could also influence spatial concentration. Furthermore, as Figure 1 shows, the increase in average spatial concentration across countries (as measured by the primacy rate) between the 1970s and the 2010s was accompanied by a simultaneous increase in the value of international trade (as a fraction of world GDP) and by a substantial reduction in the share of world population employed in agriculture.[1] While these correlations say nothing about causality, they reinforce our suspicion that these three phenomena could be related.

In this paper, I investigate the influences of local fundamentals, structural transformation, and differential trade access on spatial concentration through the lens of a modern quantitative spatial model. Specifically, I extend a state-of-the-art spatial model (see e.g. Allen and Arkolakis (2014), Allen and Donaldson (2020)) to include non-homothetic price independent generalized linear (PIGL) preferences (Eckert and Peters (2018)). I thereby obtain a tractable two-sector spatial model that features differential access to trade networks across domestic locations, structural transformation, and local fundamentals (i.e. exogenous location-specific amenities and sectoral productivities). Under mild parametric restrictions, the model delivers an analytical expression for the primacy rate (i.e. the fraction of a country's population living in its largest city), which is the measure of spatial concentration I use throughout the paper. A differential version of this analytical expression allows me to decompose changes in a country's degree of spatial concentration into separate terms that reflect the roles of

[1]As discussed below, the primacy rate is defined as the share of a country's population that lives in its largest location.

Figure 1: Concentration, Trade, Structural Transformation



Notes: the figure portrays three time series: (i) cross-country average of primacy rate i.e. the share of national population in country's largest city (data from World Urbanization Prospects 2018); (ii) global agricultural male employment as % of global male employment (data from World Bank Open Data); (iii) global imports of goods and services as % of global GDP (data from World Bank Open Data).

structural transformation, changes in trade access, and changes in local fundamentals.

I then propose a methodology to bring the model to the data so that it can be used to analyze spatial concentration in the real world. The methodology has two steps. In the first step, I recover estimates of the global trade-cost structure for years 1962-2019 by using model-implied trade gravity equations that can be estimated with data on bilateral distances and on international and intranational trade flows. To implement these gravity regressions, I first obtain measures of bilateral distance that take into account the global transportation infrastructure. For this purpose, I propose an ancillary method to transform transportation network maps into cost rasters which are then used to compute bilateral distances through a fast marching method (FMM) algorithm. In the second step, I combine the model's equilibrium conditions with data on population, sectoral employment, and per capita income for 1611 locations across 192 countries to calibrate a model of the 2005 global economy. In this context, calibration means finding vectors of local fundamental amenities and sectoral productivities that perfectly rationalize the observed spatial distribution of population, sectoral employment, and income.

Having calibrated the model, I can use it to study the influence of trade access on spatial concentration by conducting two model-driven counterfactual exercises in which I impose counterfactual trade-cost structures while keeping other exogenous variables and parameters fixed at their baseline 2005 levels. For a given counterfactual exercise, I show how to use the model's equilibrium equations to compute the spatial distributions of wages, populations, and sectoral employment that the model predicts would hold under that scenario, as well as the counterfactual primacy rate. This allows me to evaluate how the trade shocks represented by these counterfactual trade matrices would affect spatial concentration, as predicted by the full-fledged general equilibrium model. As for the choice of specific counterfactual trade-cost matrices, I run two exercises: one eliminating international "border-crossing" costs (CF1), and another increasing international trade costs back to their 1971 levels (CF2).

To be able to implement this methodology on the 2005 global economy, I obtain a wealth of data from multiple sources. Data on sector-level bilateral trade flows, which is used to estimate trade gravity equations in the first step, comes from the World Bank's World Integrated Trade Solution (WITS), which offers country-level data for the 1962-2019 period. Global transportation network maps at the 1:10m level for roads and rail are obtained from the public-domain data set Natural Earth. Data on 2005 population and sectoral employment at the level of subnational locations (states, provinces, etc), which is used for calibration in the second step, is obtained from IPUMS International, an online project that collects and harmonizes census data from multiple countries. Data on 2005 income per capita at the national level is obtained from World Bank Open Data, and at the subnational level from G-Econ, a "geophysically based" data set of the world economy at the level of 1°latitude by 1°longitude. These data sources, combined with ancillary data on geographic coordinates, import shares, and the agricultural share of GDP, gives me everything I need to estimate gravity equations and calibrate a model of the 2005 world economy with 1611 locations across 192 countries.

Having devised the methodology and collected the necessary data, I finally bring the model to the data. The results of the trade gravity regression in the first step indicate that international trade costs declined substantially between the 1960s and the 2005s for both agriculture and non-agriculture. While in 1971 the border-crossing parameter for agriculture (non-agriculture) was equivalent to a 180% (370%) ad-valorem tariff, that number declined to 130% (280%) in 2005. Calibration results from the second step are intuitive: developed and oil-rich countries have higher productivity values.

Results of the first counterfactual exercise (CF1), in which I eliminate border-crossing costs, show that population tends to move to locations that were smaller at baseline: the correlation between a location's (log of) initial share of national population and (log of) relative increase in population is -0.23. Thus, spatial concentration decreases for most countries. The opposite is true for the latter counterfactual CF2, which increases trade costs. It leads to increased spatial concentration, with the correlation between (the log of) initial share of national population and (the log of) percent increase in population being 0.25. Overall, counterfactual results imply that trade-cost shocks have meaningful effects on spatial concentration. More specifically, trade-cost increases foster concentration.

The counterfactual exercises also produce interesting results on welfare and trade volumes. Decreasing international trade costs in counterfactual CF1 leads to substantial increases in trade volumes, with international trade growing from 21% of world GDP at baseline to 78% in the counterfactual. Welfare gains are also very large, with the average country's adjusted welfare sum growing by 57%. The opposite is true for counterfactual CF2, in which raises international trade costs. International trade falls to 14% of world GDP, while the average country's adjusted welfare sum falls by 5%. Overall, this set of results suggests that international trade integration between the 1970s and the 2000s was only partial. Costs were still very high in 2005, with large increases in welfare and trade flows still left to be materialized by further integration.

Finally, I leverage the model-implied analytical expression governing changes in the primacy rate to perform an accounting exercise in which I decompose the observed 1990-2015 changes in primacy for a sample of 44 countries into three components reflecting the roles of structural transformation, differential trade access, and local fundamentals. Results show that only 1% of the sample variation in primacy changes can be accounted for by structural transformation and changes in trade access, with the bulk of the variation being accounted for by changes in local fundamentals. Thus, I conclude that most of the observed 1990-2015 changes in concentration were driven by changes in fundamental productivities and amenities, with structural change and differential trade access playing only a secondary role.

Related literature The new economic geography (NEG) literature (see e.g. Krugman (1991), Krugman and Venables (1995)) provides models of monopolistic competition and economies of scale that generate geographical concentration of economic activity under some circumstances. Within that literature, the most relevant paper for our purposes is Krugman and Livas (1996), who explicitly tackle the link between access to international trade and spatial concentration of the domestic population. My paper revisits this question through the lens of a modern quantitative spatial model that features agglomerative forces typical of NEG but also two additional forces ignored by Krugman-Livas (differential trade access and structural transformation) and provides a framework through which I can bring the model to the data, in contrast with the purely theoretical nature of much of the relevant NEG literature. An empirical exception to this rule is Ades and Glaeser (1995), who use cross-country regressions to empirically test Krugman-Livas hypothesis. However, they do not consider the importance of differential trade access, and use a cross-country methodology which has been criticized (Levine and Renelt (1992), Rodrik (2012)). In contrast, my paper fully specifies a general equilibrium model through which real-world data is interpreted.

A recent literature in international trade and economic geography emphasizes the importance of access to trade networks in determining economic outcomes. Redding and Sturm (2008) use the post-WWII division of Germany to show that locations closer to the east-west border, who lost the most market access from division, also exhibited less population growth. Similarly, Ahlfeldt et al. (2014) use a general equilibrium model and show that West Berlin neighborhoods closer to the Berlin wall became relatively less important in terms of land rents and density of economic activity. Donaldson and Hornbeck (2016) show that the historical integration of US counties through railways increased land rents due to improved market access through the rail network. Brulhart et al. (2019) use worldwide data on night lights to proxy for economic activity and show that increases in international trade are associated to disproportionate economic growth in a country's border regions relative to other regions. By incorporating domestic and international trade costs, my model naturally reflects the importance of trade access, which may help shape spatial concentration.

A few papers directly address the effects of international trade on the internal structures of countries. Fajgelbaum and Redding (2018) study Argentinean 19th-century economic development with a focus on the impact of international trade integration on structural transformation and economic development. Their analysis prominently features structural transformation and differential access to foreign markets, but not the agglomerative NEG-style forces that manifest in my model through external economies of scale in production. Moreover, structural transformation in their model is driven by comparative advantage forces, while in my model it is driven by non-homothetic preferences. Finally, their model focuses on Argentina (while mine covers the whole world) during the late 19th and early 20th century (while mine focuses on the recent past, between the 1960s and the 2000s). Cosar and Fajgelbaum (2016) develop a two-sector model in which international trade integration affects the spatial population distribution within a country, with a central role for differential trade access. However, trade-induced changes in sectoral composition are driven by comparative-advantage mechanisms, not by structural transformation, which is absent from their model. Furthermore, they assume domestic locations are homogeneous with regard to comparative advantage, while my model implicitly relaxes that assumption by allowing flexible sector-specific fundamental productivities to vary freely across locations. Additionally, their assumptions on productive technology rule out agglomerative forces. Finally, they empirically test the model's predictions using reduced-form analysis of Chinese data, while my empirical exercises use worldwide data and are based on using the calibrated model to predict counterfactual population distributions under alternative trade-cost structures. It should be mentioned that policymakers have also demonstrated interest in the apparent connection between trade integration and deconcentration of urban systems, particularly in Latin America (ECLAC (2005)), but have not generally performed formal analyses to try to assess whether such stylized facts are causal.

I follow a large international trade literature studying how to estimate trade gravity models. Anderson and van Wincoop (2003) is particularly relevant for studying the border-crossing cost. I follow Head and Mayer (2014) instructions on how to implement estimation in practice, in particular the exhortation to use Poisson Pseudo Maximum-Likelihood (PPML) as shown by Santos-Silva and Terneyro (2006).

My framework leans heavily on the quantitative spatial model literature, most of all on Allen and Arkolakis (2014) and Allen and Donaldson (2020). Other influential examples of that literature are Caliendo et al. (2018), Desmet et al. (2018), Ramondo et al. (2012, 2016), Redding (2016), Adao et al. (2020), and Redding and Rossi-Hansberg (2017), the last of which is a helpful overview of the literature. My main theoretical distinction with respect to the literature is to incorporate non-homothetic PIGL preferences into an otherwise standard spatial model, thus allowing structural change to be explicitly manifested as a force that can affect economic geography. My main distinction on the empirical front is to calibrate the model for the whole world economy, which to the best of my knowledge can only be compared to Desmet et al. (2018), with which my paper has several similarities and differences. In particular, I am highly indebted to them for their use of G-Econ data to measure local per capita income and for their methodology to transform transportation network maps into a cost raster which is then used to compute bilateral distances. On the other hand, the two papers have very different focuses. My paper features structural transformation forces, emphasizes the importance of trade access in determining spatial concentration, and focuses on long-term steady-state equilibria, while their paper is scarcely concerned with concentration, pays much more attention to innovation, growth, and international migration, and focuses on transitional dynamics. They also use data on subjective well-being to disentangle countries' welfare and amenity levels, which is somewhat moot in the context of my paper because I rule out international migration by assumption.

Finally, my representation of non-homothetic preferences as a PIGL indirect utility function borrows directly from the literature on structural transformation, chiefly Boppart (2014) and Eckert and Peters (2018). Most of this macroeconomic literature deals with aggregate economies rather than with subnational locations. An exception is Eckert and Peters (2018), who use subnational US data for 1880-2000 to assess the extent to which country-level structural transformation is associated with worker reallocation across labor markets. However, there are multiple differences between their paper and this one: I use global data rather than focusing on the US; I use data for relatively recent periods (1960s-2010s) while their data covers older periods (e.g. the 19th century); spatial concentration as a key outcome of interest for me, while they are not particularly interested in it; I analyze the geographic impacts of both structural transformation and changes in international trade costs, while they are centrally concerned with the former but not with the latter; their production function includes capital as a factor and features exogenous productivities, while mine has labor as the sole factor and features external economies of scale which generate agglomeration effects; they assume goods are freely traded, while I put trade costs at the center stage; they posit a dynamic, overlapping-generations economy with savings and investment, while my model is static and should be interpreted as representing a long-run equilibrium. In terms of results, my decomposition exercise finds that structural transformation plays a minor role in shaping 1990-2015 changes in spatial concentration, which echoes their finding that structural transformation in the US did not lead to a major spatial reallocation of workers away from labor markets that were initially specialized in agriculture.

The rest of this paper is organized as follows. Section 2 presents the theoretical framework. Section 3 explains my two-step methodology to bring the model to the data. Section 4 presents data sources and describes data adjustments. Section 5 presents results and comments on them. Section 6 concludes.

2 Framework

My model is based on an application of the quantitative spatial model of Allen and Donaldson (2020) to an international context. While they use their model to study the historical economy of the United States and its component counties, I take a broader look by applying the spatial model to the whole world, with its multiple countries which in turn are composed of subnational locations such as states, provinces, and prefectures. Moreover, their dynamic model is appropriate to study the evolution of the US spatial economy over decades and centuries, while I will instead use a static model and focus on the global economy in a single year (2005).[2] My model should thus be interpreted as representing the steady state of an Allen-Donaldson model applied to the global economy. In a nutshell, it can be argued that my paper is broader in space but narrower in time when compared to Allen-Donaldson's.

The world is composed of multiple countries, each composed of multiple locations. There are two sectors, agriculture and non-agriculture, each producing geographically differentiated goods (i.e. the Armington assumption). Each location has a continuum of perfectly competitive firms, who produce goods and sell them around the world by paying an iceberg trade costs. There are external economies of scale in production (agglomeration economies) but constant returns to scale at the firm level.

The world is populated by agents who are both consumers and workers. Each

[2] In decomposition exercises, I also compare the 2005 economy to the economy of another year, namely 1990. I use comparative-static tools to perform this comparison, which implicitly assumes that the economy was in steady state in each of these two years.

utility-maximizing agent is born in a given location, chooses a location to emigrate to, works for a firm, earns wages, consumes goods, and enjoys local amenities. I assume migration is only possible within countries, which imbues the model with a meaningful a notion of "country" (namely, a country is the territory to which an agent can feasibly migrate given the location where she was born). Households have non-homothetic preferences of the PIGL form, as in Eckert and Peters (2018). Holding prices fixed, the share of spending in non-agricultural goods increases with income. As a result, agriculture becomes a relatively less important sector as a country becomes richer (i.e. structural transformation).

General equilibrium in the world economy is defined by optimality conditions (firms maximizing profits, agents maximizing utility) and by market clearing in goods markets (local sectoral income equals worldwide sales of local sectoral good) and in labor markets (location population equals both total local immigration and total local emigration). I show that, in equilibrium, the population share of a country's largest location follows an analytical expression that depends on the relative attractiveness of that location in terms of trade access, fundamental sectoral productivities and amenities, and non-agricultural expenditure share.

In Sections 2.1-2.6, I present each aspect of the model in further detail.

2.1 Setting

In the model, the world is represented by a finite set $\mathcal{S}$ of locations, each of which denoted by $i \in \mathcal{S} = \{1, ..., N\}$. Individual locations can be interpreted as subnational units (such as provinces, states, municipalities, etc.). The set $\mathcal{S}$ of locations is partitioned into a set $\mathcal{C}$ of countries, indexed by $c \in \mathcal{C} = \{1, ..., C\}$. For convenience, I also define a function $c : \mathcal{S} \to \mathcal{C}$ which maps each location to the country to which it belongs.

Each location i in $\mathcal{S}$ is inhabited by worker-households and firms. Each firm and worker operates in either of two economic sectors: agriculture ($s = A$) and non-agriculture ($s = N$). Denote with L_i the endogenous population of location i and with $\bar{L}_c$ the exogenous population of country c.

Finally, it is convenient to define a *primacy function* $p : \mathcal{C} \to \mathcal{S}$, which maps each country c to the largest city of that country. Following the literature, we also refer to that largest city as the country's primate city or just primate. The fraction of a country's population that lives in its primate city is denoted *primacy rate*, which can be straightforwardly computed by $Primacy_c = L_{p(c)}/\bar{L}_c$. Note that the primacy function $p(.)$ is also an endogenous equilibrium object.

