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IMMIGRATION, INNOVATION, AND THE GEOGRAPHY OF GROWTH

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ABSTRACT

Between 1880 and 1920, more than 20 million immigrants settled in the United States. We study how this migration wave affected innovation and growth. Using a newly constructed dataset linking individual census records to historical immigration records and the universe of US patents, we highlight a new channel through which immigrants contributed to growth: they disproportionately settled in urban innovation hubs. To quantify the aggregate and regional effects of this mass migration episode, we develop a new spatial growth model in which skilled workers have a comparative advantage in innovation and sort endogenously across space. We find that international arrivals after 1880 raised US income per capita by 8.2% by 1940. Removing the subsequent immigration restrictions of the 1920s would have raised income per capita by a further 1.7% by 2000. Immigrants' skill composition and their concentration in urban hubs are key drivers of these effects.

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A online appendix is available at http://www.nber.org/data-appendix/w35392

1. INTRODUCTION

Between 1880 and 1920, more than 20 million immigrants made the US their home. Did their arrival contribute to US productivity growth? Two mechanisms come immediately to mind. First, by expanding the *scale* of the workforce and the size of the market, migrants could have increased the demand for innovation. Second, migrants could have increased the stock of available *skills* with Italian textile workers, German craftsmen, and British engineers bringing their existing knowledge to the American shore. In this paper, we highlight a novel third mechanism: *space*. Migrants could have contributed to US growth by settling in the urban innovation hubs of New York, Chicago, and Philadelphia, where most innovative activity took place.

We quantify the importance of these three channels and evaluate the aggregate and regional effects of immigration in the United States, by using new data and new theory. On the empirical side, we create a dataset on immigrants' patent behavior by linking, at the individual level, the complete-count Population Census, the universe of US patents, and millions of historical immigration records, which provide direct microdata on immigrants' pre-migration occupations and hence the skill content of international migrants. We then develop a spatial semi-endogenous growth model that allows us to quantify the impact of immigration on growth. We find that without the inflow of international migrants between 1880 and 1920, US income per capita would have been 8.2 percent lower by 1940, and that both immigrants' innate skills and their concentration in urban innovation hubs drive most of this effect.

Our data reveal three key empirical patterns. First, immigrants played an important role in US innovation: they created patents at roughly the same rate as natives. Second, spatial sorting played a key role because immigrants' patenting rates are substantially lower within local labor markets. Hence, immigrants' relative innovativeness reflected their disproportionate concentration in cities, where patent intensity was highest. Third, our data highlight the importance of innate innovative skill. For example, German and British immigrants were substantially more innovative than Italian and Irish immigrants, and we document that they were positively selected based on their pre-migration occupations.

On the theoretical side, we propose a spatial semi-endogenous growth model that speaks directly to this evidence. The key feature of our theory is that the local supply of innovative human capital matters. We assume that skilled workers of each nationality are heterogeneous and can work as production workers or, as in Romer (1990) or Krugman (1980), become innovators by inventing new products. Goods are tradable and the demand for new varieties stems from local forward-looking capitalists, who hire innovators to come up with new blueprints. As a result, the costs of product creation differ across people *within* a location (because skilled individuals have a comparative advantage in innovation) and *across* space because they depend on the endogenous stock of accumulated knowledge ("building on the shoulders of *local* giants") and because some locations might have higher innovation TFP than others.

Our model captures the three channels of how immigrants can contribute to growth discussed above. First, the *size* of the local workforce increases the return to innovation so that immigrant inflows induce innovation by native skilled workers. Second, the *skill* composition of the local population determines the local innovation rate: an inflow of skilled immigrants thus contributes to the creation of ideas. Finally, *spatial* differences in the quality of the local knowledge pool imply that the productivity of innovators differs across labor markets. Immigrants' bias to move to innovative urban centers thus has a direct effect on innovative activity.

We analytically characterize the spatial balanced growth path (SBGP) of the model. Since it is a semi-endogenous growth model in the tradition of Jones (1995), the long-run growth rate is tied to the rate of population growth, and the cross-sectional distribution of wages, patent activity, and population is stationary in this growth path. Hence, more populous locations are richer and have a higher stock of patents but they do not grow at a faster rate in the long run. We also show that the share of people engaged in innovation as opposed to production work is equalized across space. Patents per innovator, by contrast, are larger in locations with high innovation TFP and a large knowledge stock — that is, in cities, which in equilibrium are richer and more populous.

A key advantage of our theory is that it can be readily taken to our data. Three aspects govern the innovation side of our model. First, individuals' innate human capital determines their innovative potential. We assume that the share of skilled individuals differs across nationalities and that the innovative talent of skilled individuals is drawn from a distribution whose mean depends on a location's endogenous knowledge stock and exogenous innovation TFP. We show that we can estimate the parameters of this distribution and the share of skilled individuals by nationality directly using our linked data on the extensive and intensive margin of patenting. Second, we estimate the spatial distribution of innovation TFP, which is akin to a location fixed effect. We do so by using data on the existing stock of patents, the flow of patents per capita, and the share of people engaged in innovation. Intuitively, if a location has a large flow of patents given its population and stock of patents, but only a small share of individuals contributes to new inventions, innovation TFP must be large. Finally, as in every model of (semi-)endogenous growth, the extent to which the existing stock of knowledge makes future innovation easier is crucial. We estimate this parameter directly from the panel data on patent activity at the regional level, leveraging the autocorrelation between the local patent stock and subsequent patent flows. We estimate this intertemporal scale elasticity to be substantially below unity, consistent with growth being semi-endogenous and ideas getting harder to find (Bloom et al., 2020).

With the calibrated model in hand, we quantify the importance of international migration for US growth, more generally, and the role of immigrants' skills and the "urban innovation hubs" hypothesis, in particular. First, to capture the overall importance of international migration, we compute the economic consequences of a complete migration ban between 1880 and 1920. Such a policy will have a long-lasting negative effect on the US population, but in the long run, the economy will return to its old balanced growth path. We find that the inflow of immigrants during the Age of Mass Migration played an important role in US innovation and growth: without the inflow of international migrants between 1880 and 1920, aggregate GDP per capita would have been 8.2% lower by 1940.

To isolate the role of migrants fueling the population of urban innovation hubs and the role of skilled migration, we compare two alternative scenarios: one where the overall number of migrants remains unchanged but their initial settlement is in line with the settlement of natives — that is, relatively less urban — and one where we keep the number of immigrants constant but assume that all such immigrants are unskilled. In the first counterfactual, both the number and the skill-nationality composition of international migrants do not change, but they arrive in rural America rather than New York. This change would reduce GDP per capita by almost 2% and thus would account for about a quarter of the overall GDP impact of a full migration stop. The second counterfactual highlights the importance of innate innovative skills — the aforementioned British engineers and German craftsmen. In this case, overall GDP per capita would be reduced by 4%. Hence, migrants' bias to settle in urban innovation hubs was half as important for US growth as the entire difference in innate skills. This highlights a new and important aspect of successful immigration policy: not only does it matter who enters the country, but also where migrants settle.

Finally, we use our model to evaluate the growth consequences of the 1921 Emergency Quota Act and the 1924 Johnson–Reed Act, the first large-scale immigration restrictions in the US, which substantially reduced new arrivals, especially from Eastern and Southern Europe and Asia. We find that the removal of these bans leads to an increase in US GDP per capita of about 1.7% by 2000. There are two main reasons why this policy had relatively modest effects. First, given the size of the US population, the implied change in population growth is relatively small. Second, the policies mainly affected countries with a large share of unskilled immigrants, who, according to our estimates, contributed relatively little to overall innovation.

Related Literature The rising prominence of immigration flows, particularly high-skill immigration (see, e.g., Kerr et al. (2016), Kerr (2018), and Bernstein et al. (2022)), has led to increased interest in estimating the economic effects of immigration. Traditionally, the literature has focused on the short-term consequences on labor outcomes of natives (see, e.g., Card (1990), Burstein et al. (2020), Dustmann et al. (2017), and Peri (2016) for a survey). More recent papers, including ours, focus on the long-term impact. Sequeira et al. (2020) and Akcigit et al. (2017) document a large positive effect of 19th-century immigration inflows on contemporary economic activity and patent creation. Burchardi et al. (2026) find positive effects of immigration on local innovation and wages in the US since 1965. Our paper complements this empirically oriented literature. By proposing a spatial model of migration and growth, we quantify the aggregate and regional consequences of immigration and highlight the importance of urban innovation hubs, isolating the role of where migrants settle, not just how many arrive.

Our paper adds to the growing literature in spatial economics. Early contributions in this area focus on static models, taking regional productivity as given — see, for example, Allen and Arkolakis (2014) or the recent survey by Redding and Rossi-Hansberg (2017). A growing number of papers model the evolution of regional productivity explicitly (e.g., Desmet et al., 2018; Nagy, 2023; Peters, 2022; Eckert and Peters, 2022). We build on the idea-based, semi-endogenous growth models in the spirit of Jones (1995) or Kortum (1997) (see, for example, Akcigit (2017) and Jones (2022) for recent surveys) and propose a framework where innovators build on local ideas and sort endogenously across space. To the best of our knowledge, our paper is the first to connect a micro-founded model of spatial growth with direct evidence on regional patenting at the individual level.

On the methodological side, we relate to the growing literature in spatial economics that explicitly models forward-looking investment behavior. Kleinman et al. (2023) introduce the accumulation of physical capital in a spatial model; Walsh (2025) considers a framework of firms with free entry. We directly model the process of innovation, whereby long-lived capitalists hire local researchers to generate new product varieties.

Finally, we speak to the literature on the "Era of Mass Migration" that has used record-linking techniques to study the experience of immigrants in the late 19th and early 20th century (see, e.g., Abramitzky et al. (2014), Abramitzky et al. (2012), or Abramitzky and Boustan (2022)). Complementing this line of research, we link population census data to patents and use our microdata to estimate a structural model and quantify the aggregate impacts of immigration inflows.

The rest of the paper is structured as follows. Section 2 documents the main empirical facts about immigrants' patenting behavior and the urban innovation premium. In Section 3 we present our theory and structurally estimate it in Section 4. Section 5 quantifies the impact of immigration on US growth. A number of theoretical and empirical details are contained in the Appendix and in the Supplementary Material.

2. Immigrants and Innovation: The Role of Cities

In this section, we present the main motivating facts for our study. First, immigrants played an active part in aggregate innovation activity in the United States between 1880 and 1920. Second, this is partly due to the fact that they settled predominantly in urban innovation hubs.

Data: A New Dataset on Immigrants' Patent Activity To document these facts, we create a novel database that captures individual-level patent activity. We create these data by linking the universe of patents to tens of millions of individuals in the complete-count Population Census between 1880 and 1920. Because the Census reports detailed information on individuals' immigration status and places of residence, our matched data allow us to directly measure whether immigrants are engaged in innovation and where innovation takes place.

In order to link patents to individuals in the Census, we employ supervised, machine-learning-based record-linking techniques. Specifically, we opt for a *random forest classifier* (RFC). Our study concentrates exclusively on males, given that the majority of patent holders during the period from 1880 to 1920 were male.[1] We further restrict the sample to working-age individuals aged between 16 and 60 years. To match patents and individuals, we rely on information regarding the names and the residential locations of individuals. We match patent records within a fifteen-year window around the Census, from five years prior to ten years after. We train our RFC using a training dataset of IPUMS-linked records and apply the trained classifier to pairs of records that meet feasibility constraints, such as matching the county of residence. Subsequently, we select unique matches through a "pruning" procedure. We first retain candidate pairs whose predicted match probability is at least 0.85; these constitute the set of potential matches. Among these, a pair (r_A, r_B) is selected as a unique match if either (i) r_A and r_B are matched only to each other, or (ii) the pair's predicted match probability exceeds that of every competing pair involving r_A or r_B by at least a 15% margin.

A detailed description of our methodology is contained in Appendix Section A.2.2. In the Appendix we also provide more detailed insights into the quality of our patent-matching procedure (see Section A.2.3) and compare our data with those generated using the alternative linking methods discussed in Abramitzky et al. (2021) and Abramitzky et al. (2025); see Section A.2.4.

In Table 1 we report the matching rates for each period. On average, we achieve a matching rate ranging from one-third to one-quarter of all patents, resulting in a dataset of approximately 430,000 matched patents.

Results: Immigrants and Innovation Figure 1 summarizes two key findings of these data. First, as shown in the left panel, immigrants played a pivotal role in US innovation and were almost as likely to engage in patenting as natives. In 1910, among natives, slightly more than two out of 1,000 individuals were assigned any patent. Among immigrants, the rate is only moderately lower, even though many migrants did not speak the language and arguably faced other hurdles that might have discouraged them from engaging with the formal patent system.

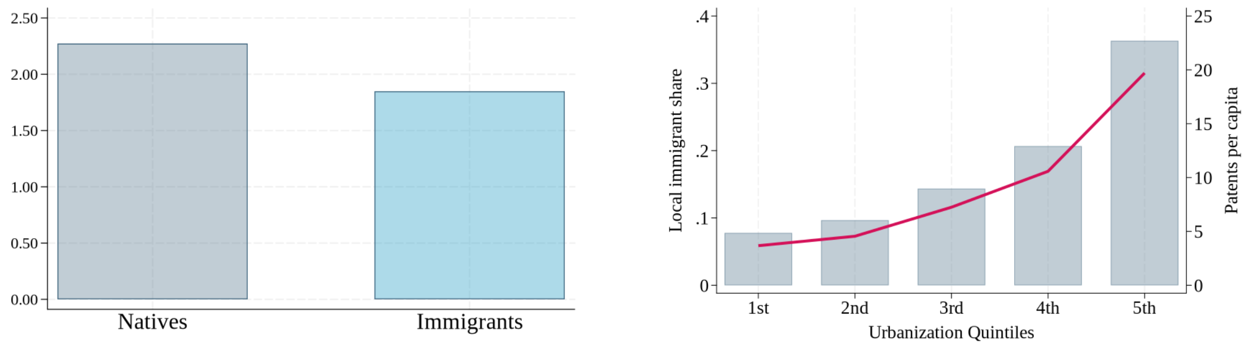
[1] We impute the gender of patent inventors based on the given names of patent holders and find that

TABLE 1: MATCHING PATENTS TO THE POPULATION CENSUS

	1880	1900	1910	1920	Total
Total number of patents issued by period	222,974	307,324	382,193	456,800	1,369,291
Number of patents matched to Census	63,975	108,600	122,861	138,363	433,799
Share of patents matched*	0.29	0.35	0.32	0.30	0.32

Notes: This table reports the total number of issued patents and the subset that we were able to match to the US Census.