2.2 Consumer-worker

Each agent is born in a specific location i in country c, then chooses to move to a location j of her choice within the same country c.[3] She then inelastically supplies one unit of labor to a firm in location j, earns wage income, enjoys locals amenities, and consumes a variety of geographically differentiated goods (Armington assumption). The resulting agent's utility is given by the following formula:

$$W_j(\epsilon) = \underbrace{C_j u_j}_{\equiv W_j} \epsilon_j, \tag{1}$$

where u_j is the local amenity, ϵ_j is an agent-specific idiosyncratic taste shock for location j, and C_j is a PIGL indirect utility function given by:

$$C_j = C(w_j, P_j^A, P_j^N) = \frac{1}{\eta}\left(\frac{w_j}{(P_j^A)^\phi (P_j^N)^{1-\phi}}\right)^\eta - \frac{\nu}{\gamma}\left(\frac{P_j^A}{P_j^N}\right)^\gamma + \frac{\nu}{\gamma} - \frac{1}{\eta}, \tag{2}$$

where w_j the local wage, and P_j^s is the local CES ideal price index for sector $s \in \{A, N\}$ which can be written as:

$$P_j^s = (\sum_{k \in \mathcal{S}} (p_{kj}^s)^{1-\sigma_s})^{\frac{1}{1-\sigma_s}}, \tag{3}$$

where $\sigma_s > 1$ is the elasticity of substitution for sector s, and p_{kj}^s is the (bilateral) price of a sector-s good produced in location k and consumed in location j. To facilitate exposition, I also defined a welfare variable W_j that is the product of the PIGL consumption variable and the local amenity: $W_j = C_j u_j$.

Inspection of equations (1) and (2) shows us that the consumption portion of the agent's utility can be described as a composition of CES preferences within sectors and PIGL preferences across sectors. As we will see, the implied demand system yields tractable equations while allowing for income effects that shift consumption from agriculture towards non-agriculture as the agent's income increases. These income effects become more apparent in the following equation for the agriculture consumption share υ_j^A, which is implied by the PIGL preferences:

$$\upsilon_j^A = \phi + \nu(\frac{P_j^A}{P_j^N})^\gamma w_j^{-\eta} \tag{4}$$

Local amenities, represented by u_j in the utility function (1), can be further decomposed into an exogenous and an endogenous component according to the equation:

$$u_j = \bar{u}_j L_j^\beta, \tag{5}$$

[3]Note that the destination location j may be the birth location i itself.

where $\bar{u}_j$ is the (exogenous) fundamental local amenity, L_j is local population, and $\beta \leq 0$ is a parameter that governs the intensity of congestion forces. Following the urban economics literature, we can interpret the endogenous component L_j^β as the negative effect of spatial congestion on agents' utility.

Each agent receives an idiosyncratic taste shock ϵ_j for each location j. These shocks follow a Frechet distribution: $\Pr(\epsilon_j \leq x) = \exp(-x^{-\theta})$, with $\theta > 1$, and the shocks are distributed i.i.d. across agents and locations. The presence of this ϵ_j term in the utility function helps to "convexify" equilibrium distributions, guaranteeing that each location j is chosen as a destination by a positive measure of agents and thus has a non-zero population L_j.

The agent's migration decision can be concisely summarized by the following maximization program:

$$\max_{j \in c(i)} W_j(\epsilon) \tag{6}$$

where $W_j(\epsilon)$ is given by equations (1) and (2).

Note that the agent is only allowed to migrate to another location within the same country where she was born. Besides increasing tractability, this assumption also establishes a meaningful conceptual notion of "country" within the context of the model. Namely, a country is the set of locations to which a person who is born in a certain location can feasibly migrate.

2.3 Firm

The goods consumed by agents are produced by firms. Each location i and sector s has a continuum of perfectly competitive firms producing the local sector-s good according to the following production technology:

$$q_i^s = A_i^s l_i^s, \text{ with: } A_i^s = \bar{A}_i^s (L_i^s)^{\alpha_s} \tag{7}$$

where q_i^s is output quantity, l_i^s is firm employment, $\bar{A}_i^s$ is the local fundamental productivity parameter, L_i^s is local employment in sector s, and $\alpha_s \geq 0$ is a parameter.

Equation (7) shows us that the productive technology features constant returns to scale at the firm level but increasing returns to scale at the local industry level. This phenomenon is usually described in the literature as *external economies of scale* or *agglomeration economies.* The strength of agglomeration economies is governed by the parameter α_s. The presence of the $(L_i^s)^{\alpha_s}$ term in equation (7) is the central way in which the agglomerative forces described by the NEG literature appear in this model.

The goods produced by a firm are sold to consumers worldwide. In order to ship a unit of its good to a location j, a firm from location i and sector s pays a multiplicative "iceberg" shipping cost given by $\tau_{ij}^s \geq 1$, with $\tau_{ii}^s = 1$.

The assumptions described above regarding perfect competition, production technology, and iceberg shipping costs imply the following pricing equation for the bilateral unit price p_{ij}^s charged by a sector-s firm from location i who sells to location j:

$$p_{ij}^s = \frac{\tau_{ij}^s w_i}{A_i^s} \tag{8}$$

2.4 Gravity Flows

Given the assumptions on consumer preferences and firm pricing embedded in equations (2), (3), and (8), it can be shown that bilateral trade flows have the following "gravity"-like form:

$$X_{ij}^A = \left[\frac{\tau_{ij}^A w_i}{A_i^A P_j^A}\right]^{1-\sigma_A} \upsilon_j^A w_j L_j \tag{9}$$

$$X_{ij}^N = \left[\frac{\tau_{ij}^N w_i}{A_i^N P_j^N}\right]^{1-\sigma_N} \upsilon_j^N w_j L_j \tag{10}$$

where $\upsilon_j^N = 1 - \upsilon_j^A$ is non-agricultural expenditure share in location j, and X_{ij}^s is the dollar value of trade flows in sector s from location i to location j. The total bilateral trade flows from location i to location j is given by: $X_{ij} = X_{ij}^A + X_{ij}^N$.

The formulas in equations (9) and (10) closely follow the usual gravity trade formulas in the trade literature (e.g. Allen and Arkolakis (2014)). The main difference is the inclusion of multiplicative terms υ_j^A and υ_j^N which account for a location's relative expenditure on agricultural and non-agricultural goods, respectively. As a location j becomes richer, its consumption basket becomes relatively heavier on non-agricultural goods.

The assumptions on agent utility, amenities, and migration decisions embedded in equations (1), (5), and (6) imply that bilateral gross migration flows also follow a "gravity"-like form as given by the following equation:

$$L_{ij} = \left(\frac{(W_j)^\theta}{\sum_{k\in\mathcal{S}}(W_k)^\theta}\right) L_i \tag{11}$$

where L_{ij} is the number of migrants who are born in location i and choose to live in location j.

Equation (11) shows us that a location j will tend to attract many migrants if it has a relatively high welfare W_j. In my model, equilibrium should be interpreted as the steady state of a more general dynamic model. In other words, one can think of this model as the sub-case (of a dynamic model) in which the total population L_i of each location i is constant across periods, which implies that *net* migration flows are zero. *Gross* migration flows L_{ij} need not be zero: it is sufficient that gross "inbound" flows ($\sum_{k\neq j} L_{kj}$) equal gross "outbound" flows ($\sum_{k\neq j} L_{jk}$) for each location j. If that equality holds, then inward and outward flows cancel out and local population remains constant.

2.5 Equilibrium

I impose four equilibrium conditions to close the model. The first condition establishes market clearing in goods markets. Namely, for each location i and sector s, the total income received by firms in that location-sector must equal their total sales across all locations in the world:

$$w_i L_i^s = \sum_{j\in\mathcal{S}} X_{ij}^s, \ \forall(i,s) \tag{12}$$

The second condition establishes that a location's population must correspond to its total immigration and total emigration:[4]

$$L_i = \sum_{j\in\mathcal{S}} L_{ij} = \sum_{j\in\mathcal{S}} L_{ji}, \ \forall i \tag{13}$$

The third condition simply links a location's population to the sum of its two subpopulations, the one that works in agriculture and the one that works in non-agriculture:

$$L_i = L_i^A + L_i^N, \ \forall i \tag{14}$$

Finally, the fourth condition requires that a country's (exogenous) population must equal the sum of the populations of all locations that compose that country:

$$\bar{L}_c = \sum_{i\in c} L_i, \ \forall c\in\mathcal{C} \tag{15}$$

Having presented the four equilibrium conditions, we are ready to formally define equilibrium:

Definition 1 (Equilibrium)**.** Given parameters $(\sigma_A, \sigma_N, \theta, \alpha_A, \alpha_N, \beta, \nu, \eta, \gamma)$ and exogenous variables $\{\ \bar{A}_i^A, \bar{A}_i^N, \bar{u}_i\ \}_{i\in\mathcal{S}}$, $\{\tau_{ij}^A, \tau_{ij}^N\}_{(i,j)\in\mathcal{S}^2}$, $\{\bar{L}_c\}_{c\in\mathcal{C}}$, an equilibrium is a set of endogenous variables $\{C_i, w_i, L_i, L_i^A, L_i^N, W_i, P_i^A, P_i^N, v_i^A, u_i, A_i^A, A_i^N\}_{i\in\mathcal{S}}$, $\{X_{ij}^A, X_{ij}^N, L_{ij}\}_{(i,j)\in\mathcal{S}^2}$ that satisfies equations (2), (3), (4),(5), (7), (9) (10) (11), equilibrium conditions (12)-(15), and such that $W_j = C_j u_j$.

It is possible to rewrite the equilibrium system in a simplified manner that conveniently reduces the number of variables and equations. Namely, given parameters and

[4]Note that the total immigration to a location j includes immigration from itself, L_{jj}. The same applies to total emigration.

exogenous variables, an equilibrium is a set of endogenous variables $\{w_i,\ L_i,\ L_i^A,\ L_i^N,\ W_i,\ P_i^A,\ P_i^N,\ \upsilon_i^A,\ u_i,\ A_i^A,\ A_i^N\}_{i\in\mathcal{S}}$ that satisfies the following four equations:

$$w_i^{\sigma_s}(L_i^s)^{1-\alpha_s(\sigma_s-1)} = (\bar{A}_i^s)^{\sigma_s-1}\sum_{j\in\mathcal{S}}(\tau_{ij}^s)^{1-\sigma_s}(P_j^s)^{\sigma_s-1}\upsilon_j^s L_j w_j \tag{16}$$

$$(P_j^s)^{1-\sigma_s} = \sum_{i\in\mathcal{S}}(\tau_{ij}^s w_i)^{1-\sigma_s}(\bar{A}_i^s(L_i^s)^{\alpha_s})^{\sigma_s-1} \tag{17}$$

$$L_i^A + L_i^N = L_i = \frac{W_i^\theta}{\sum_{k\in c}W_k^\theta}\bar{L}_c \tag{18}$$

$$W_j = \bar{u}_j L_j^\beta\Big[\frac{1}{\eta}\big(w_j(P_j^A)^{-\phi}(P_j^N)^{\phi-1}\big)^\eta - \frac{\nu}{\gamma}\big(P_j^A/P_j^N\big)^\gamma + \frac{\nu}{\gamma} - \frac{1}{\eta}\Big] \tag{19}$$

The main advantage of writing the equilibrium system in this simplified way is that it suggests an equilibrium-computing algorithm that will be useful later on.

2.6 Primacy and Market Access

I consider a special case of the model to better understand its main mechanisms. I focus on the model's predictions for the primacy rate, my main measure of spatial concentration. Assume $\sigma_A = \sigma_N = \sigma$ and $\alpha_A = \alpha_N = \alpha$. That is, agglomeration parameters and elasticities of substitution are the same in both sectors. Then it can be shown that the model yields the following equation for the primacy index of each country c in $\mathcal{C}$:

$$Primacy_c \equiv \frac{L_{p(c)}}{\bar{L}_c} = \frac{\Big(\bar{u}_{p(c)}\rho_{p(c)}\zeta_{p(c)}^{-\frac{\eta}{\Omega}}\Big)^{\frac{\theta}{1-\theta(\beta+\eta/\Omega)}}}{\sum_{k\in c}\Big(\bar{u}_k\rho_k\zeta_k^{-\frac{\eta}{\Omega}}\Big)^{\frac{\theta}{1-\theta(\beta+\eta/\Omega)}}} \tag{20}$$

where $\rho_i = [\frac{1}{\eta}(P_i^A)^{-\eta\phi}(P_i^N)^{\eta(\phi-1)} - \frac{1}{\gamma}(\upsilon_i^A - \phi)]$ is (the inverse of) the ideal total price index, $\zeta_i = [(\bar{A}_i^A)^{\sigma-1}\Pi_i^A]^{\frac{1}{1-\alpha(\sigma-1)}} + [(\bar{A}_i^N)^{\sigma-1}\Pi_i^N]^{\frac{1}{1-\alpha(\sigma-1)}}$ is a composite of fundamental productivities and producer market access, $\Pi_i^s = \sum_{j\in\mathcal{S}}(\tau_{ij}^s)^{1-\sigma}(P_j^s)^{\sigma-1}\upsilon_j^s w_j L_j$ is producer market access, and $\Omega \equiv \frac{\sigma}{\alpha(\sigma-1)-1}$.

The differential form of equation (20) is given by:

$$\begin{aligned}
\left(\frac{1-\theta(\beta+\frac{\eta}{\Omega})}{\theta}\right) d\ln(Primacy_c) = & \underbrace{\kappa_{p(c)}(-d\upsilon^A_{p(c)}) - \sum_{k\in c}\left(\frac{L_k}{\bar{L}_c}\right)\kappa_k(-d\upsilon^A_k)}_{\text{Structural Change Force}} \\
& + \underbrace{\Xi_{p(c)} d\ln(I_{p(c)}) - \sum_{k\in c}\left(\frac{L_k}{\bar{L}_c}\right)\Xi_k d\ln(I_k)}_{\text{Differential Trade Access Force \#1: Consumer Market Access}} \\
& + \underbrace{\frac{\eta}{\sigma}\Big[\sum_s \mu^s_{p(c)} d\ln(\Pi^s_{p(c)}) - \sum_{k\in c}\left(\frac{L_k}{\bar{L}_c}\right)\sum_s \mu^s_k d\ln(\Pi^s_k)\Big]}_{\text{Differential Trade Access Force \#2: Producer Market Access}} \\
& + \underbrace{d\ln(\bar{u}_{p(c)}) - \sum_{k\in c}\left(\frac{L_k}{\bar{L}_c}\right) d\ln(\bar{u}_k)}_{\text{Local Fundamental Force \#1: Amenities}} \\
& + \underbrace{\frac{\eta(\sigma-1)}{\sigma}\Big[\sum_s \mu^s_{p(c)} d\ln(\bar{A}^s_{p(c)}) - \sum_{k\in c}\left(\frac{L_k}{\bar{L}_c}\right)\sum_s \mu^s_k d\ln(\bar{A}^s_k)\Big]}_{\text{Local Fundamental Force \#2: Sectoral Productivities}},
\end{aligned} \tag{21}$$

where:

$$\mu^s_i = (\zeta_i)^{-1}[(\bar{A}^s_i)^{\sigma-1}\Pi^s_i]^{\frac{1}{1-\alpha(\sigma-1)}},$$

$$\kappa_i = \frac{1}{\gamma\rho_i}, \quad \Xi_i = \frac{I^\eta_i}{\rho_i},$$

and $I_i = (P^A_i)^{-\phi}(P^N_i)^{\phi-1}$ is the Cobb-Douglas portion of the ideal price index, which coincides with the ideal price index when preferences are homothetic ($\nu = 0, \eta = 1$).

Let us examine equations (20)-(21) more carefully. Variable Π^s_i is producer market access for firms in sector s of location i. This variable will be high if these firms' customers have high incomes ($w_j L_j$), relatively high price levels for sector-s goods (P^s_j), and are located relatively "close" (low τ^s_{ij}). Overall, producer market access Π^s_j can be interpreted as a measure of how good are the business opportunities for the producer in terms of having rich markets with a low degree of competitiveness located relatively nearby. Variable ζ_i is a cross-sector average of a location's productivity and producer market access. It will be higher whenever a location is very productive (high $\bar{A}^A_i$ or $\bar{A}^N_i$) or has privileged access to lucrative markets (high Π^A_i or Π^N_i). Finally, variable ρ_i is the inverse of the ideal price index.[5] It is high when sectoral price indices P^A_i and P^N_i are low, but also involves a second term ($-\frac{1}{\gamma}(\upsilon^A_i - \phi)$) reflecting non-homothetic preferences.

[5]That is, it can be shown that $C_j = \frac{w_j}{(\rho_i)^{-1}}$.

Equation (20) has a relatively straightforward interpretation. A country c will have a high primacy rate if its primate city $p(c)$ has a high fundamental amenity (high $\bar{u}_{p(c)}$), a low ideal price index (high $\rho_{p(c)}$), or a high composite $\zeta_{p(c)}$ of producer market access and fundamental productivities. Moreover, what matters is not the absolute value of these three variables but the relative value they assume for the primate city compared to other domestic locations, as evidenced by the denominator $\sum_{k\in c}(\bar{u}_k \rho_k \zeta_k^{-\frac{\eta}{\Omega}})^{\frac{\theta}{1-\theta(\beta+\eta/\Omega)}}$ in equation (20).

Which factors can explain changes in a country's primacy rate? We can use equation (21) to help answer this question by decomposing changes in primacy into the contributions of structural transformation, changes in trade access, and changes in local fundamentals. For example, changes in trade costs τ will directly affect producer market access Π and indirectly affect consumer market access I through their effect on sectoral price indices P^A, P^N. According to equation (21), a country's primacy rate will then increase if consumer and producer market access improve more for the primate location than for other domestic locations. In other words, since trade access improves differentially across domestic locations, the direction in which primacy moves will depend on whether the primate location's trade access is relatively privileged or harmed by the shock. Hence the idea of a "differential-trade-access" force. Analogous observations apply to structural transformation forces and local-fundamentals forces. Thus, structural transformation, differential trade access, and local fundamentals each play a particular role in shaping spatial concentration, as measured by the primacy rate. Finally, note that agglomerative NEG forces are also represented in the expression (albeit indirectly) through parameter α.

3 Bringing the Model to the Data

Having presented the model, I now tackle the question of how to bring the model to the data. By doing so, I will be able to interpret real-world data through the lens of the model and thus to estimate the contributions of different factors to spatial concentration. It will be helpful to keep this goal in mind as this Section 3 presents the specific steps I take to achieve it.

The estimation procedure has two steps. In the first step, I estimate trade costs. Using equations (9)-(10) as a guide, I run gravity regressions using data on global trade and transportation infrastructure, which then yields estimates of the structure of bilateral trade costs, and in particular of international trade costs ("border-crossing parameters"). Since I run these regressions for different years, my trade-cost estimates are also year-specific, covering years from 1962 to 2019. In the second step, I calibrate the model to the global 2005 economy using location-level data on populations, sectoral employments, and incomes, as well as the trade-cost estimates obtained in the first step. Specifically, I use the equilibrium system (16)-(19) to back out the exact values of fundamental productivities ($\bar{A}^A, \bar{A}^N$) and amenities ($\bar{u}$) that perfectly rationalize the observed 2005 data, which covers 1611 locations across 192 countries.

Having calibrated the model, I use it for a few empirical exercises. I perform a series of counterfactual exercises using the equilibrium system (16)-(19). Specifically, for each exercise, I impose a counterfactual trade cost structure τ^{cf} (while keeping parameters and exogenous variables such as $\bar{A}^A$, $\bar{A}^N$, $\bar{u}$ constant at their 2005 levels) and recompute the equilibrium spatial distributions of population (L^{cf}) and wages (w^{cf}) under this new trade-cost structure. By comparing actual and counterfactual population distributions, I can assess the effect that the counterfactual trade-cost shock would have on the spatial concentration of population. I also perform an accounting exercise using decomposition equation (21). Specifically, I repeat the calibration procedure for the global 1990 economy, then use the decomposition equation to disentangle the contributions of structural transformation, changes in trade access, and changes in local fundamentals in explaining the sample variation in observed 1990-2005 primacy changes for the 44 countries for which I have data on subnational locations for both 1990 and 2005.

3.1 First Step: Gravity

In the first step, I estimate bilateral trade costs. To do that, I start by following Ramondo et al. (2012) and imposing the following functional form for trade costs:

$$\tau^s_{ijt} = (E^s_t)^{\mathbb{1}_{j \notin c(i)}} \prod_{z=1}^{B} (C^{s,z})^{\mathbb{1}_{dist_{ij} \in b_z}} \tag{22}$$

where τ^s_{ijt} is the bilateral iceberg trade cost in sector s between locations i and j in year t, $E^s_t \geq 1$ is a sector- and year-specific border-crossing parameter, $\{C^{s,z}\}^B_{z=1}$ is a set of sector-specific "cost-of-distance" parameters, $dist_{ij}$ is the distance between locations i and j (further detailed below), and $\{b_z\}^B_{z=1}$ is a set of equally-spaced distance "bins". Thus, trade costs have two components: an "international" cost E^s_t that is paid whenever a good is shipped across international borders, and a "distance" cost $C^{s,z}$ that depends on distance in a potentially non-linear manner.

The goal of the first step is to estimate parameters E^s_t and $\{C^{s,z}\}^B_{z=1}$ which will in turn yield estimates of trade costs through equation (22). This is where using model-implied trade equations (9) and (10) is helpful. Using equation (22) to substitute for τ_{ij} into these two equations, we obtain the following estimable trade gravity equation:

$$\ln(X^s_{ijt}) = \sum_{z=1}^{B} \underbrace{(1-\sigma^s)\ln(C^{s,z})}_{\tilde{C}^{s,z}} \mathbb{1}_{dist_{ij}\in b_z} + \underbrace{(1-\sigma^s)\ln(E^s_t)}_{\tilde{E}^s_t} \mathbb{1}_{j\notin c(i)} + \omega^{s,X}_{it} + \omega^{s,M}_{jt} + \eta^s_{ijt} \tag{23}$$

where $\omega^{s,X}_{it} = (1-\sigma_s)\ln(w_i/A^s_i)$ and $\omega^{s,M}_{jt} = \ln((P^s_j)^{\sigma_s-1}\upsilon^s_j w_j L_j)$ are exporter-year and importer-year fixed effects respectively, and η^s_{ijt} is an added error term.

Given data on trade flows X^s_{ijt}, distances $dist_{ij}$, and the mapping of locations to countries (i.e. the function $c(.)$), one can estimate equation (23), thus recovering estimates of $\{\tilde{C}^{s,z}\}_z$ and $\tilde{E}^s_t$ (respectively denoted $\{\hat{\tilde{C}}^{s,z}\}_z$ and $\hat{\tilde{E}}^s_t$). Following the international trade literature, the estimation method used is Poisson Pseudo-Maximum Likelihood (PPML) (Santos-Silva and Tenreyro (2006), Head and Mayer (2014)). It should be noted that identification of the border-crossing term $\tilde{E}^s_t$ requires variation in the indicator variable $\mathbb{1}_{j\notin c(i)}$, which means in practice that there must exist data on both intranational and international trade flows for at least some countries in the estimation sample. This topic will be further discussed when I present the data in Section 4.

Given estimates $\{\hat{\tilde{C}}^{s,z}\}_z$ and $\hat{\tilde{E}}^s_t$ obtained from equation (23), and assuming specific values for parameters (σ_A, σ_N), one can then use the definitions of $\{\tilde{C}^{s,z}\}_z$ and $\tilde{E}^s_t$ to back out estimates of trade-cost parameters $\{C^{s,z}\}_z$ and E^s_t:

$$\hat{E}^s_t = \exp\Big(\frac{\hat{\tilde{E}}^s_t}{1-\sigma_s}\Big),\ \hat{C}^{s,z} = \exp\Big(\frac{\hat{\tilde{C}}^{s,z}}{1-\sigma_s}\Big), \tag{24}$$

Finally, using estimates $\hat{E}^s_t$ and $\hat{C}^{s,z}$, I compute estimated trade costs $\{\hat{\tau}_{ijt}\}_{ij}$ following the parametrization from equation (22):

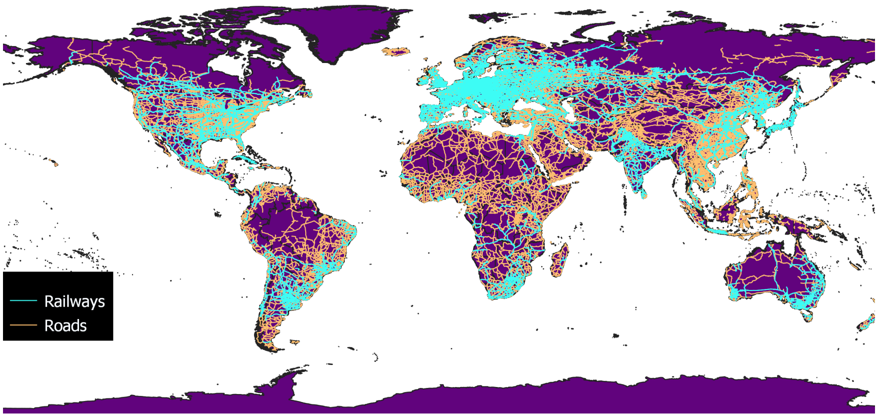
$$\hat{\tau}^s_{ijt} = (\hat{E}^s_t)^{\mathbb{1}_{j\in c(i)}} \prod_{z=1}^{B} (\hat{C}^{s,z})^{\mathbb{1}_{dist_{ij}\in b_z}} \tag{25}$$

3.1.1 Measuring Distances

One of the variables required for the estimation of gravity equation (23) described in Section 3.1 is bilateral distance, $dist_{ij}$. In this paper, I do not use straight-line distance, as is common in the literature, but rather present a methodology for accounting for transportation infrastructure when computing bilateral distances.

This methodology requires using worldwide infrastructure maps, which I obtain from the Natural Earth website (see Section 4 for details). Figure 2 presents the final map. One notes that the density of transportation infrastructure like roads and rail varies substantially across regions. For example, transportation density is generally high in Europe but low in northern Canada and northern Russia. This suggests that usual straight-line distance measurements, which ignore transportation infrastructure, could be misleading. Moreover, since much of global transportation happens over water, it could be important to account for the difference in trade costs between water and land when measuring bilateral distances.

Figure 2: Global Transportation Infrastructure



Notes: the figure portrays the global road and rail networks. Data on location of rail and road was downloaded from the Natural Earth webasite: https://www.naturalearthdata.com

Using QGIS software, I transform the global infrastructure map into the cost raster displayed in Figure 3. This is done by first partitioning the Earth's surface into grid cells measuring 1°of latitude by 1°of longitude. For each of six transportation modes m, I assume the mode-specific cost of traversing a single hypothetical grid cell using that mode is equal to κ_m, the value of which is based on estimates from Allen and Arkolakis (2014).[6] I then ascribe a traversal cost $T(x)$ to each grid cell x that corresponds to the lowest-cost transportation mode present in that grid cell.[7]

Formally, let $M(x)$ denote the set of all transportation modes present in grid cell x. Since every grid cells contains water or land, the set $M(x)$ is guaranteed to be non-empty for all cells x. The traversal cost $T(x)$ of cell x is then formally given by:

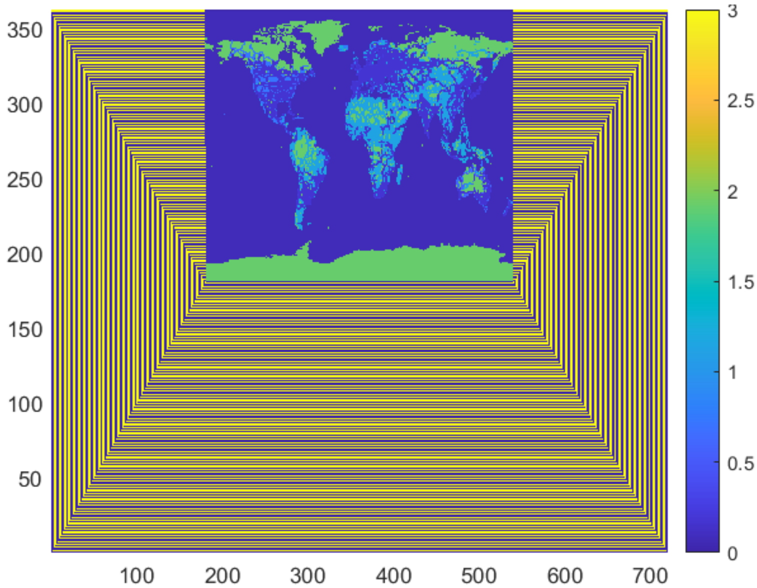
$$T(x) = \min_{m \in M(x)} \kappa_m \tag{26}$$

One notable feature in Figure 3 are the additional pipe-like cells "outside" the world map. These pipes are simply a programming device that will help with the computation of least-cost paths between pairs of cells. Specifically, a grid cell x within

[6]The values of mode-specific per-cell costs κ_m are: $\kappa_{water} = 0.0779$, $\kappa_{rail} = 0.1793$, $\kappa_{interstate\ highway} = 0.5640$, $\kappa_{non-interstate\ highway} = 0.717$, $\kappa_{arterial\ road} = 1.1270$, $\kappa_{land} = 1.9200$. See Appendix A.2 for a more detailed explanation of how these specific values were chosen.

[7]For example, suppose a grid cell x contains both land and rail. Since rail offers cheaper transportation than land, the grid cell's traversal cost $T(x)$ is set to κ_{rail}.

Figure 3: Cost Raster



Notes: the figure portrays a cost raster in which the value of each pixel is color-coded. The scale on the right-hand side indicates the mapping from colors to values.

a yellow pipe is set to have a very high traversal cost ($T(x) = 10^6 - 1$), while a blue-pipe cell x has a very low traversal costs ($T(x) = 0.00001$). This allows a traveler to move at near-zero cost from the eastern edge to the western edge of the world map (or vice-versa) as long as she stays at the same latitude. Similar low-cost pipes are placed in the North and South Poles. This allows me to implement a least-cost path algorithm in a straightforward manner by using the two-dimensional fast marching method of Allen and Arkolakis (2014). The algorithm will work despite the fact that, unlike Allen and Arkolakis (2014), I must account for the sphericity of the Earth.

Given the cost raster of Figure 3, we are finally ready to compute bilateral distances. The distance between each pair of grid cells is simply the total traversal cost of the least-cost path that connects the two grid cells. Formally, for a given origin grid cell i and destination grid cell j, define $\mathcal{P}_{ij}$ as the set of all continuous paths $\mathbb{p}$ on the world map that start at location i and end at location j.[8] Then, the distance between locations i and j is the results of the following minimization program:

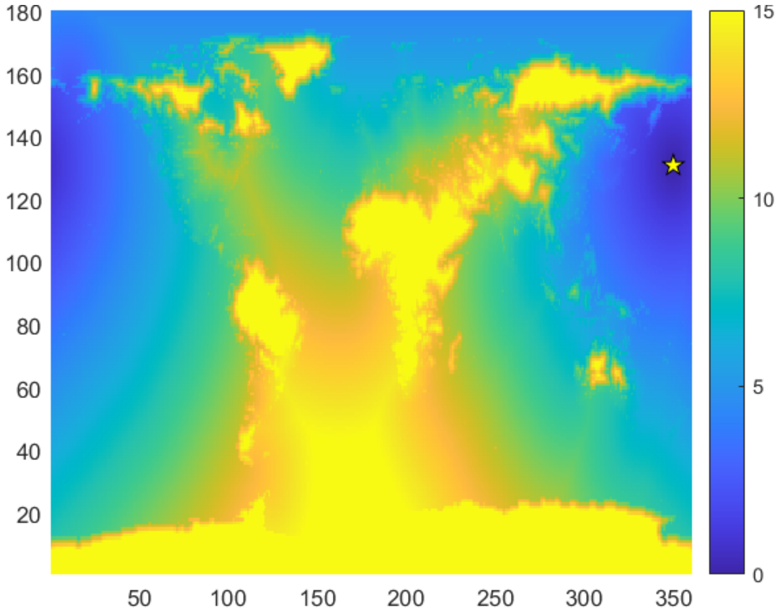
$$dist_{ij} = \min_{\mathbb{p} \in \mathcal{P}_{ij}} \sum_{x \in \mathbb{p}} T(x)$$

I implement the minimization program for all relevant grid cells using the fast

[8] A path $\mathbb{p}$ is classified as continuous if all pairs of adjacent cells within the path are either physically adjacent or connected by a blue pipe.

marching method (FMM) algorithm from Allen and Arkolakis (2014).[9] As an illustration, the heat map in Figure 4 portrays the bilateral distances between a single destination cell (market with a star) and all other cells in the world. Some of most accessible cells with respect to the star are located in the northwestern corner of the figure, showing that the blue-pipe device worked to cheaply connect the western and eastern ends of the map. Moreover, note that infrastructure matters: for example, the innermost regions of Africa are much more expensive to reach than Central Europe because rail and road networks are much denser in the latter. Finally, ocean transportation also matters: cell pairs that are connected by water pathways rather than land pathways tend to have lower bilateral distances.

Figure 4: Heat Map: Transportation Cost



Notes: the figure portrays a heat map in which the transportation cost between the pixel marked with the star and every other pixel on the map is color-coded. The scale on the right-hand side indicates the mapping from colors to values.