FIGURE 1: IMMIGRANTS IN 1910: INNOVATORS IN CITIES



Notes: The left panel shows the number of natives and immigrants with at least one patent out of 1,000 individuals. The right panel shows the share of immigrants (bars) and patents per capita (red line) across counties in 1910 by quintiles of urbanization. We compute patents per capita using the overall population of geolocalized patents, not the patents matched to the US Census. The higher patent intensity in urban areas thus does not reflect differences in match rates.

Second, as shown in the right panel, the fact that immigrants were much more likely to live in cities played an important role in overcoming such disadvantages. Specifically, we compute patent intensity — the number of patents per capita — for each county and then aggregate counties based on their urbanization rate. It is evident that historical patent activity exhibited a significant urban bias: urban locations had about four to five times as many patents per capita as their rural counterparts. Therefore, much like today, cities served as *innovative hubs*. In addition, these regional differences in patent activity strongly correlate with migrants' location choices: migrants were significantly more likely to reside in cities. While counties in the highest urbanization quintile had an immigrant share of almost 40%, less than 10% of individuals living in rural counties were born outside of the US.

The patterns illustrated in Figure 1 suggest that immigrants derived benefits from the local knowledge pool available in cities. To see this more directly, we run a set of regressions of the form

$$\mathbb{1}\{\mathcal{P}_{irt} > 0\} = \alpha \, \text{Urban}_{irt} + \beta \, \text{Immigrant}_{irt} + x'_{irt}\gamma + \delta_r + \delta_t + u_{irt}, \tag{1}$$

where $\mathcal{P}_{irt}$ is the number of patents by individual i living in region r at time t. The

approximately 98% of patent holders were male.

TABLE 2: PATENT ACTIVITY BY IMMIGRANTS

	(1)	(2)	(3)	(4)
Immigrant	-0.113***	-1.168***		
	(0.036)	(0.043)		
Urban		0.682***	0.838***	0.694***
		(0.035)	(0.179)	(0.035)
British				0.616***
				(0.078)
German				-1.059***
				(0.070)
Irish				-2.324***
				(0.127)
Italian				-2.407***
				(0.101)
Others				-1.231***
				(0.047)
Year FE	yes	yes	yes	yes
County FE	no	yes	yes	yes
Age + Educ FE	no	yes	yes	yes
Name Frequency	no	yes	yes	yes
Individual FE	no	no	yes	no
R^2	.000157	.00467	.456	.00471
N	97,515,818	87,410,901	3,996,904	87,410,901

Notes: The table reports the results of regression (1). The coefficients are scaled to reflect the change in the number of patent holders per 1,000 individuals. All columns control for year FE. Columns 2-4 control for county FE, age and education score FE, and for 100 percentiles of name frequency. Column 3 controls for individual FE. Robust standard errors are clustered at the county-year level.

dummies Urban_{irt} and Immigrant_{irt} indicate whether the individual lived in an urban area and was an immigrant. The vector x_{irt} collects additional controls, δ_r and δ_t denote region and time fixed effects, and u_{irt} is an idiosyncratic error term.

Column 1 of Table 2 documents the unconditional comparison between immigrants and natives. Consistent with Figure 1, immigrants are slightly less likely to hold a patent, though the difference is economically small. Column 2 shows that differences in spatial sorting play a crucial role in explaining why immigrants and natives patented at similar rates overall. Once we control for county fixed effects and an urban dummy, immigrants are substantially less likely to engage in patenting: within locations immigrants have, on average, one fewer patent holder per 1,000 individuals; i.e., only half as many as natives. Note that this specification also controls for age and educational-score fixed effects, and county-specific name frequency, to highlight the importance of spatial differences and to address the concern that immigrants may have distinctive names with match rates that differ systematically from those of natives.[2] At the same time, individuals living in cities have a substantially higher probability of patenting. This coefficient captures both the

[2]We use the information on educational scores contained in the US Census, which does not directly report educational attainment in our time period. We compute name frequency as the number of times we observe a given name in each county and then control for 100 percentiles of this distribution.

direct effect of urban knowledge on individual patent intensity and selection, whereby workers with innovative potential sort toward urban locations.

Column 3 provides additional evidence for a direct effect of urban hubs on innovativeness. By matching census records over time, we construct a panel of roughly four million individuals that we observe at least twice. We can therefore estimate (1) including individual fixed effects, controlling for all time-invariant heterogeneity across individuals. The urban coefficient remains sizable and similar in magnitude to that in column 2.

Finally, column 4 exploits our microdata to document that immigrants of different nationalities were highly heterogeneous in their propensity to patent. British immigrants were more likely than natives to innovate, while Italian and Irish migrants had substantially lower rates of patenting.

Taking stock, the patterns in Figure 1 and Table 2 suggest important roles for both the aggregate skill composition of immigrants and their spatial allocation in shaping US growth. To quantify this link, we now turn to a model in which these factors play a central role.

3. Theory

In this section, we present a novel model of spatial growth that embeds an idea-based growth model (Romer, 1990; Jones, 2005) into a canonical quantitative spatial framework (Allen and Arkolakis, 2014; Redding and Rossi-Hansberg, 2017). The key ingredient of our theory is the local nature of innovative human capital: ideas depend on local innovation labor whose human capital has both an innate component reflecting skill differences and a regional component reflecting innovation efficiency and the endogenous accumulation of local knowledge.

3.1 Environment

We consider an economy with R regions, denoted by r. Time is indexed by t. Individuals have preferences over a unique final good, which itself is a CES bundle of differentiated varieties produced in different regions, indexed by ω:

$$C_{rt} = \left(\sum_{r=1}^{R} \int_{\omega=0}^{N_{rt}} c_{rt}\left(\omega\right)^{\frac{\sigma-1}{\sigma}} d\omega \right)^{\frac{\sigma}{\sigma-1}}.$$

In this expression, N_{rt} denotes the number of varieties being produced in region r at a given time period t. The aggregate number of varieties available in the economy at any given time t is $N_t = \sum_r N_{rt}$, $c_{rt}\left(\omega\right)$ is the consumption of good ω in region r, and σ the elasticity of substitution across varieties.

We assume that varieties are long-lived and produced with constant returns to scale using only labor with region-specific productivity A_{rt}, which we take as exogenous. By contrast, the mass of varieties evolves endogenously as an outcome of local innovation. Letting I_{rt} denote the flow of variety creation in region r at time t, the law of motion of varieties is given by

$$N_{rt} = N_{rt-1} + I_{rt}.$$

Each variety ω is produced by a single firm that competes in a monopolistically competitive market. Inter-regional trade is subject to iceberg trade costs, denoted by τ_{rj}.

The economy is populated by two types of agents. First, there is a mass ℓ_t of *workers*, who are spatially mobile, live for a single period, and can either work as production workers or as innovators. To stress the importance of innate skills, we assume that workers are distinguished by their capacity to engage in innovation activities. Unskilled individuals can only work as production workers. By contrast, skilled individuals face an occupational choice between working in the production sector and innovating. Each skilled worker is endowed with a single efficiency unit in production and h units of innovation efficiency, which is distributed according to a cdf $F_{rt}(h)$ in location r at time t.

Motivated by our empirical analysis in Section 2, we assume that individuals of different nationalities ν differ in their innovativeness, i.e., in the relative abundance of skilled individuals. In terms of notation, we let ℓ_{rt}^{ν} denote the mass of workers of nationality ν in region r at time t and λ_{rt}^{ν} the share of skilled individuals with nationality ν in location r.[3] Together with our assumption that the distribution of innovation efficiency, $F_{rt}(h)$, varies across space, our theory generates differences in innovativeness both across space and across individuals within locations.

Second, each location is populated by a unit mass of *capitalists*. Capitalists are long-lived, discounting the future at rate β, but spatially immobile. They run local firms and are the residual claimants to corporate profits. They hire local production workers to produce existing varieties and local innovators to create new ones.[4]

3.2 Labor Supply and the Demand for Innovation

We now characterize the behavior of capitalists and workers. We denote the prevailing wage for production workers by w_{rt} and the wage for innovation human capital by χ_{rt}. Both are determined endogenously, but taken as given by all agents.

Capitalists To determine the demand for variety creation, let $V_{rt}(N)$ denote the value of the representative capitalist in location r at time t with a stock of N local varieties. Letting π_{rt} denote the profit from each variety that is produced in region r, the value of owning

[3]The total size of the population in region r is thus $\ell_{rt} = \sum_{\nu} \ell_{rt}^{\nu}$, and the overall size of the population satisfies $\ell_t = \sum_r \ell_{rt}$. Moreover, the total number of skilled workers of nationality ν is given by $\ell_t^{\nu H} = \sum_r \lambda_{rt}^{\nu} \ell_{rt}^{\nu}$.

[4]The distinction between capitalists and workers, also made in Kleinman et al. (2023), achieves tractability: because capitalists are long-lived and spatially immobile, their forward-looking behavior on innovation decisions does not interact with overall labor supply.

such a portfolio of varieties can be written recursively as

$$V_{rt}(N) = \max_{I} \left\{ \frac{N\pi_{rt}}{P_{rt}} + I\frac{(\pi_{rt} - \chi_{rt})}{P_{rt}} + \beta V_{rt+1}(N + I) \right\}.$$

The first term captures the overall profits of the N existing varieties in region r. The key choice variable of capitalists is the number of new varieties, I, that are created. Each new variety generates a flow payoff of $\pi_{rt} - \chi_{rt}$, after the payments to innovators are taken into account. In addition, because varieties are long-lived, in the next period, the stock of varieties is given by $N + I$, which has a value of $V_{rt+1}(N + I)$.

As we show in Appendix Section A.1.1, $V_{rt}(N)$ has a tractable solution. First, as in Walsh (2025), it is linear in the number of varieties, so that $V_{rt}(N) = v_{rt}N$, where v_{rt}, the value of a single variety, is given by the present discount value of profits

$$v_{rt} = \frac{\pi_{rt}}{P_{rt}} + \beta v_{rt+1}. \tag{2}$$

Second, competition for local innovators implies that innovators get paid the discounted value, in nominal terms, of the new variety; $\chi_{rt} = P_{rt}v_{rt}$.

Workers While unskilled workers always work in the production sector, a skilled worker with h efficiency units of innovative human capital selects into the innovation process if and only if $h\chi_{rt} \geq w_{rt}$. Thus, there is a region-specific human capital cutoff, $\bar{h}_{rt}$, so that all skilled workers with $h \geq \bar{h}_{rt}$ become innovators:

$$\bar{h}_{rt} = \frac{w_{rt}}{\chi_{rt}}.$$

We assume that h is drawn from a Pareto distribution:

$$F_{rt}(h) = 1 - (\psi_{rt}/h)^{\theta},$$

where $\theta > 1$ and ψ_{rt} is a region-r and time-t specific shifter that determines the distribution of innovative abilities in a particular location at a given point in time. We put more structure on ψ^{ν}_{rt} below. At this point, we simply note that some regions might be better suited to generate ideas ($\psi_{rt} > \psi_{r't}$), and that innovation human capital can grow over time ($\psi_{rt} > \psi_{rt'}$).

Given the cutoff $\bar{h}_{rt}$ and the Pareto assumption on individuals' innovative human capital, the total mass of new varieties created in region r in time t is given by[5]

$$I_{rt} = \sum_{\nu} \lambda^{\nu}_{rt}\ell^{\nu}_{rt} \left(\int_{\bar{h}_{rt}}^{\infty} h dF_{rt}(h) \right) = \frac{\theta}{\theta - 1}\bar{h}_{rt} \sum_{\nu} \lambda^{\nu}_{rt}\ell^{\nu}_{rt} \left(\frac{\psi_{rt}}{\bar{h}_{rt}} \right)^{\theta}.$$

[5] For our theoretical exposition we assume $\psi_{rt} < \bar{h}_{rt}$. In our quantitative analysis we account for $\psi_{rt} > \bar{h}_{rt}$.

Hence, total variety creation is increasing with the number of skilled individuals, $\lambda_{rt}^{\nu}\ell_{rt}^{\nu}$, and local human capital ψ_{rt}, while it is decreasing in the innovation cutoff $\bar{h}_{rt}$.

To characterize the equilibrium, it is useful to let $\varpi_{rt}^{\nu} := \ell_{rt}^{\nu}/\ell_{rt}$ denote the share of people of nationality ν in location r and define the aggregate statistic

$$\mathcal{H}_{rt} := \psi_{rt}\left(\sum_{\nu}\lambda_{rt}^{\nu}\varpi_{rt}^{\nu}\right)^{1/\theta}.$$

We refer to $\mathcal{H}_{rt}$ as the region r's *innovation capacity* because it depends on the location's innovation efficiency ψ_{rt} and its overall share of skilled individuals. Given $\mathcal{H}_{rt}$, the overall share of innovators in region r, e_{rt}, is given by

$$e_{rt} = \frac{\sum_{\nu}\lambda_{rt}^{\nu}\ell_{rt}^{\nu}\left(\psi_{rt}/\bar{h}_{rt}\right)^{\theta}}{\ell_{rt}} = \left(\frac{\mathcal{H}_{rt}}{\bar{h}_{rt}}\right)^{\theta}. \tag{3}$$

Hence, at the regional level, the overall innovator share again resembles a Pareto distribution, with an *endogenous* scale parameter $\mathcal{H}_{rt}$.