3.2 Second Step: Calibration

Having estimated trade-cost structures in the first step, I proceed to calibrate the model to the 2005 global economy. In this context, calibration means finding the vectors of fundamental productivities ($\{\bar{A}^A_{i,2005}, \bar{A}^N_{i,2005}\}_{i\in\mathcal{S}}$) and amenities ($\{\bar{u}_{i,2005}\}_{i\in\mathcal{S}}$) that

[9] For computational reasons, I do not implement the minimization program for all grid-cell pairs as this will not be necessary for the rest of the analysis. Instead, I implement the minimization program for all destination cells that house a centroid of at least one relevant polygon. Relevant polygons are polygons that represent a location/country that appears either in the estimation sample of the gravity equation (see Section 3.1) or in the calibration (see Section 3.2).

rationalize the observed 2005 spatial distribution of wages ($\{w_{i,2005}\}_{i\in\mathcal{S}}$) and sector-level populations ($\{L^A_{i,2005}, L^N_{i,2005}\}_{i\in\mathcal{S}}$) given estimated 2005 trade costs ($\{\hat{\tau}^s_{ij,2005}\}_{ij}$). What is meant by "rationalization" is that these vectors of fundamental productivities and amenities must be such that the equilibrium equations (16)-(19) hold exactly, given observed population, sectoral employment and wage distributions.

Formally, one recovers fundamental productivities and amenities by first solving the following equilibrium system for variables ($\bar{A}^A_{2005}, \bar{A}^N_{2005}, P^s_{2005}, \upsilon^s_{2005}$):

$$w^{\sigma_s}_{i,2005}(L^s_{i,2005})^{1-\alpha_s(\sigma_s-1)} = (\bar{A}^s_{i,2005})^{\sigma_s-1}\sum_{j\in\mathcal{S}}(\hat{\tau}^s_{ij,2005})^{1-\sigma_s}(P^s_{j,2005})^{\sigma_s-1}\upsilon^s_{j,2005}L_{j,2005}w_{j,2005}$$

$$(P^s_{j,2005})^{1-\sigma_s} = \sum_{i\in\mathcal{S}}(\hat{\tau}^s_{ij,2005}w_{i,2005})^{1-\sigma_s}(\bar{A}^s_{i,2005}(L^s_{i,2005})^{\alpha_s})^{\sigma_s-1}$$

$$\upsilon^A_{j,2005} = \phi + \nu(P^A_{j,2005}/P^N_{j,2005})^{\gamma}w^{-\eta}_{j,2005}$$

Intuitively, by solving this equation system I find the set of fundamental productivities that results in a set of prices such that the supply and demand for the good produced by each location-sector are perfectly balanced (while taking as given the distribution of wages, populations, and sectoral employments). The next step is to find the set of fundamental amenities that rationalizes the spatial distribution of population by solving the following equation system for variables ($\bar{u}_{2005}, W_{2005}$):

$$W_{j,2005} = \bar{u}_{j,2005}L^{\beta}_{j,2005}\Big[\frac{1}{\eta}\big(w_{j,2005}(P^A_{j,2005})^{-\phi}(P^N_{j,2005})^{\phi-1}\big)^{\eta} - \frac{\nu}{\gamma}\big(P^A_{j,2005}/P^N_{j,2005}\big)^{\gamma} + \frac{\nu}{\gamma} - \frac{1}{\eta}\Big]$$

$$L_{i,2005} = \frac{{W_{i,2005}}^{\theta}}{\sum_{k\in c}{W_{k,2005}}^{\theta}}\bar{L}_{c(i),2005}$$

$$\pi_c \equiv \Big(\sum_{k\in c}{W_{k,2005}}^{\theta}\Big)^{\frac{1}{\theta}} = 1, \forall c\in\mathcal{C}$$

Intuitively, by solving this equation system I first find the set of welfare values that makes agents desire a spatial distribution of population that corresponds to the distribution actually observed in the data, and then I back out the set of fundamental amenities needed to implement these welfare values (all while taking wages, populations, and prices as given).

Note that in addition to equilibrium conditions (18)-(19), I also use the normalization condition $\pi_c = 1$, which states that the adjusted welfare sum π_c in each country must equal one. Why is this condition necessary? The reason is that, within a given country, the average amenity level and the average welfare level are not separately

Table 1: Parameter Values

Parameter	Description	Value
σ_A, σ_N	Sector-level elasticity of substitution	4
θ	Dispersion parameter of taste shock	1.2
α_A, α_N	Sector-level agglomeration elasticity	0.1
β	Congestion elasticity	-0.345
ν	Degree of non-homotheticity	0.1
η	Concavity of Cobb-Douglas portion of utility	0.31
γ	Concavity of non-homothetic portion of utility	0.35
ϕ	Asymptotic agricultural share of consumption	0.01

Notes: for each parameter in the model, this table displays a description of the parameter and the value I impose for that parameter.

identified. For example, if a certain set of fundamental amenities and welfares rationalizes a specific data set, then that data set can be equally rationalized if we multiply all fundamental amenities in a given country by two while also multiplying all welfares in that country by two. Therefore, normalizing average welfare levels within a country is necessary to obtain an unique vector of fundamental amenities. The only relevant consequence of this normalization is that I will not be able to compare welfare levels across countries, which is not particularly problematic in the context of my model because I had already ruled out international migration by assumption. I will still be able to compare welfare levels across locations within a country and to compare welfare levels across different counterfactual scenarios for a given location or country.

Equations in this Section 3.2 contain multiple parameters (σ_A,σ_N,α_A,α_N,θ,β,η,ν,γ,ϕ) whose knowledge is necessary for calibration. Table 1 displays the specific values these parameters assume in my implementation. Elasticities of substitution σ_s use a typical value from the trade literature (e.g. Simonovska and Waugh (2011)). Agglomeration parameters α_s are based in Rosenthal and Strange (2004). Taste-dispersion parameter θ and PIGL parameter ν are chosen to guarantee equilibrium existence. Congestion parameter β is taken from Allen and Donaldson (2020). PIGL parameters η and γ are taken from Eckert and Peters (2018). Asymptotic agricultural share of consumption ϕ is set to the agricultural share of Germany's GDP in 2019.[10]

[10]Germany is chosen because it is a particularly developed economy and thus far along in its path of structural change. Other developed countries yield similar values. The German number is taken from: https://www.statista.com/statistics/295519/

3.3 Counterfactuals

Having estimated trade costs ($\{\hat{\tau}^s_{ijt}\}_{ijt}$) in the first step and computed fundamentals in the second step, I can use the calibrated model to perform empirical exercises, such as counterfactuals. Each counterfactual exercise can be thought of as the answer to the following question: how would the observed 2005 distribution of wages and populations change if the world's trade-cost structure changed while the other fundamentals remained the same? These exercises can thus help us understand the influence of trade access on the world's economic geography, in particular on spatial concentration.

Therefore, each counterfactual exercise is characterized by its specific counterfactual trade-cost matrix, τ^{cf}. Given this matrix τ^{cf} and the fundamental productivities and amenities ($\bar{A}^A_{2005}$,$\bar{A}^N_{2005}$,$\bar{u}_{2005}$) recovered in the second step, I can then compute the counterfactual equilibrium by solving the equilibrium system of equations (16)-(19) for counterfactual variables: wages, populations, sectoral employments, price levels, agricultural share of consumption, and welfare (w^{cf}, L^{cf}, $L^{cf,A}$, $L^{cf,N}$, $P^{cf,A}$, $P^{cf,N}$, $\upsilon^{cf,A}$, W^{cf}):

$$(w_i^{cf})^{\sigma_s}(L_i^{cf,s})^{1-\alpha_s(\sigma_s-1)} = (\bar{A}^s_{i,2005})^{\sigma_s-1}\sum_{j\in\mathcal{S}}(\tau_{ij}^{cf,s})^{1-\sigma_s}(P_j^{cf,s})^{\sigma_s-1}\upsilon_j^{cf,s}L_j^{cf}w_j^{cf}$$

$$(P_j^{cf,s})^{1-\sigma_s} = \sum_{i\in\mathcal{S}}(\tau_{ij}^{cf,s}w_i^{cf})^{1-\sigma_s}(\bar{A}^s_{i,2005}(L_i^{cf,s})^{\alpha_s})^{\sigma_s-1}$$

$$L_i^{cf,A} + L_i^{cf,N} = L_i^{cf} = \frac{(W_i^{cf})^\theta}{\sum_{k\in c}(W_k^{cf})^\theta}\bar{L}_{c(i),2005}$$

$$W_j^{cf} = \bar{u}_{j,2005}(L_j^{cf})^\beta\Big[\frac{1}{\eta}\big(w_j^{cf}(P_j^{cf,A})^{-\phi}(P_j^{cf,N})^{\phi-1}\big)^\eta - \frac{\nu}{\gamma}\big(P_j^{cf,A}/P_j^{cf,N}\big)^\gamma + \frac{\nu}{\gamma} - \frac{1}{\eta}\Big]$$

After solving this equation system, I can easily recover other variables of interest such as countries' primacy indices and adjusted welfare sums:

$$Primacy_c^{cf} = \frac{L^{cf}_{p_{cf}(c)}}{\bar{L}_{c,2005}} \tag{27}$$

$$\pi_c^{cf} = \big(\sum_{k\in c}(W_k^{cf})^\theta\big)^{\frac{1}{\theta}} \tag{28}$$

where $p_{cf}(.)$ is the primacy function that holds in the counterfactual equilibrium.

Note that computing adjusted welfare sums π_c^{cf} is useful because this variable offers a concept of country-level welfare. Moreover, since this variable was normalized in the second step to equal one, its counterfactual value can be straightforwardly interpreted as the country's relative welfare gain due to the counterfactual trade shock.

For example, if $\pi_c^{cf} = 1.8$ for a given country c, we can then conclude that this country's average welfare sum increased 80% due to the counterfactual change in trade costs.

Finally, given counterfactual variables ($\tau^{cf,A}$, $\tau^{cf,N}$, w^{cf}, $L^{cf,A}$, $L^{cf,N}$, L^{cf}, $\upsilon^{cf,A}$), it is straightforward to compute counterfactual trade flows according to equations (9)-(10):

$$X_{ij}^{cf,s} = \left[\frac{\tau_{ij}^{cf,s} w_i^{cf}}{\bar{A}_{i,2005}^{s} (L_i^{cf,s})^{\alpha_s} P_j^{cf,s}}\right]^{1-\sigma_A} \upsilon_j^{cf,s} w_j^{cf} L_j^{cf}$$

which then allows me to compute each country's counterfactual import share, as well as the causal effect of the counterfactual trade shock on the share of global trade in world GDP:

$$\left(\frac{M}{Y}\right)_c^{cf} = \frac{\sum_{s\in\{A,N\}}\sum_{j\in c}\sum_{i\notin c} X_{ij}^{cf,s}}{\sum_{s\in\{A,N\}}\sum_{j\in c}\sum_{i\in \mathcal{S}} X_{ij}^{cf,s}} \tag{29}$$

$$\Delta\left(\frac{M}{Y}\right)^{WLD} = \frac{\sum_{s\in\{A,N\}}\sum_{j\in c}\sum_{i\notin c} X_{ij}^{cf,s}}{\sum_{s\in\{A,N\}}\sum_{j\in c}\sum_{i\in \mathcal{S}} X_{ij}^{cf,s}} - \frac{\sum_{s\in\{A,N\}}\sum_{j\in c}\sum_{i\notin c} X_{ij,2005}^{s}}{\sum_{s\in\{A,N\}}\sum_{j\in c}\sum_{i\in \mathcal{S}} X_{ij,2005}^{s}} \tag{30}$$

Therefore, equations (27)-(30) allow us to assess the extent to which counterfactual trade shocks affected spatial concentration, welfare, and the volume of international trade. Additionally, it is also possible to assess how much spatial reallocation matters as a channel for the effects on welfare and volume by comparing the counterfactual values of these two variables against their values in an alternative "immobility" counterfactual in which the trade-cost matrix is still τ^{cf} but agents are not allowed to spatially reallocate away from their baseline location (see Appendix C for details).

3.4 Decomposition

I also use the calibrated model to perform a decomposition exercise. Specifically, I use equation (21) to decompose the changes in spatial concentration (as measured by the primacy rate) between 1990 and 2005 into the contributions of structural transformation, changes in trade access, and changes in local fundamentals (i.e. exogenous productivities and amenities). To implement the exercise, start by rewriting equation (21) in a more succinct form:

$$d\ln(Primacy_c) = \ln\left(\frac{Primacy_{c,2005}}{Primacy_{c,1990}}\right) = cont_c^{ST} + cont_c^{DTA} + cont_c^{LF}, \tag{31}$$

where:

$$cont_c^{ST} = \left(\frac{\theta}{1-\theta(\beta+\frac{\eta}{\Omega})}\right)\left[\kappa_{p(c),2005}(-d\upsilon_{p(c)}^{A}) - \sum_{k\in c}\left(\frac{L_{k,2005}}{\bar{L}_{c,2005}}\right)\kappa_{k,2005}(-d\upsilon_k^{A})\right],$$

$$cont_c^{DTA} = \Big(\frac{\theta}{1-\theta(\beta+\frac{\eta}{\Omega})}\Big)\Big\{\Xi_{p(c),2005} d\ln(I_{p(c)}) - \sum_{k\in c}\Big(\frac{L_{k,2005}}{\bar{L}_{c,2005}}\Big)\Xi_{k,2005} d\ln(I_k)$$
$$+ \frac{\eta}{\sigma}\Big[\sum_s \mu^s_{p(c),2005} d\ln(\Pi^s_{p(c)}) - \sum_{k\in c}\Big(\frac{L_{k,2005}}{\bar{L}_{c,2005}}\Big)\sum_s \mu^s_{k,2005} d\ln(\Pi^s_k)\Big]\Big\},$$

$$cont_c^{LF} = \Big(\frac{\theta}{1-\theta(\beta+\frac{\eta}{\Omega})}\Big)\Big\{d\ln(\bar{u}_{p(c)}) - \sum_{k\in c}\Big(\frac{L_{k,2005}}{\bar{L}_{c,2005}}\Big) d\ln(\bar{u}_k)$$
$$+ \frac{\eta(\sigma-1)}{\sigma}\Big[\sum_s \mu^s_{p(c),2005} d\ln(\bar{A}^s_{p(c)}) - \sum_{k\in c}\Big(\frac{L_{k,2005}}{\bar{L}_{c,2005}}\Big)\sum_s \mu^s_{k,2005} d\ln(\bar{A}^s_k)\Big]\Big\},$$

and the differential operator d refers to changes between 2005 and 1990, i.e. $dx_i = x_{i,2005} - x_{i,1990}$ for any variable x.

Empirical implementation of equation (31) requires data on population (L_{2005}) and knowledge of calibrated variables (υ^A_{2005},κ_{2005}, Ξ_{2005},I_{2005},μ_{2005}, Π_{2005}, $\bar{u}_{2005}$,$\bar{A}^A_{2005}$,$\bar{A}^N_{2005}$) for baseline year 2005, all of which were recovered in the second step. However, to compute the differentials ($d\upsilon^A$, $d\ln(I_k)$, $d\ln(\Pi^A_k)$,$d\ln(\Pi^N_k)$, $d\ln(\bar{u}_k)$, $d\ln(\bar{A}^A$, $d\ln(\bar{A}^A)$), I also need knowledge of variables (υ^A_{1990}, I_{1990}, Π^A_{1990},Π^N_{1990}, $\bar{u}_{1990}$, $\bar{A}^A_{1990}$, $\bar{A}^N_{1990}$) *for year 1990.* Thus, it is necessary to separately calibrate the model to the global 1990 economy using the same methodology from Section 3.2 that was used for baseline year 2005.[11]

Taking the variance operator of equation (31), I obtain the following decomposition for the variance of primacy changes:

$$\mathrm{Var}(d\ln(Primacy)) = \mathrm{Var}(cont^{ST}) + \mathrm{Var}(cont^{DTA}) + \mathrm{Var}(cont^{LF})$$
$$+ 2\mathrm{cov}(cont^{ST}, cont^{DTA}) + 2\mathrm{cov}(cont^{ST}, cont^{LF}) + 2\mathrm{cov}(cont^{DTA}, cont^{LF}) \quad (32)$$

Thus, after using calibration results and data to recover ($cont^{ST}_c$,$cont^{DTA}_c$,$cont^{LF}_c$) for 44 countries in my sample with the help of equation (31), I can the decompose the variance of 1990-2005 changes in primacy into components explained by structural transformation, change in trade access, and changes in local fundamentals (as well as the covariances among the three) using equation (32).[12] This allows me to measure the extent to which each of these three drivers have mattered in accounting for the changes in spatial concentration that happened in the recent past in these real-world countries.

[11]See Appendix D.1 for more details on the calibration of the 1990 economy.

[12]These 44 countries are the ones for which I have IPUMS data on subnational units for both 1990 and 2005.