Our theory has strong implications for the distribution of innovative activity across nationalities and space. As such it speaks directly to the empirical evidence in Section 2. The share of people of nationality ν that innovate in location r at time t is given by $e_{rt}^{\nu} = \lambda_{rt}^{\nu}\left(\psi_{rt}/\bar{h}_{rt}\right)^{\theta}$. *Within* locations, differences in innovation activity across nationalities, $e_{rt}^{\nu}/e_{rt}^{\nu'}$, reflect the relative abundance of skill supplies, $\lambda_{rt}^{\nu}/\lambda_{rt}^{\nu'}$. Hence, the fact that within locations immigrants have fewer patents than natives reflects the fact that the migrant population is, on average, less skilled. At the same time, innovative activity is concentrated in cities, if their innovative capacity $\mathcal{H}_{rt}$, relative to the cutoff $\bar{h}_{rt}$, is large. As a consequence, the *average* degree of patenting might not vary much between natives and immigrants, if migrants are more likely to live in urban locations.

3.3 Local Innovation and Growth

Using the definition of $\mathcal{H}_{rt}$, the total flow of local innovation can be written as

$$I_{rt} = \frac{\theta}{\theta-1}\bar{h}_{rt}^{1-\theta}\mathcal{H}_{rt}^{\theta}\ell_{rt} = \frac{\theta}{\theta-1}\bar{h}_{rt}e_{rt}\ell_{rt}. \tag{4}$$

Local innovation depends on the total size of the local population ℓ_{rt}, overall innovation capacity $\mathcal{H}_{rt}$, and the endogenous human capital cutoff $\bar{h}_{rt}$. In particular, given the population distribution $[\varpi_{rt}^{\nu}, \lambda_{rt}^{\nu}]$ and innovative ability ψ_{rt}, the human capital cutoff is the sole endogenous variable that fully determines innovative investments and innovation per researcher $I_{rt}/(e_{rt}\ell_{rt})$.

So far, we have taken individuals' innovative human capital in location r, ψ_{rt}, as exogenous.

We now put more structure on its determinants and incorporate dynamics. In the tradition of idea-based models of economic growth, we link individuals' innovative efficiency to the available stock of knowledge embodied in the existing mass of local varieties N_{rt}. Specifically, we assume ψ_{rt} is given by

$$\psi_{rt} = \zeta_r N_{rt-1}^{\vartheta}, \tag{5}$$

that is, ψ_{rt} reflects both an exogenous location-specific effect ζ_r and the endogenous amount of local knowledge N_{rt-1}. The former allows for systematic, exogenous differences in innovative ideas across space. The latter incorporates the usual mechanism of building on the shoulders of giants, whereby existing local knowledge is an input into the production of new entrepreneurial human capital and the source of long-run growth. The intertemporal scale elasticity $\vartheta \leq 1$ governs the strength of such spillovers.

Equation (5) stresses that our theory captures both the role of *places* and *people*. In particular, the local human capital supply $\mathcal{H}_{rt}$ is given by

$$\mathcal{H}_{rt} = \zeta_r N_{rt-1}^{\vartheta} \left(\sum_{\nu} \lambda_{rt}^{\nu} \varpi_{rt}^{\nu} \right)^{1/\theta},$$

and thus depends on the local skill supply, the region's innovation TFP ζ_r, and the local pool of ideas N_{rt-1}. Together with the law of motion of varieties and the definition of the entrepreneurial employment share e_{rt} in (3), we can express local variety *growth* as

$$g_{Nt} \equiv \frac{N_{rt} - N_{rt-1}}{N_{rt-1}} = \frac{\theta}{\theta - 1} \zeta_r N_{rt-1}^{\vartheta - 1} \left(\sum_{\nu} \lambda_{rt}^{\nu} \varpi_{rt}^{\nu} \right)^{1/\theta} \ell_{rt} e_{rt}^{\frac{\theta-1}{\theta}}.$$

Local growth is increasing in permanent research TFP ζ_r, population size ℓ_{rt}, the share of skilled individuals $\sum_{\nu} \lambda_{rt}^{\nu} \varpi_{rt}^{\nu}$, and the share of the population engaged in innovative activities, e_{rt}. Note that this intensive margin of innovation has decreasing returns: $(\theta - 1)/\theta < 1$. This reflects the scarcity of entrepreneurial talent: the more people are engaged in innovation, the lower the idiosyncratic talent draw of the marginal innovator. By contrast, growth is (weakly) decreasing in the mass of existing varieties, N_{rt-1}. If $\vartheta = 1$, our model is the spatial analogue of a fully endogenous growth model of Romer (1990): local growth is independent of the mass of varieties and there are strong scale effects whereby larger or more innovative locations grow at a faster rate. If $\vartheta < 1$, ideas are getting harder to find locally: a higher mass of varieties reduces future growth. This specification turns our model into a spatial version of the semi-endogenous growth model of Jones (2005) with long-run growth being proportional to population growth and a stationary population distribution — see Section 3.5 below.[6]

[6]As such, our theory captures the notion that "ideas are getting harder to find" (Bloom et al., 2020).

We also want to highlight what our specification in (5) does not capture. First, we abstract from contemporaneous complementarities, where each type's innovative human capital depends, e.g., on the current composition of the local population. Instead, we summarize the history of past innovative efforts in the scalar-valued dynamic state variable N_{rt}. Second, individuals only benefit from local knowledge; ideas developed in other locations, N_{jt-1}, do not impact the innovative opportunities of a given individual in r. This assumption, while consistent with the empirical evidence that, for example, citations are very localized, is obviously stark and meant to highlight the importance of the local human capital pool. In Section 6 below we extend our analysis by allowing for a richer form of spillovers, where ψ_{rt} is a function of the knowledge stock in all locations. Third, (5) imposes a strict separation between portable and non-portable human capital. In particular, the benefits from an innovative location only accrue as long as the individual is actually present in that location. This precludes the possibility of learning, whereby innovative human capital is a function of the migration history of the individual (see, e.g., Crews (2023) and Bilal and Rossi-Hansberg (2021)). We impose this assumption for tractability as otherwise we would need to keep track of individuals' migration histories as additional state variables.

3.4 Equilibrium

We can now characterize the equilibrium of our model. Given our results from above, we have to determine three endogenous variables: the local wage w_{rt}, the innovation cutoff $\overline{h}_{rt}$ (or alternatively the research wage χ_{rt}), and the mass and composition of people of nationality ν, ℓ^{ν}_{rt} and λ^{ν}_{rt}.

Demand and Supply for Innovation To solve for the equilibrium innovation cutoff $\overline{h}_{rt}$, note first that due to CES demand, aggregate profits $N_{rt}\pi_{rt}$ are a constant fraction of production workers' labor income:

$$\pi_{rt} = \frac{1}{\sigma-1}\frac{w_{rt}\ell_{rt}\left(1-e_{rt}\right)}{N_{rt}} = \frac{1}{\sigma-1}\frac{w_{rt}\ell_{rt}}{N_{rt}}\left(1-\left(\frac{\mathcal{H}_{rt}}{\overline{h}_{rt}}\right)^{\theta}\right).$$

Combining this equation with (2) allows us to express the innovation cutoff $\overline{h}_{rt}$ as

$$\overline{h}_{rt} = \frac{(\sigma-1)}{\frac{\ell_{rt}}{N_{rt}}\left(1-\left(\frac{\mathcal{H}_{rt}}{\overline{h}_{rt}}\right)^{\theta}\right)+\beta\left(\sigma-1\right)\frac{P_{rt}v_{rt+1}}{w_{rt}}}. \tag{6}$$

Equation (6) summarizes the *demand* for innovation. Given the population size, ℓ_{rt}, innovation capacity $\mathcal{H}_{rt}$, and the future discounted value of profits relative to the prevailing

Research productivity, i.e., variety growth per researcher, is given by $\frac{g_{rN}}{\ell_{rt}e_{rt}}$, and hence high in locations with high research TFP ζ_r and a high share of high-type individuals, and low in locations with a larger knowledge stock N_{rt-1} and a larger innovation share, e_{rt}.

real wage, $\beta\frac{v_{rt+1}}{w_{rt}/P_{rt}}$, (6) represents an increasing relationship between the mass of products produced, N_{rt}, and the innovation cutoff $\overline{h}_{rt}$. If the number of products in region r is large, the market for innovation becomes more selective: the marginal entrepreneur has to be more innovative to break even and the cutoff $\overline{h}_{rt}$ rises. Moreover, $\mathcal{H}_{rt}$ acts like a supply shifter: a higher innovative capacity raises $\overline{h}_{rt}$ for a given N_{rt} because fewer people are required to produce a given number of goods N_{rt}.

The equilibrium law of motion for local ideas,

$$N_{rt} = N_{rt-1} + \frac{\theta}{\theta-1}\ell_{rt}\left(\overline{h}_{rt}\right)^{1-\theta}\mathcal{H}_{rt}^{\theta},$$

is the second equation that links N_{rt} and $\overline{h}_{r}$. It represents the *supply* of local innovation: N_{rt} and $\overline{h}_{rt}$ are negatively related because a lower productivity cutoff increases the supply of human capital in innovation, and hence the mass of available goods N_{rt} being sold in region r.

These two equations, therefore, allow us to compute $\overline{h}_{rt}$ as a function of the pre-determined number of varieties, the overall supply of human capital, the total population, and the future value of a new variety:

$$\overline{h}_{rt} = h\left(N_{rt-1}, \ell_{rt}, \mathcal{H}_{rt}, \frac{P_{rt}v_{rt+1}}{w_{rt}}\right).$$

Three properties are instructive. First, $\overline{h}_{rt}$ is increasing in N_{rt-1} and decreasing in ℓ_{rt}: if goods are abundant relative to the population, the demand for new varieties falls, raising the selection cutoff. Second, $\overline{h}_{rt}$ is increasing in $\mathcal{H}_{rt}$: a higher supply of human capital raises the selection cutoff because fewer entrepreneurs are needed to produce a given number of ideas. Finally, $\overline{h}_{rt}$ is decreasing in the future value of variety creation because higher future profits incentivize more innovation today.

Goods Market Clearing Equilibrium wages are determined from the usual labor market clearing condition that total spending on goods produced in region r equals total income received in r, Y_{rt}:

$$Y_{rt} = N_{rt}\left(\frac{\sigma}{\sigma-1}\frac{w_{rt}}{A_{rt}}\right)^{1-\sigma}\mathcal{D}_{rt},$$

where $\mathcal{D}_{rt} = \sum_{j=1}^{R}\left(\tau_{rj}/P_{jt}\right)^{1-\sigma}Y_{jt}$ is a measure of aggregate demand and P_{jt} is the local price index. Using that total income Y_{rt} is proportional to the payments to production workers, $Y_{rt} = \frac{\sigma}{\sigma-1}w_{rt}\ell_{rt}\left(1-e_{rt}\right)$, yields a simple expression for local wages:

$$w_{rt}^{\sigma} = \left(\frac{\sigma-1}{\sigma}\right)^{\sigma}A_{rt}^{\sigma-1}\mathcal{D}_{rt}\frac{N_{rt}}{\ell_{rt}\left(1-e_{rt}\right)}. \tag{7}$$

Local wages are determined by exogenous TFP A, local market size $\mathcal{D}$, and the number of ideas per production worker $N/(\ell(1-e))$.

Spatial Mobility We model agents' spatial labor supply using the usual discrete choice methodology and assume that the utility of individual i of nationality ν of skill group s to reside in location r given that she currently resides in location o is given by

$$U_{rt}^{i(\nu,s)} = \mu_{ro} B_{rt}^{\nu s} \frac{y_{rt}^{i(s)}}{P_{rt}} v_{rt}^{i},$$

where $B_{rt}^{\nu s}$ is a regional amenity, μ_{ro} parameterizes the moving costs to migrate from o to r, y_{rt}^{i} is the expected income of individual i (which depends on the individual's skill), and v_{rt}^{i} is an individual preference shock that we assume is Fréchet distributed with shape ε. Below, we impose additional assumptions on $B_{rt}^{\nu s}$.

We assume that individuals move before they know the realization of h. Hence, they base their moving decisions on the expected income. Flow income for unskilled individuals is given by the local wage, that is, $y_{rt}^{L} = w_{rt}$. By contrast, expected income for skilled individuals is given by

$$y_{rt}^{H} = w_{rt} + \int_{\bar{h}_{rt}}^{\infty} (\chi_{rt} h - w_{rt})\, dF_{rt}(h) = \left(1 + \frac{1}{\theta - 1} \left(\frac{\psi_{rt}}{\bar{h}_{rt}}\right)^{\theta}\right) w_{rt}. \tag{8}$$

Intuitively, skilled individuals' expected income reflects the local wage and the option value of innovation. This option value exactly reflects the inframarginal returns of innovation, which are given by $\frac{1}{\theta-1}\left(\psi_{rt}/\bar{h}_{rt}\right)^{\theta} = \frac{1}{\theta-1} e_{rt}^{H}$, where e_{rt}^{H} is the probability that a skilled individual innovates in location r.

In addition to the bilateral moving costs μ_{ro}, we follow Bilal (2023) and assume that individuals face a "Calvo"-type friction, where, at each point in time, only a share χ of individuals is allowed to move. Doing so allows us to capture an extensive margin of moving in a parsimonious way. As a consequence, the share of individuals of nationality ν and skill group s migrating from o to r is given by $\chi m_{rot}^{\nu,s}$, where

$$m_{rot}^{\nu s} = \frac{\left(\mu_{ro} B_{rt}^{\nu s} y_{rt}^{s} / P_{rt}\right)^{\varepsilon}}{\sum_k \left(\mu_{ko} B_{kt}^{\nu} y_{kt}^{s} / P_{kt}\right)^{\varepsilon}} \tag{9}$$

denotes the moving probability conditional on receiving the moving opportunity.

Demographics To capture the changing demographics, whereby migrants' children are US-born and the immigrant population grows because of new in-migration, we assume a simple stochastic law of motion. Each period, each individual faces a death rate d and a mass η^{B} of children is born. All newly born children are natives, even though their parents are immigrants. For simplicity, we assume that children keep the skills of their parents, i.e., the children of high-skill British immigrants will be high-skill US natives. However, it would be straightforward to allow for only a partial inheritability of skills at the expense of additional notation. The immigrant population is replenished through new migration from abroad.

Specifically, let $M_{rt}^{\nu s}$ denote the mass of new international migrants of nationality ν with skill s arriving in r at time t. The mass of immigrants of nationality ν and skill s in region r evolves according to

$$\ell_{rt}^{\nu s} = (1-\chi)\left((1-d)\,\ell_{rt-1}^{\nu s} + M_{rt-1}^{\nu s}\right) + \chi \sum_{o} m_{rot}^{\nu,s}\left((1-d)\,\ell_{ot-1}^{\nu s} + M_{ot-1}^{\nu s}\right). \tag{10}$$

Similarly, the stock of natives with skill s evolves according to

$$\begin{aligned}\ell_{rt}^{USs} \quad = \quad & (1-\chi)\left(\left(1+\eta^{B}-d\right)\ell_{rt-1}^{USs} + \eta^{B}\sum_{\nu\in\text{Imm}} \ell_{rt-1}^{\nu s}\right) \\ & + \chi \sum_{o} m_{rot}^{USs}\left(\left(1+\eta^{B}-d\right)\ell_{ot-1}^{USs} + \eta^{B}\sum_{\nu\in\text{Imm}} \ell_{ot-1}^{\nu s}\right).\end{aligned} \tag{11}$$

Note that $\eta^{B}\sum_{\nu\in\text{Imm}}\ell_{rt}^{\nu s}$ are the newly born children among immigrants of skill group s in region r, which add to the stock of natives. Also note that even though we take the inflow of immigrants, M_{rt}^{ν}, as exogenous, migrants' spatial labor supply still responds to local wages because, like everyone else, they have the option to move.

This system of equations determines the spatial allocation of individuals given the current population distribution and the exogenous inflow of international migrants and the vectors of wages, prices, and innovation cutoffs.

Spatial Sorting

Our theory highlights that the skill composition of the local workforce is a key determinant of local innovation capacity: everything else equal, $\mathcal{H}_{rt}$ is increasing in λ_{rt}^{ν}. This distribution of skills is, of course, endogenous, reflecting workers' optimal location decisions. To see this specifically, consider the relative likelihood of skilled individuals and unskilled individuals of the same nationality ν in location o to move to location r relative to location j. Using (8) and (9), this is given by

$$\frac{m_{rot}^{\nu H}/m_{jot}^{\nu H}}{m_{rot}^{\nu L}/m_{jot}^{\nu L}} = \left(\frac{B_{rt}^{\nu H}/B_{jt}^{\nu H}}{B_{rt}^{\nu L}/B_{jt}^{\nu L}}\right)^{\varepsilon}\left(\frac{y_{rt}^{H}/y_{jt}^{H}}{y_{rt}^{L}/y_{jt}^{L}}\right)^{\varepsilon} = \left(\frac{B_{rt}^{\nu H}/B_{jt}^{\nu H}}{B_{rt}^{\nu L}/B_{jt}^{\nu L}}\right)^{\varepsilon}\left(\frac{1+\frac{1}{\theta-1}e_{rt}^{H}}{1+\frac{1}{\theta-1}e_{jt}^{H}}\right)^{\varepsilon}, \tag{12}$$

where e_{rt}^{H} is the probability of a successful innovation in location r for skilled individuals of *any* nationality.

This expression highlights three properties about the endogenous sorting in our model. First, sorting can be driven by labor supply: if location r's amenities are particularly sought after by skilled individuals, the share of skilled workers will be higher. Second, the incentives to sort due to labor demand are fully summarized by the local innovation probabilities (which, of course, are endogenous). Skilled individuals are drawn to locations where it is likely that they can actually participate in the innovation process. These are locations that are intrinsically productive in innovation (high ζ_r), that have a large local idea pool (high N_{rt-1}), and where the competition for innovators is weak (low $\bar{h}_{rt}$). Third, sorting is independent of the location of origin o, reflecting our assumption that the bilateral moving costs, μ_{ro}, are independent of individuals' skill level.

3.5 Spatial Balanced Growth Path

Consider now a stationary equilibrium, or *spatial balanced growth path* (SBGP). Along a SBGP, the aggregate population $\ell_t \equiv \sum_r \ell_{rt}$ grows at a constant rate $\eta > 0$, exogenous productivity A_{rt} grows at rate g_A, and the distribution of economic activity is stationary. In Appendix Section A.1.2, we provide a formal characterization of the SBGP; here, we highlight three key properties.

First, local knowledge N_{rt} and wages w_{rt} grow at rates g_N and g_w, which are given by

$$1 + g_N = (1+\eta)^{\frac{1}{1-\vartheta}} \quad \text{and} \quad 1 + g_w = (1+g_A)(1+g_N)^{\frac{1}{\sigma-1}}.$$

As in Jones (1995), population growth η is the ultimate driver of long-run growth, with the scale elasticity ϑ amplifying the link between population and income growth. Intuitively, as stressed in (4), along a SBGP, the stock of knowledge is proportional to $\bar{h}_{rt}\ell_{rt}$. Since human capital $\bar{h}_{rt}$ is proportional to N_{rt}^{ϑ} by (5), we have $N_{rt} \propto \ell_{rt}^{\frac{1}{1-\vartheta}}$, so that the scale elasticity ϑ shapes the link between population and income growth. The mapping from variety growth to income growth is then determined by the elasticity of substitution. Without any inter-temporal elasticity $\vartheta = 0$, the effect of variety growth is simply $g_w \approx \frac{1}{\sigma-1}\eta$ as in the static model of Krugman (1980). With the possibility of building on the shoulders of local giants ($\vartheta > 0$), population growth has a multiplier $\frac{1}{\sigma-1}\frac{1}{1-\vartheta}\eta$ as in Jones (1995).

Our theory also implies that the share of innovators, e_{rt}, is common across locations and, as we show in Appendix Section A.1.2, given by

$$e_{rt} = e^* = \frac{1}{1 + \frac{\theta}{\theta-1}\frac{1+g_N}{g_N}(\sigma-1)\left(1-\beta(1+g_A)(1+g_N)^{\frac{1}{\sigma-1}-\vartheta}\right)}.$$

Hence, locations with high innovation efficiency ζ_r or a large population ℓ_{rt} generate more ideas per person, *not* by having more innovators but rather by generating more ideas per innovator. The share of innovators e_r is (i) increasing in the growth rate g_N (as a higher growth requires more innovation inputs), (ii) decreasing in the elasticity of substitution σ (as more substitutability lowers markups and hence the returns to innovation), and (iii) increasing in the tail of the Pareto distribution θ (as a thicker tail reduces the mass of "superstar" inventors, so that more people have to work in the idea-creation sector).

Finally, the human capital cutoff and the local stock of local knowledge are given by

$$\overline{h}_{rt} \propto \zeta_r^{\frac{1}{1-\vartheta}} \ell_{rt}^{\frac{\vartheta}{1-\vartheta}} \left(\sum_{\nu} \lambda_r^{\nu} \varpi_r^{\nu} \right)^{\frac{1}{\theta}\frac{1}{1-\vartheta}} \quad \text{and} \quad N_{rt} \propto \overline{h}_{rt} \ell_{rt}$$

These expressions highlight the mechanics of local agglomeration. The local innovation cutoff and the stock of local knowledge are determined by three forces: (i) innovation efficiency ζ_r, (ii) the size of the local population ℓ_{rt}, and (iii) the share of skilled residents. The scale elasticity ϑ again emerges as the crucial elasticity and acts as an amplifying force. Immigrants, by shaping labor supply both across space and time, therefore affect the geography of economic growth.

4. Structural Estimation

We now structurally estimate our model. Specifically, we estimate the structural parameters $\mathscr{P}$, the set of region-specific local fundamentals $\mathscr{F} = \{A_r, \zeta_r, \mathcal{B}_r\}$ (local TFP, innovation efficiency, and amenities), and the initial conditions $\mathscr{I} = \{N_{r0}, \ell_{r0}^{\nu}, \lambda_{r0}^{\nu}\}$, that is, the prevailing stock of knowledge, the number of people of nationality ν, and their skill composition.

We take a location in our theory to be a State Economic Area (SEA), which ensures that boundary definitions are consistent throughout our sample period and that we observe patents in all locations. There are 452 SEAs in the US, and we use a crosswalk provided by IPUMS to aggregate county-level data to the SEA level. We treat 1880 as the first period of our analysis.

4.1 Data

We estimate our model using a combination of micro, macro, and spatial data. In addition to the matched data on individual patenting described in Section 2, we also employ (i) newly acquired microdata on immigration records from the Castle Garden Immigration Database (CG) and the Hamburg Passenger Lists (HPL), (ii) data on average wages at the county level from the Census of Manufactures, (iii) data on the population of patents from PatentCity, and (iv) time-series data on aggregate GDP per capita from Historical Statistics of the United States.

Immigration Records The CG data, compiled by the Battery Conservancy, encompasses a comprehensive list of all immigrants entering the United States via the port of New York between 1820 and 1914, totaling approximately 11 million individual records. The HPL records all passengers departing from the port of Hamburg to the United States between 1850 and 1914, comprising approximately 6 million records.[7]

Crucially for our purposes, both datasets report immigrants' *pre*-migration occupations, information that we use to measure the skill content of international arrivals.[8] As with patents, we match these immigration records to the Population Census. We link all immigration records up until the respective Census year. For example, when linking the 1900 Census, we attempt to link all immigration records up until 1900. To do so, we insist that individuals in the Census and the immigration records have a matching foreign birthplace (at the country level) and race, and that the immigration year reported in the CG/HPL is within two years of the Census-recorded immigration year. For the entire four decades from 1880 to 1920, we match more than 600,000 immigrants between the ages of 16 and 60; see Appendix Table A.6 for a summary of the match rates.

Table 3 summarizes the distribution of pre-migration occupations by immigrants' nationality. The most striking pattern is the heterogeneity in the importance of skilled occupations such as craftsmen, managers, operatives, and technical or sales workers. British and German immigrants were much more likely to work in such occupations prior to migrating compared to Irish and Italian immigrants.[9] This pattern is consistent with the higher patenting rates of British and German immigrants documented in Table 2, suggesting that pre-migration skills shaped post-arrival innovative activity.

Wages and Aggregate GDP Because the Census microdata does not contain information on individual earnings, we measure average local earnings from the county-level tabulations of the Census of Manufactures for 1880, 1900, and 1920 from the NHGIS. We compute average wages by dividing total manufacturing payroll by total manufacturing employment and aggregate the county-level data to the SEA level. To measure aggregate GDP, we use the canonical Historical Statistics of the United States, which reports a time-series for real GDP growth.

Regional Data on Patenting We measure aggregate patenting at the regional level from the PatentCity Database (Bergeaud and Verluise, 2024). From these data, we compute the decadal flow of patents in region r between time t and $t+9$, $\mathcal{P}_{rt}$, and the stock of patents filed in location r up to time t, $\mathcal{S}_{rt}$, by cumulating the flow of patents, i.e., $\mathcal{S}_{rt} := \sum_{k=0}^{t-1} \mathcal{P}_{rk}$.

[7] We have complete access to the records of the Hamburg Passenger Lists through a collaborative arrangement with the Hamburg State Archive.

[8] Since the original databases presented information as unorganized string variables, we created a crosswalk to the official occupational classification used by the US Census. This process utilized the lexical database "WordNet" from the NLTK library in Python. WordNet, with its extensive network of synonyms arranged hierarchically, allowed us to classify immigrants' pre-migration occupations based on shared synonyms with the US Census system. For a comprehensive explanation of our occupational classification methodology, please refer to Section OA.1.3 in the Online Appendix.

[9] Note that we classify individuals with missing information on pre-migration occupations as unskilled. We do so based on the assumption that skilled individuals are more likely (and able) to document this information in their arrival records. For our estimation, we use this information only for the initial sorting upon arrival (see (18)), not to estimate migrants' skill content.

TABLE 3: PRE-MIGRATION SKILLS AND THE COMPOSITION OF IMMIGRATION

Occupation	Immigrants	Distribution of Occupations (%)				
		Immigrants	British	German	Italian	Irish
Craftsmen	67,488	20.4	20.9	23.3	14.8	9.5
Managers, Officials, Proprietors, and Clerks	6,629	2.0	3.3	2.1	0.5	1.3
Operatives	5,321	1.6	2.3	1.5	2.2	0.8
Professional and Technical	7,029	2.1	2.6	2.4	1.2	0.7
Sales Workers	26,399	8.0	5.1	10.5	1.7	2.1
Farmers and Farm laborers	79,353	24.0	8.6	29.9	28.1	8.9
Laborers	2,005	0.6	0.6	0.7	0.7	0.2
Service Workers	6,067	1.8	1.1	1.8	3.7	1.9
Other	130,951	39.5	55.5	27.7	47.0	74.6
Number of People	.	331,242	42,188	191,779	29,701	26,407
Immigrant Group Share	.	.	12.7	57.9	9.0	8.0

Notes: The table reports the distribution of immigrants according to their pre-migration occupations. The "Other" category captures observations with missing or unreported occupation data.

4.2 Measurement: Patents, Ideas, and Innovative Skills

We relate patenting in the data to the creation of varieties in our theory. To operationalize this mapping, we assume that the flow of patents of individual i in region r at time t, $\mathcal{P}^i_{rt}$, is proportional to the number of created varieties conditional on patenting, i.e.,

$$\mathcal{P}^i_{rt} = \begin{cases} 0 & \text{if } h^i < \bar{h}_{rt} \\ \varsigma h^i & \text{if } h^i \geq \bar{h}_{rt} \end{cases}, \tag{13}$$

where $\varsigma > 0$ is a constant of proportionality. If $\varsigma < 1$, not every productive idea is patented; if $\varsigma > 1$, it takes multiple patents to implement a marketable idea. As we show below, we do not have to take a stand on ς to estimate our model.