4 Data

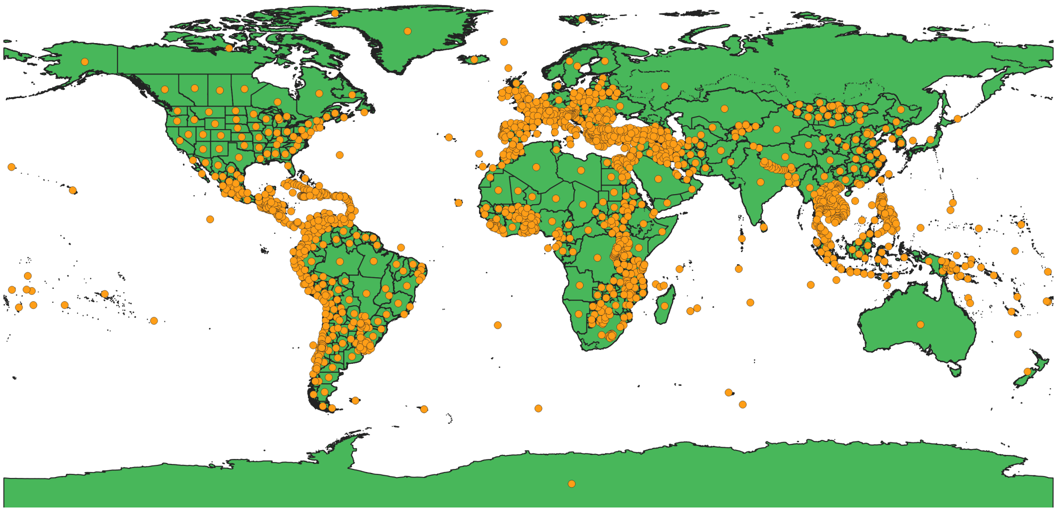
In this section, I describe the data sources from which I obtained the variables used to bring the model to the data. I also describe data adjustments that were necessary to bring the data into an appropriate format for usage in my empirical applications.

4.1 Population

4.1.1 IPUMS International

My main source of location-level population is IPUMS International, a project that harmonizes and disseminates census data from multiple countries around the world. I use the version of the data at the first level of geographic disaggregation, which typically partitions countries into states or provinces. For each country, whenever 2005 data is not available, I use data from the closest year to 2005 as long as that year is within the 1995-2011 interval. My final IPUMS samples covers 79 countries, totaling 1511 locations. Figure 5 displays the world map with countries partitioned into IPUMS locations (with geometric centroids overlayed).

Figure 5: Countries, Subnational Locations, and Geometric Centroids



Notes: the figure portrays a world map partitioned into countries and within-country subnational units corresponding to the geographic coding of the IPUMS International data set for year 2005. Subnational units are typical states or provinces. In addition, for each country or subnational unit, the map displays the geometric centroid (in orange) of the polygon that represents that location.

IPUMS data includes local employment by industry, which is coded according to variable INDGEN ("Industry, general recode"). I aggregate this variable's multiple categories into two groups: agriculture (category 010, "Agriculture, fishing, and forestry") and non-agriculture (categories 020-130). The resulting variables (agricultural and non-agricultural employment) are the data analogues of model variables

L^A_{2005} and L^N_{2005}.

4.1.2 World Bank Open Data

IPUMS data by subnational location does not cover every country: for example, note that Australia is not divided into provinces in Figure 5. Therefore, sectoral population data at the national level is needed. For these countries, I obtain national 2005 population data (L_{2005}) from World Bank Open Data, which covers the 1960-2019 period. I then distribute this national population between the agricultural and non-agricultural sectors (L^A_{2005},L^N_{2005}) using another variable from World Bank Open Data, the agricultural share of GDP (formally "Agriculture, forestry, and fishing, value added (% of GDP)"). Conveniently, this variable uses the same sectoral coding as the one from variable INDGEN in IPUMS, thus guaranteeing comparability. The agricultural share of GDP is missing for some countries for 2005, so in these cases I impute it using the closest year (as long as that year is within the 1995-2015 time window).

Even for countries for which IPUMS data at the subnational level is available, World Bank Open Data's national population data is helpful. To guarantee comparability, I adjust these countries' sector-location population distributions so that the implied national population matches its World Bank Open Data 2005 national population. Specifically, the population in sector s of location i is set to:

$$L^s_{i,2005} = L^{s,IPUMS}_{i,2005} \frac{\bar{L}^{WBOD}_{c(i),2005}}{\sum_{j \in c(i)} L^{IPUMS}_{j,2005}}$$

where $L^{s,IPUMS}_{i,2005}$ is the population of sector s of location i in 2005 according to IPUMS, $L^{IPUMS}_{i,2005}$ is the population of location i in 2005 according to IPUMS, and $\bar{L}^{WBOD}_{c,2005}$ is the 2005 national population of country c according to World Bank Open Data.

4.2 Per capita income

To obtain data on 2005 local wages (w_{2005}), I follow Desmet et al. (2018) and use the data set G-Econ 4.0. This is a project that builds a "geophysically based data set on economic activity for the world". The basic units of measurement are grid cells measuring 1-degree longitude by 1-degree latitude, for each of which output (gross cell product) and population are estimated.

I divide output by population to obtain an estimate of each cell's per capita income for year 2005, which proxies for wages in my empirical applications. The basic data set cointains 24,903 cells (some of which involve more than one country) but only 17,043 of them have enough information to compute income per capita.

Given this wage proxy for grid cells, I use this data to compute wages at the level of IPUMS subnational locations. Note that each location i is represented by a polygon

pol_i, as seen in Figure 5. I set the wage of that location i to be a weighted average of the wages of the grid cells that overlap its polygon pol_i, where the weights are given by the land area of the intersection of each grid cell with the polygon. Formally, let all grid cells in the world be indexed by $g = 1, ..., G$ and let the wage of grid cell g be denoted by $wagecell_{g,2005}$. Then, the wage $w_{i,2005}$ of each location i represented a polygon pol_i is set to:

$$w_{i,2005} = \sum_{g=1}^{G} wagecell_{g,2005} \Big(\frac{Area(g \cap pol_i)}{Area(pol_i)} \Big)$$

For countries for which IPUMS data at the subnational level is not available, I simply obtain 2005 per capita income (officially "GDP per capita (current US$)") from World Bank Open Data, which covers the 1960-2017 period.

4.3 Trade flows

World Integrated Trade Solution (WITS) is a data service by the World Bank "in collaboration with the United Nations Conference on Trade and Development (UNCTAD) and in consultation with organizations such as International Trade Center, United Nations Statistical Division (UNSD) and the World Trade Organization (WTO)". From this source I obtain country-level bilateral trade flows in US dollars for 1962-2019. The data lists trade flows separately by sector, including agriculture. I compute non-agricultural trade flows by subtracting bilateral agricultural trade flows from total bilateral trade flows. Whenever that results in a negative value for, I replace that value with zero.

As mentioned in Section 3.1, identification of the border-crossing parameter when estimating the trade gravity equation requires data on both intranational and international trade flows. WITS only covers international trade.[13] So, I augment the data set by imputing sector-level trade flows from a country i to itself (i.e. X^s_{ii}) using two additional country-level variables from World Bank Open Data: agricultural share of GDP $Agsh$, which was already mentioned in Section 4.1.2, and import share Msh (officially "Imports of goods and services (% of GDP)").

The imputing procedure for X^s_{ii} goes as follows. First use WITS data to compute each country-sector international *exports* each year: $EXP^s_{it} = \sum_{j \neq i} X^s_{ijt}$; and each country's international *imports* each year: $IMP_{it} = \sum_{j \neq i}(X^A_{jit} + X^N_{jit})$. To obtain implied national GDP Y_{it}, divide international exports IMP_{it} by import share Msh_{it}:

[13] As a robustness check, in Appendix B I rerun gravity regressions for year 2010 using WITS data and compare its results to the analogous gravity regression that uses the German data set *Verkehrsverflechtungsprognose 2030*, which has (non-imputed) intranational trade data for Europe in 2010. Check Appendix B for details and results.

$$Y_{it} = \frac{IMP_{it}}{Msh_{it}}$$

This national GDP can be distributed between agricultural and non-agricultural GDP using data on the agricultural share of GDP. Specifically, national agricultural and non-agricultural GDP (Y_i^A, Y_i^N) are given by:

$$Y_{it}^A = Y_{it} \times Agsh_{it},\ Y_{it}^N = Y_{it} \times (1 - Agsh_{it})$$

Finally, I compute intranational trade X_{iit}^s in sector s of country i as the difference between sectoral GDP and sectoral exports:

$$X_{iit}^s = Y_{it}^s - EXP_{it}^s$$

Any resulting negative intranational trade flows ($X_{iit}^s < 0$) are dropped from the sample.

4.4 Transportation infrastructure

I download maps of global transportation infrastructure from Natural Earth, a public domain data set (Desmet et al. (2018)). I use the "large-scale" version of the data set containing cultural aspects of the terrain.[14] From the list of cultural aspects, I select the layers "roads" and "railroads".

In Natural Earth, roads are categorized, so it is necessary to create a mapping from those categories to the ones for which we have estimates of traversal costs (see Section 3.1.1). I classify "beltway" and "major highway" as interstate highways, "secondary highway" as non-interstate highway, and the remaining road types as arterial roads. I delete all road features that correspond to over-water transportation (ferries).

Using these transportation network maps, I generate the cost raster of Figure 3 following the procedure described in Section 3.1.1.

4.5 Geographic coordinates

I use the maps provided by IPUMS International to obtain geographic coordinates for countries and subnational locations. For subnational locations, I use the GIS boundary file titled "spatially harmonized first-level geography" (world_geolev1_2019.shp), which is displayed in Figure 5. For countries, it's the GIS boundary file titled "world map" (world_countries_2017.shp). In either case, I use QGIS to compute the geometric centroids of the polygons representing each country or location. This process yields a total of 248 country centroids and 2023 subnational location centroids (see Figure 5).

[14] Download links can be found at: https://www.naturalearthdata.com/downloads/10m-cultural-vectors/

4.6 Bilateral Distances

For each pair of subnational locations and/or countries, bilateral distances $dist_{ij}$ are computed using the centroids obtained in Section 4.5. First, I locate the two 1°x 1°grid cells in which the two centroids are located. Then, as described in Section 3.1.1, I apply the fast marching method (FMM) algorithm using the cost raster mentioned in Section 4.4 (see Figure 3) to compute the bilateral distance between the two cells.

Note that after obtaining bilateral distances I must partition the distance range into bins to implement the trade gravity regression (as explained in Section 3.1). To do that, I first take the maximum bilateral distance in the data set (which is the distance between Greenland and Russia, approximately 33.35) and multiply it by 1.05 to obtain an upper bound d_{max}. I then divide the interval $[0, d_{max}]$ into $B = 30$ equally spaced distance bins.

4.7 Final calibration sample

After performing all data adjustments described in this Section 4 and dropping countries for which it was not possible to obtain estimates of sector-level population and/or per capita income (neither at the national nor subnational level), I arrive at the final sample that will be used in the calibration exercise. This includes $N = 1611$ locations across $C = 192$ countries.

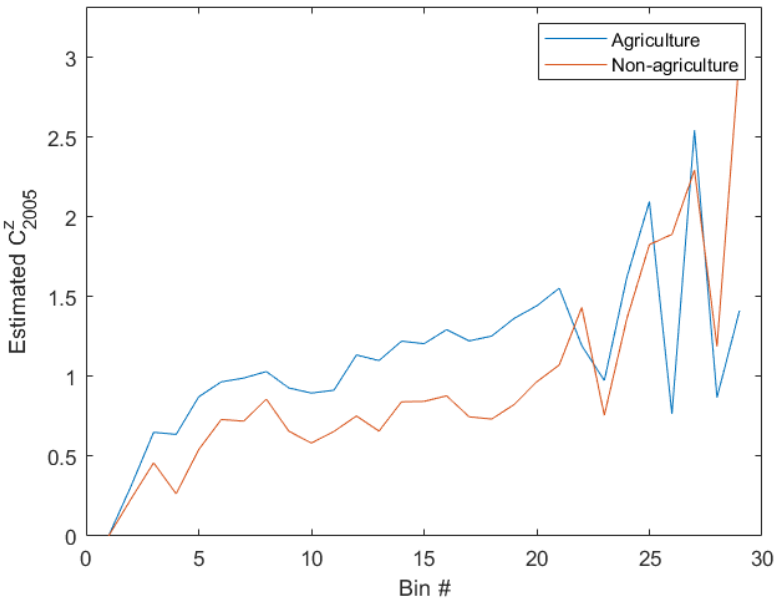
5 Results

In this Section, I present the results of the empirical exercise by which I bring the model to the data. I first present results of trade gravity estimation (first step). Then I discuss the calibration results (second step) and the results of the counterfactual exercises. I use counterfactual results to further discuss the effects of trade shocks on welfare and trade volumes, as well as the extent to which these effects are influenced by population mobility across space and sectors. Finally, I present the result of the decomposition of 1990-2005 primacy changes into the contributions of structural transformation, changes in trade access, and changes in local fundamentals.

5.1 Results of First Step: Gravity

I now present results for the main trade gravity regressions, as described in Section 3.1, using WITS trade data. Estimated sector-level costs of distance bins $\{C^{s,z}\}_{z=1}^{B}$ for year 2005 are displayed on Figure 6. The costs of traversing a given distance seems to be slightly higher for agriculture than non-agriculture, but overall the estimates are roughly similar.

Figure 6: Cost of Distance Bins (2005)



Notes: the figure portrays the estimated values of the agricultural and non-agricultural distance costs $\hat{C}^{A,z}$ and $\hat{C}^{N,z}$ for each one of the distance bins $z \in \{0, ..., B\}$.

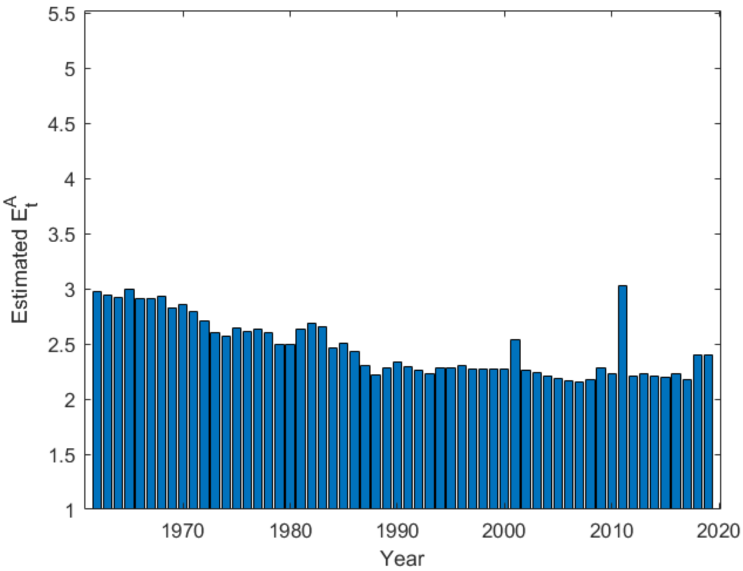
Figures 7 and 8 present estimates of sector-level border-crossing parameters $\hat{E}^s_t$, by year. Overall, border-crossing costs are substantially lower for agriculture than for non-agriculture. For both sectors, there seems to have been a substantial decrease in trade costs between the 1960s and today. For example, the agricultural border-crossing cost in the early 1960s was equivalent to a 200% ad-valorem tariff, decreasing to approximately 130-150% in the late 2010s. Similarly, for the non-agricultural sector border-crossing costs seem to have declined from around 400% to 270% between the 1960s and the 2010s. These estimates are consistent with findings in the trade literature that point to a trend of declining international trade costs over the second half of the twentieth century.

As described in Section 3.1, I use the estimated distance costs and border-crossing costs presented in this section to construct estimated trade-cost matrices for years 1971, 1990 and 2005 ($\hat{\tau}_{1971}$,$\hat{\tau}_{1990}$,$\hat{\tau}_{2005}$). These trade-cost matrices that will be used in the calibration, counterfactual exercises, and decompositions below.

5.2 Results of Second Step: Calibration

I now present the results of the second step, namely calibration. As described in Section 3.2, I back out the fundamental productivity ($\bar{A}^A_{2005}$,$\bar{A}^N_{2005}$) and fundamental amenity ($\bar{u}_{2005}$) vectors that rationalize the observed 2005 worldwide distribution of wages, population, and sectoral employment across 1611 locations in 192 countries.