Furthermore, we need to take into account that we only successfully match a subset of patents to individuals. We thus assume that individual i is matched to their patents with probability q^M_t.[10] We calibrate q^M_t to ensure that our model is consistent with both the micro and macro data on patenting and hence set q^M_t to the match rates reported in Table 1. The share of people with a patent in the model, e_{rt}, is then related to the measured share of patent holders, $\mathcal{M}_{rt}$, according to $\mathcal{M}_{rt} = q^M_t e_{rt}$. To discipline the spatial distribution of skilled individuals, λ^ν_{rt}, we utilize occupations as reported in the US Census as a proxy for innovative skills. Specifically, as in Table 3, we define individuals as working in high-skilled occupations if they work in professional, technical, and managerial occupations or as craftsmen.

[10] Conditional on being matched, we assume that the individual is matched to all patents they issued, because we match on the individual's name. Formally, letting M_i denote an indicator variable that takes the value one if individual i is matched to a patent, we assume that $M_{it} = 1$ with probability $q^M_t P\left(\mathcal{P}^i_{rt} > 0\right)$ and $M_{it} = 0$ with probability $1 - q^M_t P\left(\mathcal{P}^i_{rt} > 0\right)$.

4.3 Estimation of Structural Parameters $\mathscr{P}$

Even though many of our parameters are estimated jointly, our theory allows for a tight mapping between specific structural parameters and empirical moments. We describe this mapping here.

We calibrate three parameters exogenously from the literature. We set $\sigma = 5$, which lies between the median and average estimates reported by Broda and Weinstein (2006) and within the range reported by Oberfield and Raval (2021). For the migration elasticity, we target $\varepsilon = 2$, in line with estimates reported in Fajgelbaum et al. (2019) and Peters (2022). For investors' rate of time preference β we assume an annual discount rate of 10%. Given that we take each period in the model to be a decade, this implies that $\beta = 0.9^{10} \approx 0.35$.

The dispersion of human capital: θ To estimate θ, we exploit information on the distribution of the number of patents. Let $Q_{rt}^{p|\nu}$ be the share of innovators of nationality ν in region r at time t with at least p patents. Our theory implies that

$$Q_{rt}^{p|\nu} \equiv P_{rt}^{\nu}\left(\mathcal{P}_i \geq p | \mathcal{P}_i > 0\right) = P_{rt}\left(h \geq \varsigma^{-1} p | h \geq \bar{h}_{rt}\right) = \left(\varsigma \frac{\bar{h}_{rt}}{p}\right)^{\theta},$$

where ς is the constant of proportionality defined in the measurement equation (13). Note that $Q_{rt}^{p|\nu}$ does not vary across types ν within a location r once we condition on patent holders. Hence, we estimate θ from the regression

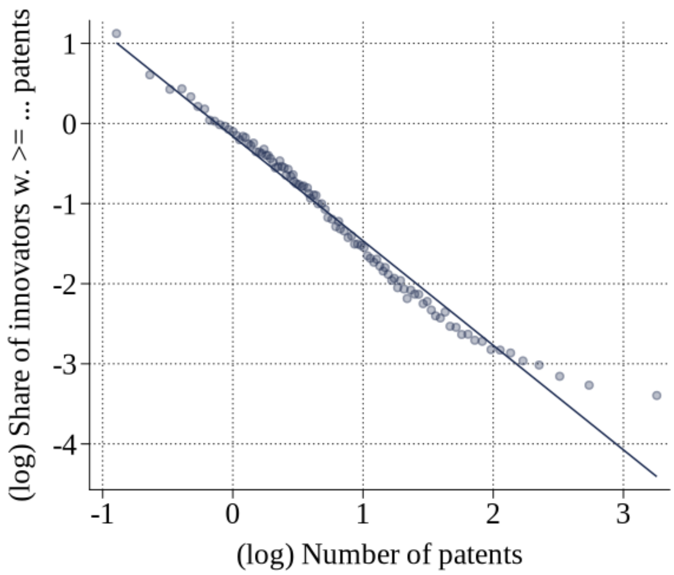
$$\ln Q_{rt}^{p|\nu} = \delta_{rt} - \theta \ln p + u_{rt}^{p\nu}, \tag{14}$$

where δ_{rt} is a region-year fixed effect. The relationship between $\ln Q_{rt}^{p|\nu}$ and $\ln p$ should be linear, and θ is exactly the slope coefficient. To implement (14), we compute $Q_{rt}^{p|\nu}$ for all ν-groups within all localities for $p = 1, 2, 3, \ldots$. In Figure 2 we depict a binscatter of the relationship in (14) after controlling for a set of region-year fixed effects. Consistent with the theory, the estimates indicate a tightly estimated and approximately linear relationship, except at the upper tail where the slope flattens. Quantitatively, the slope in Figure 2 implies that $\theta = 1.3$. In Section A.3.1 in the Appendix, we report the regression results of (14) for a variety of specifications.

Scale Effects: ϑ To estimate the strength of scale effects ϑ, we exploit the autocorrelation between the local patent stock and the flow of new patents. Our model implies that (see equations (3) and (4)) the number of new ideas per capita is given by

$$\frac{I_{rt}}{\ell_{rt}} = \frac{\theta}{\theta - 1} e_{rt}^{\frac{\theta-1}{\theta}} \mathcal{H}_{rt} = \frac{\theta}{\theta - 1} e_{rt}^{\frac{\theta-1}{\theta}} \zeta_r N_{rt-1}^{\vartheta} \left(\sum_{\nu} \lambda_{rt}^{\nu} \omega_{rt}^{\nu}\right)^{1/\theta}.$$

FIGURE 2: ESTIMATION OF PARETO TAIL: θ



Notes: The figure contains a binscatter plot of (14) after controlling for a full set of SEA-Decade fixed effects.

Using the measurement equation (13), we can thus relate the flow of patents per capita in region r, $\mathcal{P}_{rt}/\ell_{rt}$, to the stock of patents, $\mathcal{S}_{rt}$, to arrive at the empirical relationship,

$$\ln\left(\mathcal{P}_{rt}/\ell_{rt}\right) = \alpha + \ln\zeta_r + \vartheta\ln\mathcal{S}_{rt} + \left(\frac{\theta-1}{\theta}\right)\ln e_{rt} + \frac{1}{\theta}\ln\left(\sum_{\nu}\lambda^{\nu}_{rt}\varpi^{\nu}_{rt}\right).$$

The variation in patents per capita is due to four sources: (i) systematic differences in regional patent productivity (ζ_r), (ii) local learning opportunities related to the existing stock of ideas $(\mathcal{S}_{rt})$, (iii) the profitability of variety creation captured by the share of innovators e_{rt}, and (iv) the supply of human capital as summarized by the composition of the local population $(\lambda^{\nu}_{rt}\varpi^{\nu}_{rt})$.

To turn this relationship into a regression, we estimate it at the region-*industry* level to control for differences in the local industrial composition. Specifically, our estimation equation is

$$\text{(15)} \qquad \ln\left(\mathcal{P}_{rjt}\right) = \delta_{jt} + \delta_r + \vartheta\ln\mathcal{S}_{rjt} + \phi\ln e_{rt} + \xi\ln\ell_{rt} + \rho\ln\left(\sum_{\nu}\lambda^{\nu}_{rt}\varpi^{\nu}_{rt}\right) + u_{rjt},$$

where $\mathcal{P}_{rjt}$ and $\mathcal{S}_{rjt-1}$ are the patent flows and stocks in industry j in region r at time t, δ_{jt} is an industry-time fixed effect to control for industry-specific trends and δ_r is a region fixed effect. Hence, we identify ϑ from the within-industry relationship between changes in local patent flows and patent stocks, controlling for the local population composition and the local innovator share, which vary over time. In Section 4.4 below we discuss in detail how we measure the skill supply $\sum_{\nu}\lambda^{\nu}_{rt}\varpi^{\nu}_{rt}$.

TABLE 4: ESTIMATION OF SCALE EFFECTS: ϑ

	(1)	(2)	(3)	(4)	(5)	(6)
log Patent stock	0.445***	0.442***	0.401***	0.490***	0.509***	0.470***
	(0.029)	(0.029)	(0.044)	(0.025)	(0.058)	(0.041)
SEA FE	yes	yes	yes	yes	yes	yes
Industry-Year FE	yes	yes	yes	yes	yes	yes
Skill composition	no	yes	yes	yes	yes	yes
Share of innovators	no	yes	yes	yes	yes	yes
Unit elasticity of ℓ	no	no	yes	no	no	no
Estimator	OLS	OLS	OLS	IV	OLS	OLS
Industry Def.	3 dig	3 dig	3 dig	3 dig	1 dig	2 dig
R^2	.773	.774	.751	.214	.902	.825
N	52,682	52,516	52,516	36,676	8,861	33,181

Notes: This table contains the estimates of ϑ in regression (15). All specifications control for SEA and Industry-Year fixed effects. Industries are defined at the three-digit level. From columns 2 to 6, we also control for the skill supply, $\sum_\nu \lambda^\nu_{rt}\varpi^\nu_{rt}$. In column 3, we impose the unit elasticity of ℓ. In column 4 we report the IV estimates. In columns 5 and 6, we classify industries at the one- and two-digit level. Standard errors are clustered at the SEA-Year level.

We estimate (15) using both OLS and a Bartik IV strategy, where we construct the predicted patent stock in industry j in region r, $\mathcal{S}_{rjt}$, from the 1880 cross-sectional distribution of patents across region-industry cells and the aggregate number of patents in each industry. Identification requires the initial 1880 distribution to be orthogonal to subsequent region-industry-specific shocks to patent creation.

In Table 4 we report the results. Column 1 includes SEA and industry-year effects plus $\ln \ell_{rt}$ and yields a scale elasticity of 0.45. Column 2 adds the overall skill supply $\ln\left(\sum_\nu \varpi^\nu_{rt}\lambda^\nu_{rt}\right)$ and the local innovator share with essentially no change in the estimated scale elasticity. Column 3 imposes $\xi = 1$ (unit elasticity of population). Column 4 reports the Bartik IV estimate, which is somewhat larger but qualitatively very similar. Columns 5 and 6 show that our results are robust to defining industries at the 1- or 2-digit level. For our quantitative analysis, we set $\vartheta = 0.45$.

Local Amenities: Congestion, Homophily, and Urban Bias We posit that local amenities, $B^{\nu s}_{rt}$, have four underlying determinants and parametrize them as follows:

$$B^{\nu s}_{rt} = \mathcal{B}_r \ell_{rt}^{-\varrho} \left(\varpi^\nu_{rt}\right)^{\iota} \left(1 + \text{urb}_{rt}\right)^{\mathbf{1}\{\nu=\text{Imm}\}\gamma^I + \mathbf{1}\{\nu=\text{Skilled}\}\gamma^S}. \tag{16}$$

Here, $\mathcal{B}_r$ is an exogenous local fundamental, $\ell_{rt}^{-\varrho}$ summarizes local congestion due to a larger population, ϖ^ν_{rt} is the population share of type ν in location r and captures nationality-specific homophily as in Altonji and Card (1991) and Burchardi et al. (2026), and urb_{rt} is the measured urbanization rate, allowing for the fact that urban locations can be particularly attractive for immigrants ($\gamma^I > 0$) or skilled individuals ($\gamma^S > 0$).

To derive an estimation equation for the homophily elasticity ι, we take the logs of

TABLE 5: ESTIMATION OF HOMOPHILY AND MIGRATION ELASTICITY

	(1)	(2)	(3)	(4)
Log Nationality Share	0.216***	0.219***	0.263***	0.419***
	(0.019)	(0.019)	(0.018)	(0.086)
Log Trade Cost	-3.050***	-3.051***	-3.152***	-3.145***
	(0.418)	(0.418)	(0.401)	(0.403)
Innovation Share		3.870**	6.018**	17.610*
		(1.322)	(1.713)	(7.227)
Origin-Type-Year FE	Yes	Yes	Yes	Yes
Destination–Year FE	Yes	Yes	Yes	Yes
IV	No	No	Card	Burchardi et al.
R^2	.847	.847	.168	.154
N	184,158	184,158	174,461	171,387

Notes: The table reports estimates of equation (17). Columns (1) and (2) present OLS estimates. Column (3) presents estimates using the instrument from Card (2001). Column (4) presents estimates using the extension of the Card instrument proposed by Burchardi et al. (2026). Details for the construction of both instruments are reported in Appendix A.3.1.

expression (9) and consider a fixed-effects regression of the form:

$$\ln m^{\nu}_{rot} = \delta_{rt} + \delta^{\nu}_{ot} + \beta_1 e^{\nu}_{rt} + \iota\varepsilon \times \ln \varpi^{\nu}_{rt} + \varepsilon \ln \mu_{rot} + u^{\nu}_{rot}, \tag{17}$$

where m^{ν}_{rot} is the share of migrants of nationality ν from origin o choosing to migrate to region r and δ's are fixed effects, which absorb a number of endogenous variables, including total population and local wage.[11] Since we lack specific information on the ratio $\psi_{rt}/\overline{h}_{rt}$ in equation (9), we approximate it with the share of innovators among each nationality in the region, e^{ν}_{rt}. The coefficient on ϖ^{n}_{rt}, the population share of nationality n in location r, allows us to identify the product of the migration elasticity ε and the homophily elasticity ι.

To implement this empirical specification, we link the individual-level census data from 1880 to 1920 over time and construct nationality-specific migration flows across SEAs (see Appendix Section A.2). In column 1 of Table 5, we report the baseline OLS regression, including the full set of fixed effects. The coefficient on $\ln \varpi^{n}_{rt}$ is 0.216. To address endogeneity, we instrument ϖ^{n}_{rt} using (i) the shift-share instrument of Card (2001), which interacts total immigration from each nationality with its historical spatial distribution in 1880, 1900, and 1910, and (ii) the predicted ancestry distribution of Burchardi et al. (2026). The Card instrument is our preferred specification, since the pre-1920 sample is relatively short for a reliable first stage of the Burchardi et al. (2026) instrument. These IV strategies raise the coefficient to 0.263 (column 3) and 0.420 (column 4). Given our calibration of $\varepsilon = 2$, we choose $\iota = 0.13$ for our quantitative analysis.

[11] Note that, strictly speaking, (16) requires that δ_{rt} would be skill specific. Given that we observe migrants' pre-migration occupations only for a limited number of individuals, we estimate (17) for the entire sample and do not control for an interaction of the destination fixed effect and individual skills.

We estimate the parameters determining the urban bias for immigrants (γ^I) and skilled individuals (γ^S) within our model. Specifically, we choose these parameters to match the share of immigrants and the share of skilled individuals in "urban hubs" (locations with an urbanization rate above 80%) relative to rural locations (regions with an urbanization rate below 20%) in 1920. That way we guarantee that our model replicates the salient features of how immigrants and skilled individuals sort across space. Doing so yields $\gamma^I = 0.98$ and $\gamma^S = 0.76$, indicating that urban amenities are particularly valuable for skilled individuals and immigrants. For the congestion elasticity, we set $\varrho = 0.3$, corresponding to the typical expenditure share on housing, which we take to capture a key channel of local congestion.

Spatial Frictions: Trade, Mobility Costs, and Moving Opportunities In our model, both the flow of goods and people are subject to frictions. For the bilateral trade costs τ_{ij}, we draw on the measured trade costs constructed by Hornbeck and Rotemberg (2024) for the period 1880–1920, which are based on waterway and railroad distances between counties. We aggregate their county-level estimates to the SEA level using county population as weights. We then parameterize migration costs as a power function of trade costs, $\mu_{ij} = \tau_{ij}^{\alpha_\mu}$, and leverage the relationship implied by equation (17). As seen in Table 5, across specifications, the point estimates of $\varepsilon\alpha_\mu$ range from -3.05 to -3.15. Given that we target $\varepsilon = 2$, we adopt $\alpha_\mu = -1.5$ as our baseline value.

The remaining parameter governing spatial mobility is the probability of receiving a moving opportunity, χ. In our data, approximately 30 percent of the population moved across SEA boundaries over this period. Conditional on the other parameters, we calibrate χ to ensure that in our model 30 percent of individuals relocate across SEAs.

International Arrivals: $M_{rt}^{\nu s}$ Our theory takes the inflow of migrants, $M_{rt}^{\nu s}$, as exogenous. We model this initial allocation of migrants upon arrival parallel to our treatment of amenities in (16) and assume that

$$M_{rt}^{\nu s} = M_t^{\nu} \lambda_t^{\nu s} \frac{(1+\mathrm{urb}_{rt})^{\alpha^s} \ell_{rt}^{\xi} (\varpi_{rt}^{\nu})^{\varsigma}}{\sum_k (1+\mathrm{urb}_{kt})^{\alpha^s} \ell_{kt}^{\xi} (\varpi_{kt}^{\nu})^{\varsigma}}, \tag{18}$$

where M_t^{ν} is the aggregate mass of migrants of nationality ν arriving in year t, and $\lambda_t^{\nu s}$ is the share with skill s. The parameters α^s, ξ, and ς thus govern the extent to which individuals that arrive in the US sort based on the local urbanization rate, overall size, and the share of individuals of their own nationality ν. In line with (16) we allow the effect of the urbanization rate to differ between skilled and unskilled immigrants. Equation (18) is purely a measurement equation; after arrival, immigrants face the same migration opportunities as natives. Using (18), we can estimate $(\alpha^s, \xi, \varsigma)$ from the regression

$$\ln M_{rt}^{\nu s} = \delta_t^{\nu s} + \alpha^s \ln(1+\mathrm{urb}_{rt}) + \xi \ln \ell_{rt} + \varsigma \ln \varpi_{rt}^{\nu} + u_{rt}^{\nu s}. \tag{19}$$

We construct $M_{rt}^{\nu s}$ from our matched data between the Census and immigration records. As in Table 3, we classify migrants with professional, technical, managerial, or craftsmen pre-migration occupations as skilled, and measure $M_{rt}^{\nu H}$ ($M_{rt}^{\nu L}$) as the mass of high-skilled (low-skilled) nationality-ν immigrants in region r arriving within the last 5 years. As we show in Appendix Section A.3.2, we find that $0 < \alpha^L < \alpha^H$, $\xi > 0$, and $\varsigma > 0$, that is, international arrivals feature a bias towards heavily populated and urban locations (especially among the skilled), and nation-specific homophily plays an important role, highlighting the importance of existing immigration networks for new arrivals.

With the estimates $(\alpha^s, \xi, \varsigma)$ at hand, we can compute $M_{rt}^{\nu s}$ from (18) for our entire time series, given measures of $\{\text{urb}_{rt}, \ell_{rt}, \varpi_{rt}^{\nu}, M_t^{\nu}, \lambda_t^{\nu s}\}_t$. From the Census data for the years 1880–2010, we can directly compute $\{\text{urb}_{rt}, \ell_{rt}, \varpi_{rt}^{\nu}\}_t$. For most years, we can also directly measure the flow of new immigrant arrivals, M_t^{ν}. However, in the years 1940, 1950, and 1960 the Census does not contain information on immigrants' year of arrival. As we explain in detail in Appendix Section A.3.1, we therefore rely on information from the Department of Homeland Security for these decades. Finally, we assume that the aggregate skill composition $\lambda^{\nu s}$ is time-invariant and describe in detail below how we estimate it.

Demographics: η, η^B, and d Given the inflows $M_{rt}^{\nu s}$ and the observed initial population in 1880, we calibrate the birth and death rates η^B and d to (i) match population growth between 1880 and 2000 and (ii) the decadal time-series of the aggregate share of immigrants between 1880 and 2000. We also need to take a stand on the long-run growth rate of immigrant inflows η. While η does not affect any allocations between 1880 and 2000 directly, it determines the long-run BGP, because η is also the rate of population growth in the long run. We target an annual growth rate of 1.2%, which is in line with the observed population growth between 1880 and 2000, and hence set $M_{2000+10t}^{\nu s} = (1+\eta)^t M_{2000}^{\nu s}$. Furthermore, we assume that the initial spatial allocation of arrivals remains constant at its 2000 value: $M_{rt}^{\nu s} / M_t^{\nu} = M_{r2000}^{\nu s} / M_{2000}^{\nu}$.

Exogenous technological progress g_A and the cardinality of knowledge Our model features two sources of growth: the endogenous accumulation of ideas and exogenous growth in overall productivity g_A. Because our model features transitional dynamics, the level of the initial knowledge stock, N_{r0}, is consequential: holding everything else constant, starting from a lower level of N_{r1880} increases overall growth because the economy is further away from a balanced growth path. We therefore set the initial stock of knowledge, N_{r0}, as proportional to the observed local patent stocks, $N_{r1880} = \overline{N}\mathcal{S}_{r1880}$, and treat $\overline{N}$ as a structural parameter that we estimate. Specifically, we estimate $\overline{N}$ and g_A by targeting two moments: GDP pc in 2000 (relative to 1880), y_{2000}/y_{1880}, and average patent growth between 1880 and 1910. While we calibrate these parameters jointly, g_A is mostly informed by the long-run growth of GDP pc and $\overline{N}$ is mostly informed by the growth of patents.

4.4 Local fundamentals $\mathscr{F}$ and Initial Conditions $\mathscr{I}$

Next, we explain how, given the values of the structural parameters, we identify the fundamentals $\mathscr{F} = \{A_r, \zeta_r, \mathcal{B}_r\}$ and the initial conditions $\mathscr{I} = \{N_{r1880}, \ell^{\nu}_{r1880}, \lambda^{\nu}_{r1880}\}$.

Initial conditions $\mathscr{I} = \{N_{r1880}, \ell^{\nu}_{r1880}, \lambda^{\nu}_{r1880}\}$ As explained above, we tie the initial stock of knowledge, N_{r1880}, directly to the observed stock of patents in 1880 and the estimated scaling parameter $\overline{N}$. Similarly, the population distribution, ℓ^{ν}_{r1880}, is directly observed in the 1880 US Census.

To estimate the relative skill supply we rely on observed patent outcomes. Our theory highlights that relative innovation propensities *within* labor markets are informative about relative skill supplies, i.e., $e^{\nu}_{rt}/e^{US}_{rt} = \lambda^{\nu}_{rt}/\lambda^{US}_{rt}$. To implement this idea empirically, we assume that the share of high-skilled individuals of nationality ν in location r is proportional to that of natives, i.e.[12]

$$\lambda^{\nu}_{rt} = \kappa^{\nu}\lambda^{US}_{rt}. \tag{20}$$

Hence, Italian immigrants might have fewer skilled workers overall, and they might live in different locations; however, their sorting across space is the same as that of natives. As a consequence, the share of innovators among nationality ν in location r at time t satisfies

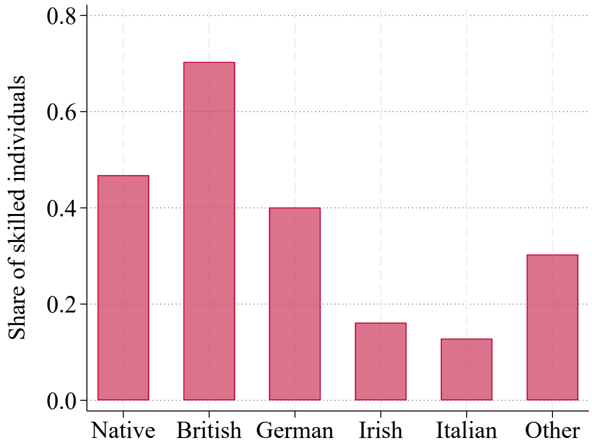
$$\ln e^{\nu}_{rt} = \ln\left(\lambda^{\nu}_{rt}\left(\frac{\psi_{rt}}{\bar{h}_{rt}}\right)^{\theta}\right) = \ln\kappa^{\nu} + \ln\left(\lambda^{US}_{rt}\left(\frac{\psi_{rt}}{\bar{h}_{rt}}\right)^{\theta}\right) = \ln\kappa^{\nu} + \delta_{rt}. \tag{21}$$

Hence, we can identify the relative skill supply of all nationalities, κ^{ν}, from a regression of (the log of) the share of patent holders on a nationality fixed effect and a location-time fixed effect. Note that this is exactly the variation we exploited in Section 2 to estimate migrants' innovativeness within local labor markets. In particular, the region-time fixed effect δ_{rt} controls for exogenous innovation TFP ζ_r, the endogenous variables N_{rt-1} and $\bar{h}_{rt}$, and the extent of spatial sorting of natives λ^{US}_{rt}. Moreover, (21) identifies the share of skilled individuals entirely from the extensive margin of patenting and does not rely on a particular cardinality of patents.

In Appendix Table A.9, we report the estimates of equation (21) for a variety of specifications. They mirror the results in Table 2: relative to natives, British immigrants are more likely to patent, German immigrants slightly less so, and Italian and Irish immigrants substantially less. Our theory thus provides a clean structural interpretation of these estimates: the estimated coefficients identify the relative skill supply κ^{ν}.

[12]Note that this assumption is in line with our migration module. Equation (16) implies that $\frac{B^{\nu H}_{rt}/B^{\nu H}_{jt}}{B^{\nu L}_{rt}/B^{\nu L}_{jt}} = \left(\frac{1+\text{urb}_{rt}}{1+\text{urb}_{jt}}\right)^{\gamma^S}$. Equation (12) therefore implies the relative moving probabilities by skill are equalized across nationalities. In the absence of new migration inflows, (20) would therefore hold along an SBGP.

FIGURE 3: SHARE OF SKILLED INDIVIDUALS IN 1880



Notes: In this figure we depict the share of skilled individuals by nationality in 1880.

Given the estimates for κ^{ν} we can use (20) to compute the local skill supply as a function of the skill supply of natives. To measure λ^{US}_{r1880} we use occupational data for US-born individuals in the Census and set it equal to the share of US-born individuals in region r working in high-skilled occupations in the non-agricultural sector. By using only natives' occupations we avoid concerns that immigrants' occupations may be distorted by discrimination or occupational downgrading. Furthermore, by focusing on the occupational distribution outside of agriculture, we avoid conflating spatial differences in skill supplies with differences in the sectoral composition.

In Figure 3 we report the implied aggregate share of skilled individuals by nationality, $\lambda^{\nu}_{1880} = (\sum_r \kappa^{\nu} \lambda^{US}_{r1880} \ell^{\nu}_{r1880}) / \sum_r \ell^{\nu}_{r1880}$. Among natives, our procedure leads us to infer that around 40% of individuals are skilled and have the ability to innovate (of course, in equilibrium only a small fraction actually engages in innovation). Among British immigrants, the share of skilled individuals is larger and equal to about 70%. By contrast, Italian and Irish immigrants are mostly unskilled.