Figure 7: Estimated Border-Crossing Cost, Agriculture



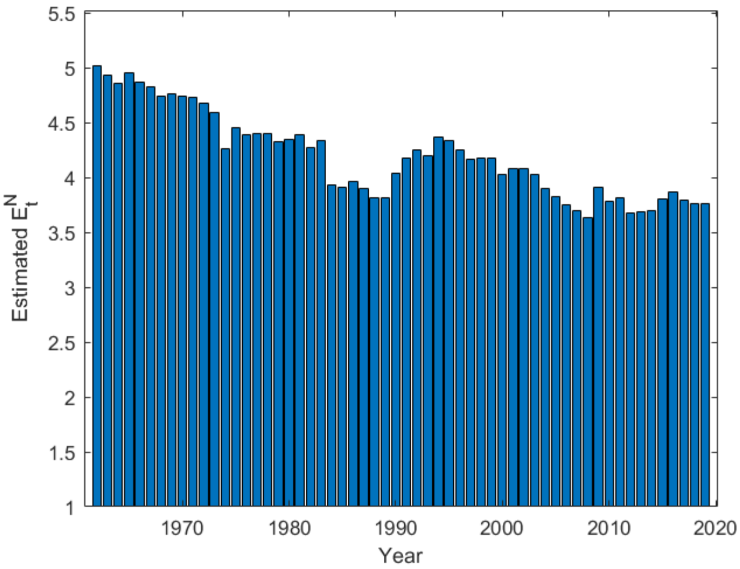
Notes: the figure portrays the estimated agricultural border-crossing cost $\hat{E}_t^A$ for each year t between 1962 and 2019.

Figures 9 and 10 display estimated fundamental productivities in 2005.

As one can see in the figure, the spatial distribution of fundamental productivities is somewhat intuitive. Developed countries and oil-rich countries tend to display particularly large values. Within countries like China, richer regions (e.g. eastern China) tend to have somewhat higher fundamental productivities than poorer regions (e.g. western China).

Figure 11 displays the estimates of fundamental amenities. It should be emphasized that cross-location comparisons of amenities are meaningful within countries but *not across* countries. As explained in section 3.2, within-country average fundamental amenities are not separately identified from within-country average welfare, making it necessary to normalize each country's adjusted welfare sum to an arbitrary number ($\pi_{c,2005} = 1$). However, it is still possible to compare fundamental amenities within a country. As a general rule, the calibration tends to yield relatively high estimates of fundamental amenities for well-populated regions within a country. From the perspective of the model, this is necessary to rationalize a large number of people in those locations whenever their superior income or market access is not sufficient to fully counterbalance their substantial congestion given the assumption of costless internal migration.

Figure 8: Estimated Border-Crossing Cost, Non-Agriculture



Notes: the figure portrays the estimated non-agricultural border-crossing cost $\hat{E}_t^N$ for each year t between 1962 and 2019.

5.3 Results of Counterfactual Exercises

5.3.1 Counterfactual trade matrices

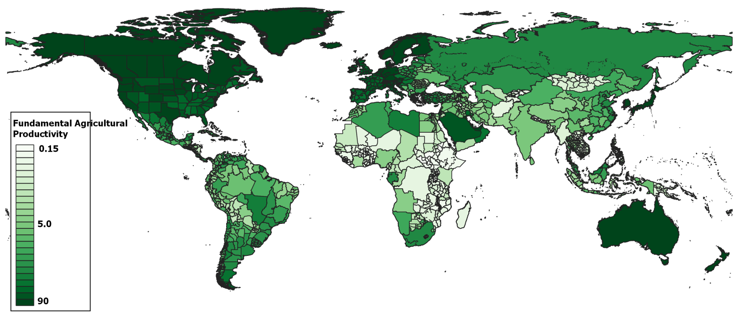
As described in Section 3.3, each counterfactual exercise is characterized by its counterfactual trade-cost structure. Thus, before presenting results for counterfactual exercises, it is necessary to present the specific counterfactual trade-cost matrices that will be used in these exercises. I run two counterfactual exercises. The first exercise, CF1, lowers international trade costs by simply eliminating border-crossing costs from the estimated trade-cost structure. One can think of this scenario as the elimination of all international trade barriers, be them policy-driven (e.g. tariffs, non-tariff barriers) or not (e.g. language differences, social networks). Formally, trade costs in counterfactual CF1 are given by:

$$\tau_{ij}^{s,cf1} = \prod_{z=1}^{B} (\hat{C}_{2005}^{s,z})^{\mathbb{1}_{dist_{ij} \in b_z}}$$

The second counterfactual exercise, CF2, increases trade costs back to their 1971 levels. This counterfactual should be interpreted as answering the question: how would the global 2005 distribution of population and wages change if trade costs rose to their 1971 levels while the remaining economic fundamentals remained the same? Formally, the counterfactual trade-cost matrix is given by:

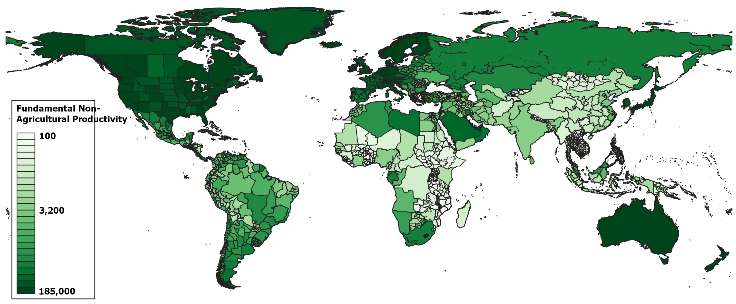
$$\tau_{ij}^{s,cf2} = \hat{\tau}_{ij,1971}^{s}$$

Figure 9: Fundamental Productivities, Agriculture (2005)



Notes: the figure portrays the calibrated fundamental agricultural productivity $\bar{A}^{A}_{i,2005}$ in year 2005 for each location i in the world.

Figure 10: Fundamental Productivities, Non-Agriculture (2005)



Notes: the figure portrays the calibrated fundamental non-agricultural productivity $\bar{A}^{N}_{i,2005}$ in year 2005 for each location i in the world.

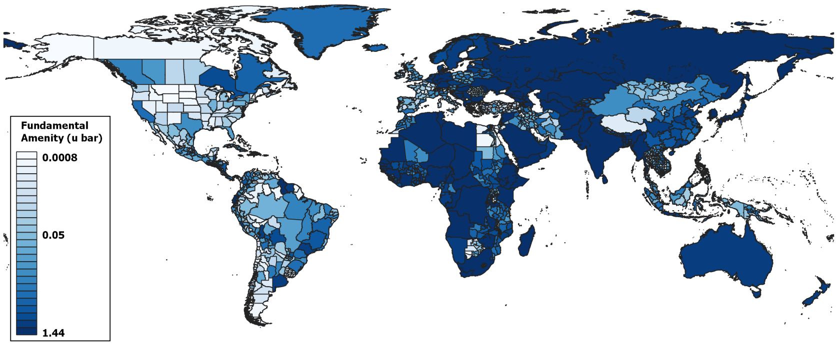
5.3.2 Counterfactual Results

In each counterfactual exercise, I impose one of the counterfactual trade matrices listed in Section 5.3.1 and then compute the counterfactual spatial equilibrium which includes variables such as counterfactual wages w^{cf} and counterfactual populations L^{cf}. Given these variables, I compute the percentage increase in population between the baseline 2005 equilibrium and the counterfactual equilibrium for each and every location i: $100 \times (\frac{L_i^{cf}}{L_{i,2005}} - 1)\%$.

Figures 12 and 13 display the percentage increase in population for every location in the world for each of the counterfactual exercises. Note that in every map there are many locations with zero change in population. These are countries for which we do not have data at the subnational level. They were thus included in the analysis as single units, which when combined with the assumed cross-country population immobility implies that their population must remain constant under any counterfactual trade-cost structure.

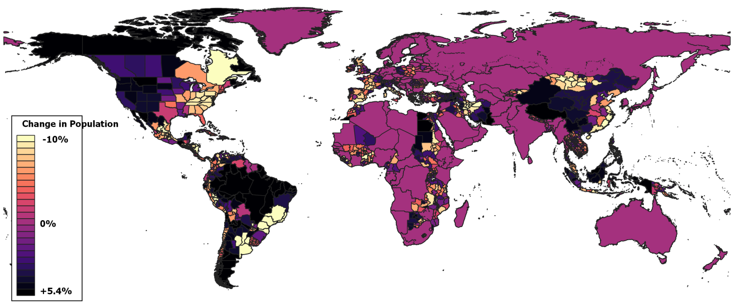
When examining the maps in Figure 12 and 13, one should note that the range of

Figure 11: Fundamental Amenities (2005)



Notes: the figure portrays the calibrated fundamental amenity $\bar{u}_{i,2005}$ in year 2005 for each location i in the world.

Figure 12: Results: Counterfactual CF1 (No-border Crossing Cost)

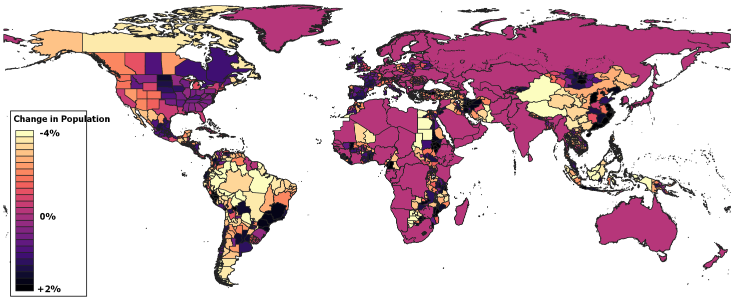


Notes: for each location in the world, the figure portrays the percentage change in population in the counterfactual equilibrium CF1 (in which I eliminate all border-crossing costs) with respect to the 2005 baseline.

percent population changes is modest. For example, in counterfactual CF1 (elimination of border-crossing costs) no location gains more than 5.5% or loses more than 10% of its baseline population. This implies that, given model parameters and calibrated fundamentals, trade shocks seem to influence the spatial distribution of population only moderately. This observation may help explain the result presented below that changes in trade access account for little of the actually observed change in concentration in recent decades.

For each counterfactual, which locations grow within a country and which locations shrink? Casual inspection of Figures 12 and 13 suggests that the geographic pattern of population changes for counterfactual CF1, where trade costs fall, is the opposite of the pattern for counterfactual CF2 where trade costs increase. When we decrease trade costs in CF1, locations that housed a low fraction of the national population at baseline (e.g. northwestern USA, western China, northwestern Brazil) tend to be the ones that grow the most, thus reducing population concentration at the national level. On the other hand, when trade costs rise in CF2, the locations that grow the most

Figure 13: Results: Counterfactual CF2 (1971 Trade Costs)



Notes: for each location in the world, the figure portrays the percentage change in population in the counterfactual equilibrium CF2 (in which raise trade costs back to their 1971 levels) with respect to the 2005 baseline.

Table 2: Correlation of Baseline Population Share and Population Relative Change

Counterfactual	CF1	CF2
$\rho\Big(\ln(\frac{L_i^{cf}}{L_{i,2005}}), \ln(\frac{L_{i,2005}}{\bar{L}_{c(i),2005}})\Big)$	-0.227	0.249

Notes: for each counterfactual exercise, the table displays the correlation (across all locations in the world) between the log of the location's initial share of the national population ($\ln(L_{i,2005}/\bar{L}_{c(i),2005})$) and the log of the relative change in the location's population in the counterfactual equilibrium with respect to baseline ($\ln(\mathrm{L}_i^{cf}/L_{i,2005})$).

tend to be the ones that had a high fraction of the national population at baseline (e.g. northeastern USA, eastern China, southeastern Brazil), thereby increasing the spatial concentration of population.

Table 2 provides a more systematic assessment of these casual observations. For each counterfactual exercise, it displays the correlation coefficient between (the log of) a location's baseline share of the national population and (the log of) its relative population change between the baseline and the counterfactual equilibrium. For counterfactual CF1, which decreases trade costs, the correlation is negative (around -0.25), while the opposite holds for counterfactual CF2, which increases trade costs and for which the correlation is positive (around 0.25).

It short, these results indicate that international trade integration tends to cause spatial deconcentration of population, while increased trade costs have an opposite, concentrating effect. Note that this is consistent with the predictions of Krugman and Livas (1996). Thus, a prediction originally made in a simple stylized model also seems to hold in a model that is much more sophisticated (including elements such as structural change and differential access to foreign markets) and that is closely calibrated to the world economy using real-world data.

Table 3: Change in International Trade (as % of world GDP)

Counterfactual #	CF1	CF2
Long-Run CF	+57 p.p.	-7 p.p.
CF (strong immobility)	+57 p.p.	-5 p.p.
CF (weak immobility)	+57 p.p.	-7 p.p.

Notes: for each counterfactual exercise, the table's first row displays the counterfactual change in international trade (as a % of world GDP) with respect to the calibrated 2005 economy. The second and third rows display the corresponding counterfactual change for the strong-immobility and weak-immobility counterfactuals, respectively, in which the spatial distribution of population is not allowed to adjust in the counterfactual equilibrium (see Appendix C for details).

5.3.3 Trade Volumes and Welfare

Counterfactual exercises also allow us to predict the effects that each counterfactual trade shock would have on welfare and on trade volumes. These effects are central topics of interest in the trade literature. Within that context, this model's predictions are useful because they come from a full-fledged general equilibrium model that includes several important mechanisms such as trade diversion, cross-sectoral reallocation, geographic reallocation, and structural change. Therefore, its predictions regarding welfare and trade volumes are arguably an useful addition to the ones from traditional models, which often lack mechanisms such as spatial population reallocation, for example.

The first row of Table 3 presents the effect of counterfactual trade-cost structures on trade volumes by displaying the value of international trade as a fraction of world GDP in each scenario. International trade corresponds to 21% of world GDP in the calibrated 2005 world economy. Counterfactual exercise CF1, which eliminates international trade costs, has very large effects on trade volumes: trade as a fraction of world GDP grows by 57 percentage points, reaching 78%. This suggests that global trade is not close to being completely free, even for practical purposes, since there is much potential trade that is repressed by currently standing border-crossing costs. Counterfactual CF2, which raises international trade costs to 1971 levels, cause the fraction of trade in global GDP to decline by 7 p.p., reaching 14%.

The first row of Table 4 presents the effect of counterfactual trade structures on welfare by displaying the percent change in the cross-country average of adjusted welfare sums (variable π_c) in each scenario. Eliminating international trade costs in counterfactual CF1 yields substantial average welfare increases of 57%. Once again, the results imply that international trade costs were sufficiently high in 2005 that there were still major gains to be had from lowering those costs. In that sense, the process of international trade integration was still not close to being completed. Increasing international trade costs to 1971 levels in counterfactual CF2 decreases average welfare by about 5%.

Table 4: % Change in Cross-country Average of National Welfare ($\pi_c \equiv (\sum_{k\in c} W_k^\theta)^{\frac{1}{\theta}}$)

Counterfactual #	CF1	CF2
Long-Run CF	56.9%	-5.1%
CF (strong immobility)	+56.8%	-4.4%
CF (weak immobility)	+56.9 %	-5.1%

Notes: for each counterfactual exercise, the table's first row displays the counterfactual change in the cross-country average of country-level adjusted welfare sums ($\pi_c = (\sum_{k\in c} W_k^\theta)^{\frac{1}{\theta}}$) with respect to the calibrated 2005 economy. The second and third rows display the corresponding counterfactual change for the strong-immobility and weak-immobility counterfactuals, respectively, in which the spatial distribution of population is not allowed to adjust in the counterfactual equilibrium (see Appendix C for details).

Taken at face value, these numbers seem to suggest that trade integration between the 1970s and the 2000s, albeit meaningful, was very incomplete. From the perspective of the 1970s, most of the welfare gains and trade intensification that would occur in a free-trade world had not been materialized by 2005. Therefore, understanding what the remaining trade barriers are and how to decrease them in order to further trade integration would appear to be a valuable endeavor.

5.4 Decomposition

I also take advantage of the calibrated 2005 model to perform an additional empirical exercise in which I separate the relative contributions of structural transformation, changes in differential trade access, and changes in local fundamentals for the 1990-2005 changes in spatial concentration observed in the data, as measured by the primacy rate. To do so, I use the methodology described in Section 3.4, which allows me to decompose the variance of (the log of) primacy change in a sample of 44 countries into multiple components as stated in equation (32). Results are presented in Table 5.

The first two rows of Table 5 show that the variances of the impacts of structural change (Var($cont^{ST}$)) and of differential trade access (Var($cont^{DTA}$)) are relatively small, accounting for only around 1% of the total sample variance of primacy changes. On the other hand, the variance of the impact of local fundamentals (productivities and amenities) is slightly higher than the total variance of primacy changes. This is possible because two of the covariances are negative, which allows the sum of variances to be larger than the total variance of primacy changes.