Local Fundamentals $\mathscr{F} = \{\zeta_r, A_r, \mathcal{B}_r\}$ To identify each region's innovation TFP ζ_r, note that the endogenous innovation cutoff $\bar{h}_{rt}$ is proportional to the average number of patents per innovator

$$\bar{h}_{rt} = \frac{\theta - 1}{\theta} \frac{I_{rt}}{e_{rt}\ell_{rt}} = \frac{q^M}{\varsigma} \frac{\theta - 1}{\theta} \frac{\mathcal{P}_{rt}}{\mathcal{M}_{rt}\ell_{rt}},$$

where the second equality exploits the measurement equations $\mathcal{M}_{rt} = q^M e_{rt}$ and $\mathcal{P}_{rt} = \varsigma I_{rt}$. Using the expression for $\bar{h}_{rt}$ and exploiting equation (20), we can express the share of innovators in location r as

$$(22) \qquad e_{rt} = \sum_{\nu} \omega^{\nu}_{rt} \lambda^{\nu}_{rt} \left(\frac{\psi_{rt}}{\bar{h}_{rt}}\right)^{\theta} = \psi^{\theta}_{rt} \left(\frac{\theta\varsigma}{q^M(\theta - 1)}\right)^{\theta} \lambda^{US}_{rt} \left(\frac{\mathcal{M}_{rt}\ell_{rt}}{\mathcal{P}_{rt}}\right)^{\theta} \left(\sum_{\nu} \omega^{\nu}_{rt} \kappa^{\nu}\right).$$

Because we already estimated ϑ, θ, and κ^{ν}, equation (22) expresses each location's innovation productivity ψ_{rt} directly as a function of observables. Note, in particular, that identification uses both the observed number of patents *per innovator* and the share of people who patent — two moments that require our matched data between patents and the US Census.[13] In a second step, we can then use the identity $\psi_{rt} = \zeta_r N_{rt-1}^{\vartheta}$ to decompose ψ_{rt} into the variation explained by the local knowledge stock, N_{rt-1}^{ϑ}, and the variation that is, residually, attributed to exogenous research TFP ζ_r. Note that the relative importance of local knowledge is modulated by the scale elasticity ϑ. Without intertemporal spillovers, $\vartheta = 0$, ζ_r has to do all the work. If $\vartheta > 0$, the measured patent stock has the potential to explain the estimated variation in innovative human capital ψ_{rt}.

To identify the distribution of local productivity A_r we rely on observed wages w_{rt}. Using the observed distribution of patent stocks, N_{rt}, and production workers, $\ell_{rt}(1 - e_{rt})$, we can compute $\{A_r\}_r$ directly from (7). Note that this computation does not involve any measures of skill shares or innovation human capital.

Finally, we identify the exogenous level of local amenities, $\mathcal{B}_r$, from the observed population distribution of unskilled natives. Using (9) and (16), the moving probabilities can be computed as

$$m_{rot}^{USL} = \frac{\left(\mu_{ro}\mathcal{B}_r L_{rt}^{-\varrho}\left(\varpi_{rt}^{US}\right)^{\iota} w_{rt}/P_{rt}\right)^{\varepsilon}}{\sum_k \left(\mu_{ko}\mathcal{B}_k L_{kt}^{-\varrho}\left(\varpi_{kt}^{US}\right)^{\iota} w_{kt}/P_{kt}\right)^{\varepsilon}}. \tag{23}$$

Given the structure of the model, all components of the migration probabilities are observed except for $\mathcal{B}_r$. Hence, for any candidate vector $\{\mathcal{B}_r\}$, the implied migration probabilities $m_{rot}^{US,L}(\{\mathcal{B}_r\})$, together with the laws of motion in equations (10) and (11), determine the mass of low-skilled natives in each region in the next period, $\ell_{r,t+1}^{US,L}$, given the current distribution $\ell_{rt}^{US,L}$.[14] We thus recover $\{\mathcal{B}_r\}$ by requiring that the observed distribution of low-skilled natives across regions, $\ell_{rt}^{US,L}$, is consistent with equation (23).

Note that (7), (22), and (23) should, in principle, hold at every point in time. Given the time-invariance of the local fundamentals $\{\zeta_r, A_r, \mathcal{B}_r\}$, this will generically not be the case. We therefore solve these equations independently for all decades between 1880 and 1920, and then recover $\{\zeta_r, A_r, \mathcal{B}_r\}$ as the regional fixed effect from these estimates — see Appendix Section A.3.1 for details. The resulting calibrated model therefore does not replicate the cross-sectional data exactly. However, we show below that it still provides

[13] Note also that the cardinality of the skill supply, λ_{rt}^{US}, is not essential for identification. If we had assumed that λ_{rt}^{US} was proportional to the share of skilled natives in the manufacturing sectors, we would have simply changed the level of ψ_{rt}: twice as many potential innovators, or each twice as likely to innovate, would yield observationally equivalent outcomes.

[14] Here $\ell_{r,t+1}^{US,L}$ denotes the population after migration but before natural population changes from births and deaths.

an excellent fit while reducing sensitivity to measurement error in regional wages or innovation shares.

4.5 Results and Model Fit

In Table 6 we summarize the estimated structural parameters. As discussed in the main text, we estimate a scale elasticity of around 0.45, which implies that our model features semi-endogenous growth and is consistent with a stationary distribution of economic activity across space. It also implies a direct decomposition of aggregate growth along the BGP:

$$\underbrace{g}_{1.38\%} = \underbrace{g_A}_{0.83\%} + \underbrace{\frac{1}{1-\vartheta}\frac{1}{\sigma-1}\eta}_{0.55\%}$$

Hence, in the long run, roughly 40% of long-run growth is driven by the accumulation of ideas, with the rest attributed to sources that we take to be exogenous and that do not respond to changes in immigration policy. The estimate $g_A = 0.83\%$ is required for our model to match income per capita growth between 1880 and 2000.

In terms of the underlying supply of human capital, our estimate of $\theta \approx 1.3$ implies that the distribution of innovative talent is very thick-tailed. Given that, on average, 7.7% of all high-skilled individuals become innovators, they earn, on average between 1880 and 1920, a premium of $1 + \frac{1}{\theta-1}e^H_{rt} \approx 1.26$ relative to unskilled individuals. The observed differences in patent probabilities across nationalities within locations imply substantial differences in relative skill supplies κ^ν.

Regarding the spatial labor supply function, we estimate a strong role of homophily towards one's own nationality, especially among recent arrivals ($\varsigma > \iota$). We also estimate an urban amenity premium for immigrants and skilled individuals ($\gamma^I > 0$ and $\gamma^S > 0$), which is required to match the empirically observed degree of urban sorting by skilled individuals and by immigrants.

In Figure 4 we display the cross-sectional fit of our model. Our model replicates the spatial patterns of economic activity in 1900 very well: urban locations are more populous and richer, generate more patents per capita, and contain a higher share of skilled individuals among natives.

In Figure 5 we report the cross-sectional variation of the estimated time-invariant fundamentals (A_r, $\mathcal{B}_r$, ζ_r) and the initial knowledge stock $\ln N^{\vartheta}_{r1880}$. To highlight the systematic differences between rural and urban areas, we construct population-weighted deciles by urbanization (so that each decile accounts for 10% of the population) and then compute averages within each decile (again, weighted by population).[15] For each outcome, we normalize the lowest urban decile to unity and hence plot the premium relative to the most rural locations.

[15] In the Appendix A.3.1, we report the estimates for the fundamentals $(\zeta_r, A_r, \mathcal{B}_r)$ for each location r.

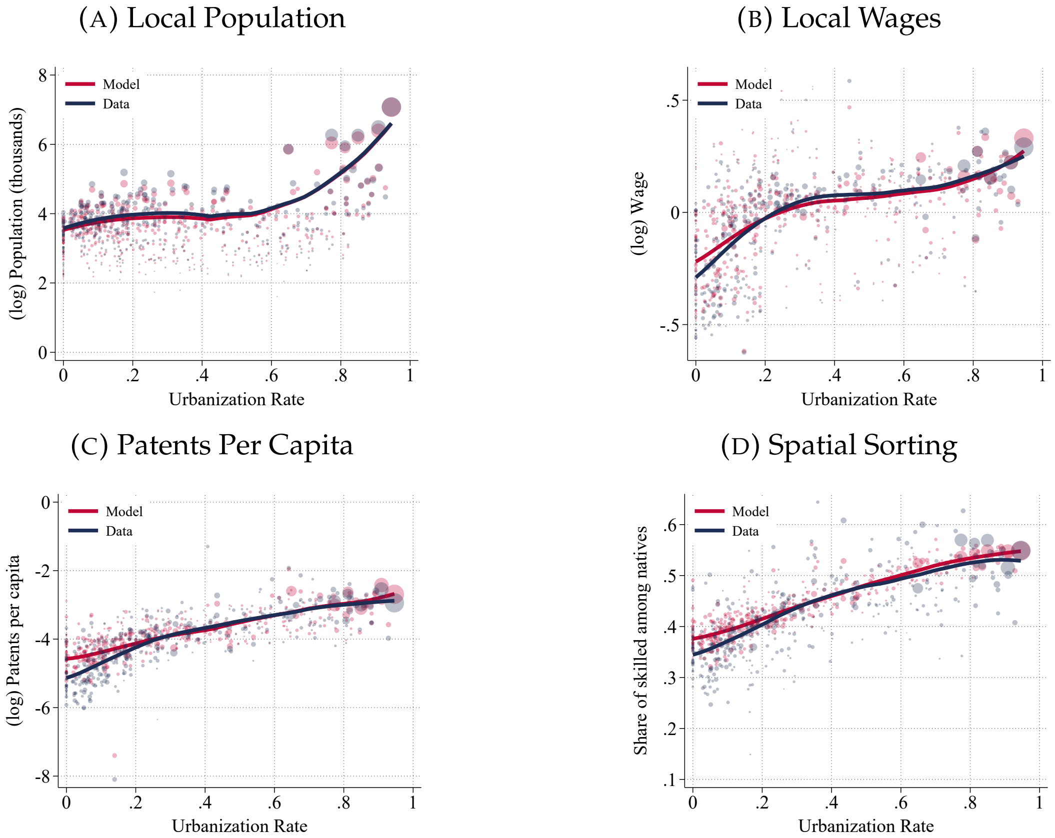
TABLE 6: STRUCTURAL PARAMETERS

	Structural Parameters		Source/Target
ϑ	Scale elasticity	0.45	Table 4
θ	Human capital distribution	1.3	Figure 2
κ^{UK}	Share of skilled British (rel. to natives)	1.30	Table A.9
κ^{GER}	Share of skilled Germans (rel. to natives)	0.76	Table A.9
κ^{ITA}	Share of skilled Italians (rel. to natives)	0.23	Table A.9
κ^{IRL}	Share of skilled Irish (rel. to natives)	0.28	Table A.9
κ^{OTH}	Share of skilled other immig. (rel. to natives)	0.59	Table A.9
ι	Own-nationality homophily	0.13	Table 5
χ	Mobility hazard	0.304	Cross-SEA moving rate
γ^I	Urban amenity for immig.	0.976	Immig.-urbanization gradient (Fig. 6)
γ^S	Urban amenity for skilled	0.759	Skill-urbanization gradient (Fig. 4)
α^L	Urban amenity for unskilled arrivals	0.228	Table A.8
α^H	Urban amenity for skilled arrivals	0.447	Table A.8
ξ	Population elasticity for arrivals	0.734	Table A.8
ς	Homophily for arrivals	0.530	Table A.8
η	Growth rate of intl. migration	0.012	Long-run pop. growth = 1.2%
η^B	Birth rate	0.029	Pop. growth 1880-2000 (Fig. A.5)
d	Death rate	0.019	Time series of immig. share (Fig. A.5)
g_A	Exogenous TFP growth	0.008	Long-run growth rate (Fig. A.5)
σ	Elasticity of substitution	5	Set exogenously
ϱ	Local congestion elasticity	0.3	Set exogenously
ε	Migration elasticity	2	Set exogenously
β	Discount rate for capitalists	0.35	Set exogenously

In Panel (A) we focus on the innovation side and plot overall innovation human capital (ψ_{r1890}) and its components, i.e., local knowledge (N^{ϑ}_{r1880}) and exogenous research TFP (ζ_r). Overall innovative human capital is substantially higher in urban labor markets: between the highest and lowest urbanized locations, it differed by a factor of five. Strikingly, this "innovative premium" of cities is entirely explained by their measured local knowledge stock. For the first eight deciles, our model infers exogenous research TFP ζ_r to be basically flat. At the very top, it is, if anything, lower because we measure the stock of patents to be much higher (recall that we infer $\zeta_r = \psi_{rt}/N^{\vartheta}_{rt-1}$ residually).

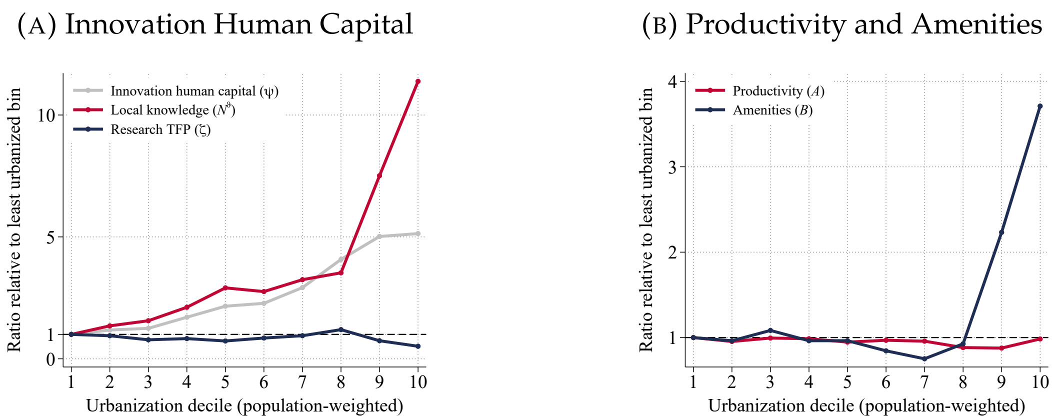
In Panel (B) we display the same results for amenities $\mathcal{B}_r$ and exogenous productivity A_r. Similar to research TFP ζ_r, productivity is not systematically correlated with urbanization. Hence, measured differences in local knowledge, together with the structure of our theory and the estimated scale elasticity ϑ, are sufficient to explain the fact that cities have higher wages and more patents per capita. As for amenities, we find that exogenous amenities are higher in the most urban locations to rationalize the very large population differences between cities and rural areas. We find this not surprising given that amenities also implicitly control for differences in the size of different SEAs and that cities, in our theory, suffer from congestion so that overall amenities are given by $\mathcal{B}_r \ell_{rt}^{-\varrho}$.

Figure 4: Model Fit: Cross-sectional Moments



Notes: Panels (a)–(d) report the correlation between the 1880 urbanization rate and four targeted moments — local population, local wages, patents per capita, and the share of high-skilled individuals among natives — read off in 1900; the model (data) is shown in red (blue), and each dot is a State Economic Area (SEA) with size proportional to its population.