In any case, the results indicate that the vast majority of the variance in observed primacy changes can be accounted for by local fundamentals. Therefore, while the counterfactual results of Section 5.3.2 suggest a potentially substantial influence of trade access on spatial concentration, in practice it is dwarfed by the magnitude of changes in productivities and amenities, which end up being dominant. This reinforces the importance of fundamentals in the determination of spatial equilibria, as empha-

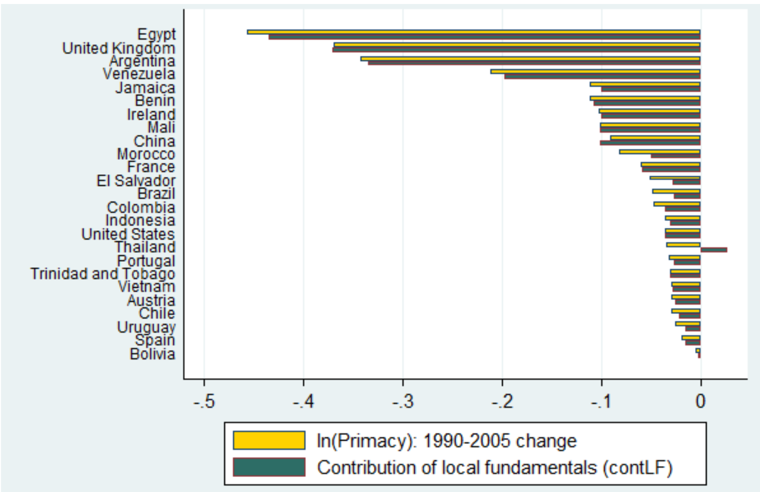
Table 5: Decomposition of Variance of 1990-2015 Changes in Primacy

		in %
Var($cont^{ST}$)	0.000002	0.008%
Var($cont^{DTA}$)	.0002	0.99%
Var($cont^{LF}$)	.0202	103.7%
2cov($cont^{ST}, cont^{DTA}$)	-0.000005	-.03%
2cov($cont^{ST}, cont^{LF}$)	.00005	0.25%
2cov($cont^{DMA}, cont^{LF}$)	-.001	-4.93%
Var($d\ln(Primacy)$)	.0195	100%

Notes: the table displays the values of the sample variances and covariances of the terms in equation 32, namely the 1990-2015 change in primacy ($d\ln(Primacy_c)$) and the contributions of structural transformation ($cont_c^{ST}$), differential trade access ($cont_c^{DTA}$), and local fundamentals (($cont_c^{LF}$)). The values are displayed both in absolute terms and as a percentage of the variance of primacy changes (Var($d\ln(Primacy_c)$)).

sized by a more traditional urban economics literature, relative to considerations of access to trade networks and structural transformation that have been the focus of more recent literatures in spatial economics, trade, and macroeconomics.

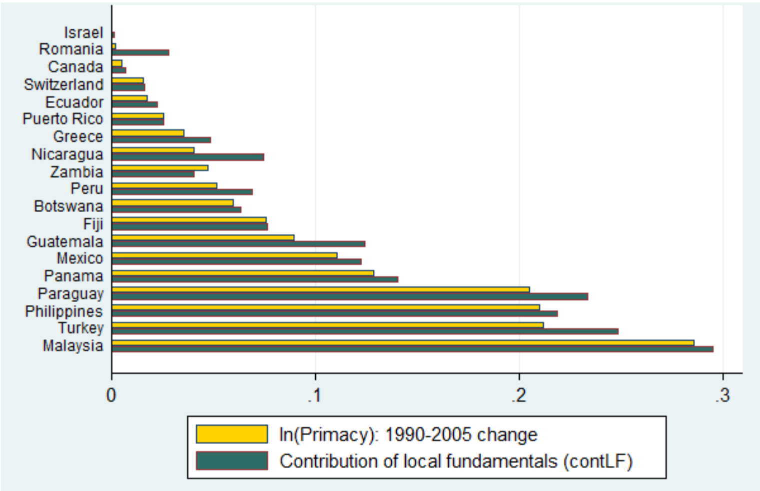
Figure 14: Contribution of Local Fundamentals for Primacy Reductions



Notes: the figure displays the value of the 1990-2005 change in the log of primacy ($d\ln(Primacy_c)$) for each country in the sample for whom this change was negative, as well as the contributions of local fundamentals (($cont_c^{LF}$)).

Figures 14 and 15 show 1990-2005 changes in primacy and the contribution of local fundamentals country-by-country. For example, Figure 14 shows that Brazil's primacy rate decreased by 0.049 between 1990 and 2005, with changes in local fundamentals accounting for 0.027 (that is, slightly over half) of this decrease. Thus, in the case of Brazil, changes in differential market access and in local fundamentals contributed roughly equal parts to the change in primacy. Analogous analyses can be made for

Figure 15: Contribution of Local Fundamentals for Primacy Increases



Notes: the figure displays the value of the 1990-2005 change in the log of primacy ($d\ln(Primacy_c)$) for each country in the sample for whom this change was positive, as well as the contributions of local fundamentals ($(cont_c^{LF})$).

other countries by adequately inspecting Figures 14 and 15.[15] However, the case of Brazil is atypical since the change in primacy in most countries is almost entirely explained by changes in local fundamentals. This can be seen by noting that the values of the golden and gray bars are very close in most countries. This echoes the results of the variance decomposition, implying that changes in local fundamentals were the dominant factor to explain 1990-2005 changes in concentration observed in the sample.

6 Conclusion

In this paper, I investigate the drivers of spatial concentration, disentangling the contributions of three different factors: structural transformation, differential trade access, and location-specific fundamentals (i.e. exogenous productivities and amenities). To do so, I augment a modern quantitative spatial model (Allen and Arkolakis (2014), Allen and Donaldson (2020)) with non-homothetic PIGL preferences (Eckert and Peters (2018)), obtaining a two-sector spatial model that features the three driving factors of concentration, which is measured by the primacy rate, namely, the fraction of a country's population that lives in its largest city. I show that changes in the primacy rate can be analytically decomposed into separate terms reflecting the contribution of the the three drivers.

[15]For completeness, Table 7 in Appendix 7 presents 2005 primacy rates, 1990-2005 changes in primacy, and the contribution of structural change, differential trade access, and local fundamentals for each country in the sample.

To assess the relative importance of these factors in practice, I develop a methodology to bring the model to the data in two steps: first, I use global data on transportation infrastructure, international and intranational trade to estimate sector- and year-specific bilateral trade costs between 1962 and 2019; second, I use location-level data on population, sectoral employment and per capita income to calibrate the spatial model to the 2005 global economy, which is composed of 1611 locations across 192 countries. The calibrated model can be used to study the influence of trade access on spatial concentration through a series of counterfactual exercises in which I impose a series of alternative trade-cost structures on the 2005 world economy: eliminating international trade costs, eliminating all trade costs, raising international trade costs by 10%, and raising trade costs back to their 1971 levels. Moreover, an additional empirical exercise allows me to use the analytical expression mentioned above to decompose the variance of observed 1990-2015 primacy changes in a sample of 44 countries into components reflecting the relative roles of structural transformation, differential trade access, and local fundamentals.

Counterfactual results suggest that the net effect of lowering international trade costs is deconcentrating for most countries. For example, the substantial decline in international trade costs between the 1970s and 2000s had a non-negligible negative in spatial concentration by increasing the populations of locations that were initially more empty at the expensive of initially populous locations. However, results of the decomposition exercise show that, from an accounting perspective, the vast majority of the variance in the primacy changes actually observed in the data between 1990 and 2005 can be explained by changes in local fundamentals, that is, in exogenous productivities and amenities. Structural transformation and changes in trade access account for only approximately 1% of the total variance. Therefore, although these two factors may have had significant effects on concentration, in practice their magnitude appears to have been small enough to be dominated by changes in local fundamentals.

A limitation of the paper are the assumptions governing agent migration. Namely, I assume that migration is costless within countries and infinitely costly across countries. It should be possible to relax this strong assumption by extending the empirical methodology and gathering more migration data (both within and across countries). This would yield a more complete model of the world economy and also open up the possibility of international labor reallocation as a response to shocks in trade costs and other variables, thereby enriching our understanding of the mechanisms through which the effects of these shocks operate. Another limitation is that most parameters I used were borrowed from the literature rather than estimated within the context of the model, which would be preferable. By conveniently gathering additional data on population and income per capita for additional time periods and by wisely choosing instrumental variables that provide sources of exogenous variation to international trade costs (e.g. policy-driven trade liberalizations), it should be possible to estimate some of the model's parameters using an instrumental-variable approach similar in spirit to Adao et al. (2020).

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A Calibrating Traversal Costs

In Section 3.1.1, I mention that I build the world transportation cost raster using transportation-specific traversal costs that were adapted from Allen and Arkolakis (2014). Here I give a more detailed explanation of this procedure. I do that in two steps. First, I present a general microfoundation of trade costs that justify an exponential form for these costs. Then, by comparing this formula to formulae derived in Allen and Arkolakis (2014), I map the traversal cost variable in my model to the equivalent variables in their model, thus clarifying the relationship between the two and allowing me to borrow their values in a relatively straightforward manner, given the appropriate adaptations.

A.1 Microfoundations of Trade Costs

Assume that a truck is carrying an iceberg between points i and j through a continuous path $\mathcal{T}$, with points along the path indexed by variable x. The iceberg's melting rate is $1-r(x)$ per hour. Thus, at the end of each hour only a fraction $r(x)$ of the iceberg mass at the start of the hour remains. The instantaneous truck speed is given by function $s(x)$. Note that I allow the melting rate and truck speed to vary along different points of the path. I also assume both functions r and s are continuous.

Divide the complete path from i to j into a finite number B of segments indexed by $k = 1, ..., B$, with corresponding lengths $[dx_1, ...dx_B]$. Given an initial quantity of ice q_0, the final quantity of ice when the iceberg arrives at final point j is approximately equal to:

$$q_f \approx q_0 \prod_{k=1}^{B} r(x_k)^{\frac{dx_k}{s(x_k)}} \tag{33}$$

where x_k is an arbitrarily chosen point in segment k.

Note that τ_{ij}, the conventionally defined multiplicative "iceberg" trade cost between i and j, is equivalent to q_0/q_f in this formulation. To find the exact value of q_0/q_f, I take the expression in equation 33 to the limit as we divide the path into a higher and higher number ($B \to \infty$) of smaller and smaller segments ($dx_k \to 0^+$ for $k = 1, ..., B$):

$$\tau_{ij} = \frac{q_0}{q_f} = \lim_{dx \to 0} \prod_{k=1}^{B} \left(r(x_k)^{\frac{1}{s(x_k)}} \right)^{dx_k} = \pi_i^j \left(r(x)^{\frac{1}{s(x)}} \right)^{dx} \tag{34}$$

where the symbol π indicates the geometric integral. By the properties of the geometric integral, it then follows that:

$$\tau_{ij} = e^{\int_i^j \ln(r(x)^{\frac{1}{s(x)}})dx} = e^{\int_i^j \frac{1}{s(x)} \ln(r(x))dx}$$

Therefore, I have found an expression for the iceberg trade cost between two regions that is a function only of a regular integral that is taken over an expression depending only the speed function (s) and the net-of-melting rate (r). This expression forms the basis for the calibration of the (mode-specific) traversal costs of the next section.

A.2 Mode-Specific Traversal Costs

In this section, I calibrate values for the mode-specific traversal costs used in Section 3.1.1. I do that by drawing a parallel between my derived equation A.1 and the mode-specific costs estimated by Allen and Arkolakis (2014).

First consider equation (22) in Allen and Arkolakis (2014). Assuming a single mode of transportation m and setting $b_m = 0$ and $\theta = 1$, we get that the model transportation cost is proportional to $T(i,j) = e^{a_m d_m(i,j)}$. Now, consider that $d_m(i,j)$ can be represented as an integral $\int_i^j \tau_{mode}(x)dx$, where x indexes the points along the path and $\tau_{mode}(x)$ is the relative slowness of that mode of transportation on that point. Comparing this expression to equation A.1, we can then draw the following parallel:

$$a_m \tau_{mode}(x) = \frac{1}{s(x)} \ln(r(x))$$

Therefore, I can take the values for mode-specific variable costs a_m from the first row of Table II of Allen and Arkolakis (2014) and adjust them by a representative of $\tau_{mode}(x)$, which I take from their Appendix B3, to obtain a measure of the mode-specific traversal cost which I use in the main analysis.

B Robustness of Gravity Results

B.1 Alternative Data Set: GSV

In my main estimates of the gravity equation (see Sections 3.1 and 5.1), I use the WITS trade data described in Section 4.3. One disadvantage of this data set is that it does not include data at the subnational level nor intranational trade data at the country level. Since my main parameter of interest in the gravity estimation (namely, the border-crossing cost) is identified by comparing intranational to international trade flows in a given period (see Section 3.1), I must deal with these data limitations by imputing WITS intranational trade flows at the country level (as explained in Section 4.3 above). Therefore, identification of border-crossing costs is partially based on imputed data, which may be unsatisfactory. In that aspect, it would be preferable to have non-imputed data on intracountry trade flows.

To partially allay these concerns, I perform a robustness check in which I repeat gravity estimation for year 2010 using an alternative data source that does include trade flows at the subnational and within-country levels. By verifying that gravity results under WITS and this alternative data set are qualitatively similar, one becomes more confident in using WITS data in the main analysis.

This alternative data set data set is the German Survey *Verkehrsverflechtungsprognose 2030* (GSV), which covers bilateral trade flows in euros across 249 regions within 24 European countries, plus 16 non-European countries and regions.[16][17] Unfortunately, unlike WITS, the data only covers year 2010. Thus, we can think of GSV as being richer but less comprehensive than WITS.

To permit comparability across WITS and GSV data, I adjust GSV bilateral trade flows to be consistent with WITS. Specifically, I first aggregate GSV flows "up" to the country level and compare these aggregated flows to the corresponding WITS flows. Then, for each origin-country by destination-country by sector triplet, I multiply the original GSV trade flows by a constant such that the adjusted GSV flows match the corresponding WITS flows at the country level. Formally:

[16] Flows are converted into US dollar using the exchange rate of 1.33 USD per euro from: https://www.statista.com/statistics/412794/

[17] Trade flows are reported at the level of 15 disaggregated sectors. I classify sector *ss1* ("Agriculture") as agriculture and the remaining sectors *ss2*-*ss15* as non-agricultural

$$X_{ij}^{s,GSV_1} = X_{ij}^{s,GSV_0} \frac{X_{c(i),c(j)}^{s,WITS}}{\sum_{i \in c(i)} \sum_{j \in c(j)} X_{ij}^{s,GSV_0}}$$

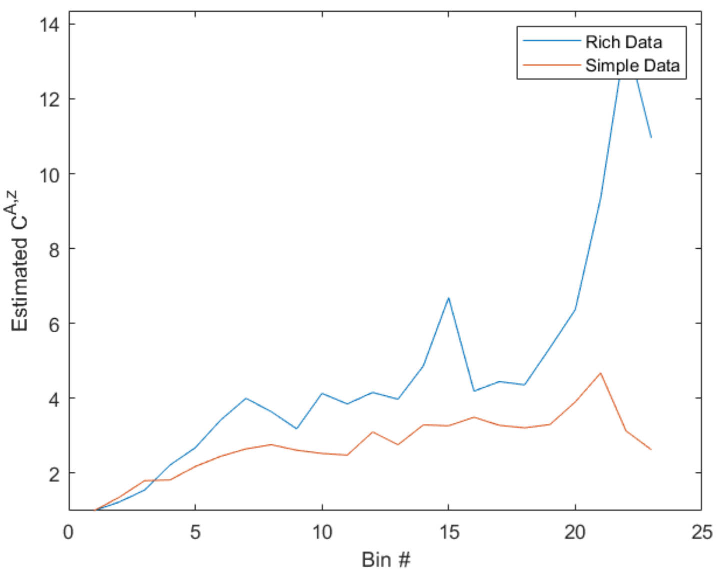
where X_{ij}^{s,GSV_1} is the final, adjusted value of GSV sector-s trade flows from location i to location j, X_{ij}^{s,GSV_0} is the corresponding raw, unadjusted value, and $X_{c(i),c(j)}^{s,WITS}$ is the value of sector-s trade flows from country $c(i)$ to country $c(j)$.

B.2 Results: Comparing WITS to GSV (2010)

I now present results of running trade gravity regressions *for year 2010 only* separately for WITS and GSV data sets. I then compare the estimated trade-cost structures implied by these alternative methods, verifying that they yield qualitatively (and, to some extent, quantitatively) comparable results. This gives further credence to the decision of proceeding with the main analysis using the WITS data.

Figures 16-17 presents estimates of the sector-level costs of distance bins, $\{C^{s,z}\}_{z=1}^{B}$, for each of the two data sets (WITS and GSV). The figures show that the estimates are quite similar for the non-agricultural sector, although less so for agriculture.

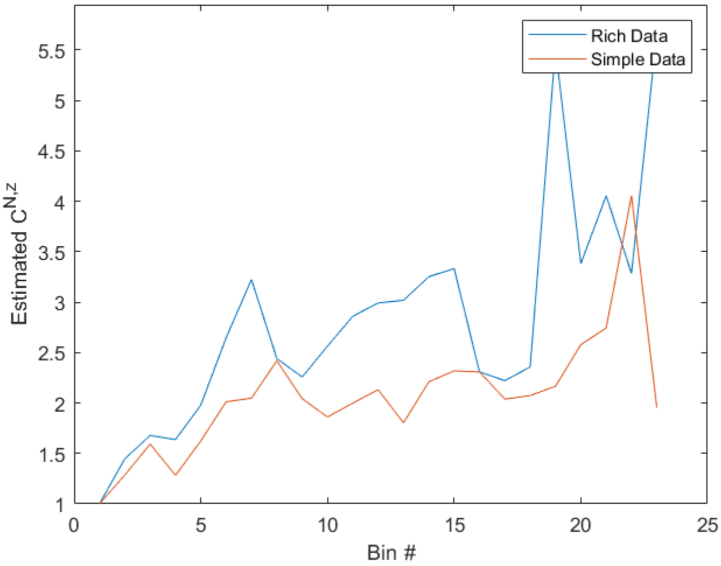
Figure 16: Estimated Cost of Distance Bins, Agriculture (2010)



Notes: the figure portrays the estimated values of the agricultural distance cost $\hat{C}^{A,z}$ in year 2010 for each distance bin $z \in \{0, ..., B\}$ for each of two data sets: the "simple" data set refers to the WITS trade data set (which is the same data I used in the main gravity estimation of Section 5.1), and the "rich" data set refers to the German survey data set *Verkehrsverflechtungsprognose 2030* (GSV), which covers multiple European countries and their subnational units for year 2010 only.

Table 6 presents estimated sector-level border-crossing parameters ($\hat{E}_{2010}^{A}$,$\hat{E}_{2010}^{N}$) for each data source. For the non-agricultural sector, the border-crossing estimate is very similar: $\hat{E}_{2010}^{N} = 3.73$ for the GSV data set versus $\hat{E}_{2010}^{N} = 3.81$ for the WITS data. Note that these are very high costs: an estimate of 3.81 is equivalent to an

Figure 17: Estimated Cost of Distance Bins, Non-Agriculture (2010)



Notes: the figure portrays the estimated values of the non-agricultural distance cost $\hat{C}^{N,z}$ in year 2010 for each distance bin $z \in \{0, ..., B\}$ for each of two data sets: the "simple" data set refers to the WITS trade data set (which is the same data I used in the main gravity estimation of Section 5.1), and the "rich" data set refers to the German survey data set *Verkehrsverflechtungsprognose 2030* (GSV), which covers multiple European countries and their subnational units for year 2010 only.

ad-valorem tariff of 281%. For the agricultural sector, estimates are lower and also not that similar across data sets: $\hat{E}^{A}_{2010} = 1.87$ for GSV versus $\hat{E}^{A}_{2010} = 2.39$ for WITS. However, they are qualitatively in the same ballpark. Moreover, part of the difference could be explained by differences in sample coverage: WITS covers the whole world while GSV is mostly restricted to European countries.

C "Immobility" Counterfactuals

Counterfactual exercises allow us to better understand the effects of changes in trade access not only on the spatial distribution of population, but also on welfare and on the volume of international trade (see Sections 3.3, 5.3.2 and 5.3.3). Additionally, these exercises also allow me to investigate the extent to which this spatial reallocation itself works as a contributing mechanism to the effects on welfare and trade volume. In other words: if spatial reallocation in reaction to trade shocks is not allowed to take place, does the final effect of trade shocks on welfare and trade volumes look very different?

My framework provides a convenient setting to study this question. For each counterfactual trade-cost matrix τ^{cf}, I can compute an "immobility" counterfactual equilibrium, in addition to the "long-run" counterfactual equilibrium computed with the methodology of Section 3.3. In this immobility counterfactual, I compute the equilibrium distribution of wages $w^{cf,immob}$ (and potentially sector-level population

Table 6: Estimated Border-Crossing Parameters (2010)

	"Rich"		"Simple"	
	(1)	(2)	(3)	(4)
$\hat{E}^A_{2010}$	1.871		2.39	
$\hat{E}^N_{2010}$		3.73		3.81
N	32,483	34,165	18,357	18,394
WITS data?	Yes	Yes	No	No
GSV data?	No	No	Yes	Yes

Notes: the table displays the estimated values of the agricultural and non-agricultural border-crossing costs $\hat{E}^A_{2010}$ and $\hat{E}^N_{2010}$ in year 2010 for each of two data sets: the "simple" data set refers to the WITS trade data set (which is the same data I used in the main gravity estimation of Section 5.1), and the "rich" data set refers to the German survey data set *Verkehrsverflechtungsprognose 2030* (GSV), which covers multiple European countries and their subnational units for year 2010 only.

$L^{cf,immob,A}$,$L^{cf,immob,N}$) under counterfactual trade-cost matrix τ^{cf} while keeping the spatial population distribution *fixed* at 2005 levels (i.e. $L_i^{cf,immob} = L_{i,2005}$ for all locations i). In other words, I allow wages but not population to adjust in response to the trade-cost shock. In that sense, immobility counterfactuals can be interpreted either as a short run equilibrium (in which workers have not yet had enough time to reallocate) or as a long-run equilibrium in which severe mobility frictions stop workers from reallocating.

Immobility counterfactuals come in two versions: in the *strong* immobility counterfactual I do not allow population to reallocate either across sectors or locations, while in the *weak* immobility counterfactual I allow population to reallocate across sectors but not across locations. Formally, a strong-immobility counterfactual equilibrium is obtained by solving the following equation system for variables ($w^{cf,Simmob,A}$, $w^{cf,Simmob,N}$, $P^{cf,Simmob,A}$, $P^{cf,Simmob,N}$,$\upsilon^{cf,Simmob,A}$):

$$(w_i^{cf,SI,s})^{\sigma_s}(L^s_{i,2005})^{1-\alpha_s(\sigma_s-1)} = (\bar{A}^s_{i,2005})^{\sigma_s-1} \sum_{j\in\mathcal{S}}(\tau_{ij}^{cf,s})^{1-\sigma_s}(P_j^{cf,SI,s})^{\sigma_s-1}\sum_{r\in\{A,N\}}\upsilon_j^{cf,SI,s\times r}L^r_{j,2005}w_j^{cf,SI,r}$$

$$(P_j^{cf,SI,s})^{1-\sigma_s} = \sum_{i\in\mathcal{S}}(\hat{\tau}^s_{ij,2005}w_i^{cf,SI,s})^{1-\sigma_s}(\bar{A}^s_{i,2005}(L^s_{i,2005})^{\alpha_s})^{\sigma_s-1}$$

$$\upsilon_j^{cf,SI,A\times s} = \phi + \nu(P_j^{cf,SI,A}/P_j^{cf,SI,N})^{\gamma}(w_j^{cf,SI,s})^{-\eta}$$

Note that wages are now allowed to vary by sector, owing to the fact that workers cannot reallocate across sectors. Therefore, wage differences across sectors within a given location are not arbitraged away by workers moving from the lower-wage to the higher-wage sector. Mathematically, since sector-level populations (L^A, L^N) are not "free" variables anymore, it is necessary to allow wage vectors to vary by sector so that goods market-clearing equations can simultaneously hold for the agricultural and non-agricultural sectors. Moreover, in the right-hand side of these market-clearing equations there is now an internal summation term across sectors. This is necessary to separately account for the demand from a location's agricultural and non-agricultural workers. This demand may differ across the two groups of workers because their wages (and hence agricultural shares of consumption expenditure) may now be different.

A weak-immobility counterfactual equilibrium can similarly be obtained by solving the following equation system for variables ($w^{cf,WI}$, $P^{cf,WI,A}$, $P^{cf,WI,N}$,$\upsilon^{cf,WI,A}$):

$$(w_i^{cf,WI})^{\sigma_s}(L_i^{cf,WI,s})^{1-\alpha_s(\sigma_s-1)} = \\ (\bar{A}_{i,2005}^s)^{\sigma_s-1}\sum_{j\in\mathcal{S}}(\tau_{ij}^{cf,s})^{1-\sigma_s}(P_j^{cf,WI,s})^{\sigma_s-1}\upsilon_j^{cf,WI,s}L_{j,2005}w_j^{cf,WI}$$

$$(P_j^{cf,WI,s})^{1-\sigma_s} = \sum_{i\in\mathcal{S}}(\tau_{ij}^{cf,s}w_i^{cf,WI})^{1-\sigma_s}(\bar{A}_{i,2005}^s(L_i^{cf,WI,s})^{\alpha_s})^{\sigma_s-1}$$

$$\upsilon_j^{cf,WI,A} = \phi + \nu(P_j^{cf,WI,A}/P_j^{cf,WI,N})^{\gamma}(w_j^{cf,WI})^{-\eta}$$

$$L_{i,2005} = L_i^{cf,WI,A} + L_i^{cf,WI,N}$$

Note that, unlike in the strong-immobility counterfactual, the weak-immobility counterfactual forces wages to be the same for both sectors in a given location. This is possible because sector-level populations are allowed to reallocate from one sector to the other within a given location, thus arbitraging away any cross-sectoral differences in wages.

For either the strong- or weak-immobility counterfactual, it is relatively straightforward to compute the effect of trade shocks on welfare ($\pi^{cf,SI}$,$\pi^{cf,WI}$) and trade volume (($(\frac{M}{Y})^{cf,SI}$, $(\frac{M}{Y})^{cf,WI}$,$(\frac{M}{Y})^{cf,SI,WLD}$,$(\frac{M}{Y})^{cf,WI,WLD}$) using similar equations to (28)-(30). I can then compare these effects to their counterparts in the long-run counterfactual and assess how much of the effect of trade-cost shocks on welfare and trade volumes is mediated by population reallocation. That is, I can uncover the extent to which trade-induced labor reallocation contributes to the increase in trade volumes and gains from trade brought about by trade integration.

C.1 Results of Immobility Counterfactuals

As described in the last section, I rerun each counterfactual exercise without allowing population to reallocate geographically ("weak" immobility) or without allowing it to reallocate either geographically or across sectors ("strong" immobility). For each of these exercises, I compute the counterfactual fraction of international trade in world

GDP and the counterfactual cross-country average of adjusted welfare sums (π_c) and present them in Tables 3 and 4, respectively.

For each of the two tables, both the strong and weak Immobility rows have very similar results to the long-run counterfactual row. For example, while increasing trade costs to 1971 levels decreases the cross-country average of adjusted welfare sums by 5.1% when mobility is allowed, the corresponding decrease is 4.4% and 5.1% with strong and weak immobility, respectively. That same counterfactual increase in trade costs decreases the fraction of trade in world GDP from 21% to 14% when mobility is allowed, whereas this fraction falls to 16% and 14% when assuming strong and weak immobility, respectively.

Therefore, given parameters and the exogenous variables calibrated to the 2005 economy, the results imply that internal mobility within countries and across sectors are relatively secondary factors mediating the effects of trade-cost shocks on both trade volumes and welfare. In other words, when observing the world through the lens of this model, we conclude that the reallocation of workers across sectors and locations does not seem to be a major mechanism contributing to the effects of international trade integration on trade volumes and on national welfare levels.

D Details of the Decomposition Exercise

D.1 Calibrating the 1990 Economy

As explained in Sections 3.4 and 5.4, I use the calibrated model to perform a decomposition exercise in which I separate the contributions of structural transformation, differential market access, and local fundamentals in explaining the 1990-2015 changes in my measure of spatial concentration (i.e. the primacy rate) observed in the data. As explained above, doing so requires knowledge of calibrated fundamentals ($\bar{u}$, $\bar{A}^A$, $\bar{A}^N$) and variables (υ^A, I,Π^A,Π^N) not only for 2005 but also for 1990. Therefore, to obtain these variables I must separately calibrate the model to the global 1990 economy.

Calibration procedures and data sources for 1990 are remarkably similar to the ones for 2005, which were described in sections 3.2 and 4. In particular, I use IPUMS International data for population and sectoral employment and G-Econ 4.0 data for per capita income. IPUMS data on the population share of each location within a country is taken from 1990 or from the closest available year (as long as that year is between 1985 and 1995). The final 1990 calibration sample features 1152 locations across 188 countries. The substantial difference in the number of locations with respect to the 2005 sample is explained by the fact that IPUMS International covers fewer countries at the subnational level in 1990 compared to 2005.

D.2 Decomposition Results: Country-by-Country

Table 7 presents complete results for the decomposition exercise of Section 5.4 for each country. Specifically, the table displays the primacy rate in 2005, the 1990-2005 change in (the log of) the primacy rate, and the contributions of structural transformation ($cont_c^{ST}$), differential trade access ($cont_c^{DTA}$), and local fundamentals ($cont_c^{LF}$).

As an example, consider the case of Brazil. Its log primacy rate decreased by 0.049 between 1990 and 2005, leading to a 2005 primacy rate of 0.227. Changes in differential market access and in local fundamentals contributed roughly equal parts to this change in primacy ($cont_{BRA}^{DTA} = 0.022$, $cont_{BRA}^{LF} = 0.027$), with structural change having a much smaller influence ($cont_{BRA}^{ST} \approx 0$). However, for most countries, the fraction of the primacy change accounted for by local fundamentals is much higher. For example, the change in log primacy in Argentina was -0.342, with -0.334 (97.6%) of that being accounted for changes in local fundamentals. Similar analyses can be performed for other countries by inspecting Table 7.

Table 7: Countries' Primacies and Contributing Factors

Country	$Primacy_{c,2005}$	$d\ln(Primacy_c)$	$cont_c^{ST}$	$cont_c^{DTA}$	$cont_c^{LF}$
Argentina	0.371	-0.342	0.000	-0.008	-0.334
Austria	0.203	-0.029	-0.000	-0.003	-0.026
Bolivia	0.295	-0.005	0.000	-0.003	-0.002
Botswana	0.193	0.060	-0.000	-0.003	0.064
Brazil	0.227	-0.049	-0.000	-0.022	-0.027
Canada	0.384	0.005	-0.000	-0.002	0.007
Chile	0.345	-0.029	-0.000	-0.007	-0.022
China	0.092	-0.091	-0.000	0.011	-0.101
Colombia	0.229	-0.048	0.000	-0.012	-0.036
Benin	0.112	-0.111	-0.000	-0.003	-0.108
Ecuador	0.649	0.018	-0.000	-0.005	0.023
El Salvador	0.332	-0.052	0.000	-0.024	-0.028
Fiji	0.427	0.076	-0.000	-0.001	0.077
France	0.206	-0.061	0.000	-0.002	-0.059
Greece	0.268	0.036	0.001	-0.014	0.049
Guatemala	0.291	0.090	-0.000	-0.035	0.125
Indonesia	0.201	-0.037	0.001	-0.006	-0.032
Ireland	0.288	-0.103	0.000	-0.003	-0.100
Israel	0.242	0.000	0.000	-0.001	0.001
Jamaica	0.230	-0.112	0.000	-0.012	-0.100
Malaysia	0.284	0.286	-0.000	-0.009	0.296
Mali	0.182	-0.101	0.001	-0.000	-0.102
Mexico	0.138	0.111	-0.001	-0.011	0.123
Morocco	0.130	-0.082	-0.000	-0.032	-0.050
Nicaragua	0.330	0.041	-0.000	-0.035	0.075
Panama	0.567	0.129	0.000	-0.012	0.141
Paraguay	0.279	0.205	0.000	-0.029	0.234
Peru	0.355	0.052	0.000	-0.017	0.069
Philippines	0.054	0.210	0.008	-0.016	0.219
Portugal	0.203	-0.032	0.000	-0.005	-0.027
Puerto Rico	0.728	0.026	0.000	0.000	0.026
Romania	0.094	0.003	0.001	-0.027	0.028
Vietnam	0.107	-0.030	0.000	-0.002	-0.028
Spain	0.173	-0.020	0.000	-0.005	-0.015
Switzerland	0.184	0.016	0.000	-0.001	0.017
Thailand	0.090	-0.034	0.001	-0.062	0.027
Trinidad and Tobago	0.875	-0.031	0.000	0.001	-0.031
Turkey	0.186	0.212	0.000	-0.037	0.249
Egypt	0.198	-0.456	0.000	-0.022	-0.434
United Kingdom	0.144	-0.369	0.000	0.000	-0.370
United States	0.117	-0.037	-0.000	0.000	-0.037
Uruguay	0.455	-0.026	-0.000	-0.010	-0.015
Venezuela	0.120	-0.212	0.002	-0.016	-0.198
Zambia	0.304	0.047	0.000	0.006	0.041

Notes: for each country in the sample of the decomposition exercise, the table displays the primacy rate in 2005, the change in the log of primacy between 1990 and 2005 ($d\ln(Primacy_c)$), and the contributions of structural transformation ($cont_c^{ST}$), differential trade access ($cont_c^{DTA}$), and local fundamentals ($cont_c^{LF}$).