Figure 5: Urban Premia: Fundamentals and Local Knowledge



Notes: The figure summarizes the local fundamentals and initial knowledge stock across population-weighted urbanization deciles, expressed relative to the least-urban decile (dashed line at 1). We depict innovation human capital $\psi_r = \zeta_r N^{\vartheta}_{r1880}$, the knowledge stock N^{ϑ}_{r1880}, and research TFP ζ_r in panel (A) and location productivity A_r and the exogenous component of amenities $\mathcal{B}_r$ in Panel (B).

4.6 Model Validation

In Figure 6 we report several additional moments to validate our model. Panel (A) shows that our simple demographic model with constant birth and death rates, in combination with the observed immigration inflows, replicates the well-known U-shaped immigration shares of the US. Starting with the immigration restrictions of the 1920s, the immigrant share fell from about 20% to 5% and recovered in the 1960s owing to more liberal immigration policies. Panel (B) shows that our model is also successful in generating the empirically observed urban gradient of immigrants, even though we parametrize immigrants' taste for urban amenities only with a single elasticity. In panel (C) we report the overall share of innovators in the US economy over time. Our model predicts that around 2% to 3% of individuals actively engage in the creation of new ideas. In the data, less than 1% of individuals get assigned patents, presumably because many innovations might not be patented but still generate economic value. Interestingly, both in the data and in the model, the share of innovators is declining over time. In our theory this is due to transitional dynamics, whereby ideas are relatively scarce in the late 19th century and accumulate over time. This pattern of "catch-up growth" through innovation is also visible in the cross-section. As seen in panel D, the growth rate of patents is slightly higher in rural areas. Hence, even though cities are innovation hubs in that they generate many more patents per capita, *proportional* patent growth is slightly lower because "ideas are getting harder to find" (Bloom et al., 2020).[16]

Figures 4 and 6 show that our model rationalizes the key cross-sectional patterns between urbanization, population density, local wages, immigration and innovative activity. We now turn to the model's predictive power for *local growth*, which is not targeted in our estimation. More specifically, we consider a regression of the form

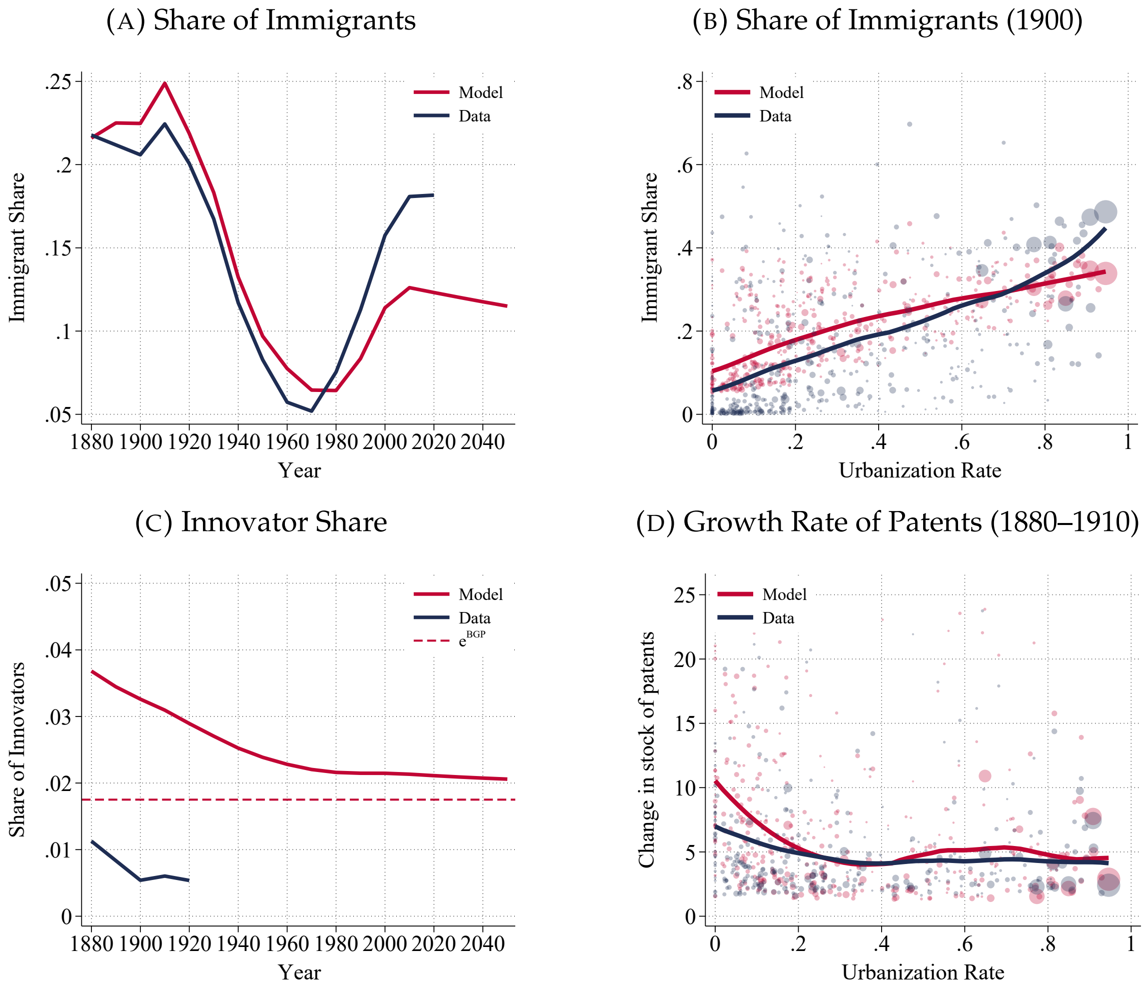
$$x_{rt}^{DATA} = \delta_r + \delta_t + \beta_x x_{rt}^{MODEL} + v_{rt}, \tag{24}$$

where x_{rt}^{DATA} and x_{rt}^{MODEL} denote local outcomes in the data and model, respectively. Given the presence of a location fixed effect, δ_r, the coefficient β_x measures the correlation between local *growth* of outcome x in the model and the data. In the model, the cross-sectional variation in local growth is due to (i) transitional dynamics in the accumulation of knowledge, (ii) transitional dynamics for the local population, and (iii) immigration shocks. We consider the regression in (24) for the main outcomes of our theory: the local population, the share of immigrants, local wages, patents per capita, and the share of innovators.

As seen in Table 7, the model's prediction for population growth, the change in the share

[16]This mechanism is also present in the time-series. As we show in Figure A.5 in the Appendix, our model implies that research productivity has been falling by a factor of 16 during the 20th century. This is qualitatively in line with the findings in Bloom et al. (2020), even though they report even larger declines, possibly because they focus on growth rates within narrowly defined goods or industries.

FIGURE 6: ADDITIONAL IMPLICATIONS



Notes: The top row displays the share of immigrants in the time series (Panel A) and as a function of the urbanization rate in 1900 (Panel B). The bottom row depicts the aggregate share of innovators (Panel C) and the correlation between the growth rates of patents and the urbanization rate (Panel D). In panel C we also put a horizontal dashed line for the innovation share along the BGP, e^{BGP} (which, recall, is equalized across space).

of immigrants, local wage growth, and the growth in patents per capita are positively correlated with the data, highlighting that the key forces of our theory are also empirically important. By contrast, as seen in column 5, the correlation for the change in the share of innovators is negative, owing to the fact that the model predicts too high a level (and hence a decline in) innovation shares for rural locations, where the stock of knowledge is very low and hence innovation incentives are high.

5. THE ROLE OF IMMIGRATION FOR US GROWTH

We now use our model to quantify the impact of international migration on US growth. To do so, we consider two counterfactuals. In our first exercise, we focus directly on the Era of Mass Migration and ask how much growth the US would have lost if it had closed its doors to the roughly 23 million international migrants that arrived between 1880 and 1920. In our second exercise, we evaluate the effects of two specific US immigration policies:

Table 7: Model vs Data

	(1)	(2)	(3)	(4)	(5)
	$\ln \ell_{rt}$	ϖ^{IMM}	$\ln w_{rt}$	$\ln(I_{rt}/\ell_{rt})$	$\ln e_{rt}$
Model Prediction	1.769***	0.856***	0.125***	0.366***	-0.270***
	(0.032)	(0.026)	(0.017)	(0.034)	(0.010)
Year FE	yes	yes	yes	yes	yes
SEA FE	yes	yes	yes	yes	yes
R^2	.993	.974	.999	.965	.866
N	1,704	1,704	1,704	1,704	1,704

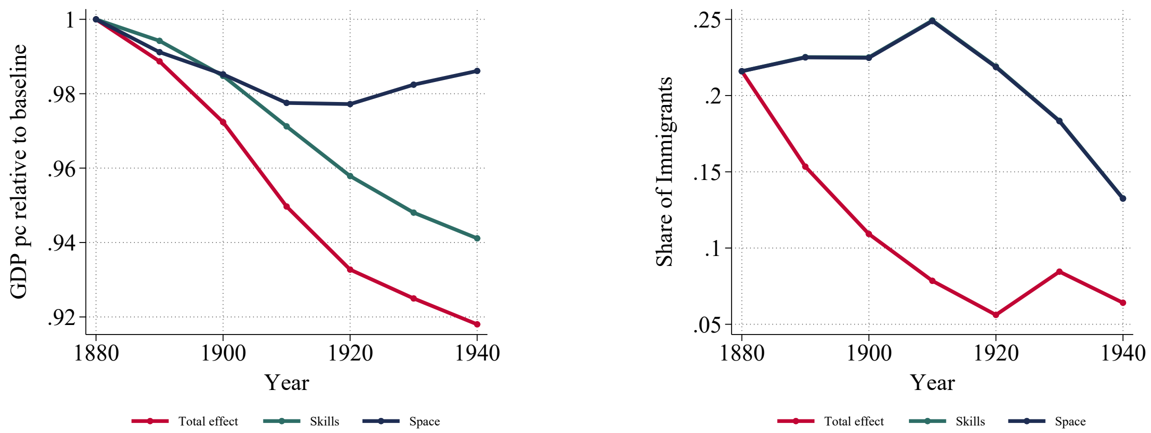
Notes: The table contains the results of regression (24) for different outcomes. All specifications contain time and SEA fixed effects. We weight all local outcomes by the size of the local population.

the 1921 Emergency Quota Act and the 1924 Johnson–Reed Act, which severely limited international migration, especially from Southern and Eastern Europe and Asia.

5.1 The Era of Mass Migration: 1880–1920

Figure 7: The Aggregate Impact of International Migration

(A) GDP per capita (B) Share of Immigrants



Notes: The figure shows the change in aggregate income per capita, relative to the baseline economy (Panel A) and the aggregate share of immigrants (Panel B). We depict the baseline calibration in grey, the counterfactual with no immigrant inflows between 1880 and 1920 in red, the "no skilled immigrants" counterfactual in green, and the "no urban bias" counterfactual, where immigrants initially settle in proportion to the spatial allocation of natives in blue.

What would US growth have looked like if all immigration inflows between 1880 and 1920 were set to zero? The answer is shown in the red lines of Figure 7. The left panel depicts the impact on aggregate GDP per capita, relative to the baseline economy; the right panel shows the aggregate share of immigrants. In the absence of new migration flows, the share of immigrants would fall from 21.6% in 1880 to 6.4% by 1940, and the overall population would be 27.3% lower than the baseline by 1940 (see Appendix Section A.3.2). As a consequence, we find that GDP per capita by 1940 would have been 8.2% lower. Interestingly, these missing cohorts of immigrants cast a long-lasting shadow due to the cumulative loss of ideas. By 2000, income per capita would have been 9.6% lower.

Our theory highlights that migration affects US growth through three channels: *scale*, whereby immigrants increase the size of the population; *skills*, whereby some immigrants bring innovative skills; and *space*, whereby immigrants increase population growth in urban innovation hubs. To isolate the role of these channels, we compute two alternative counterfactuals.

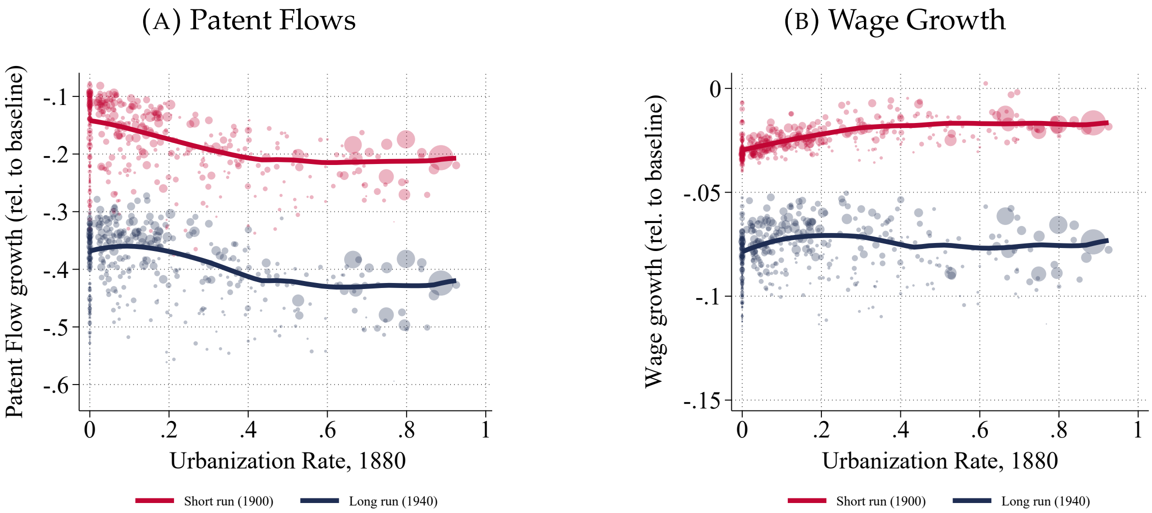
First, to quantify the importance of *skills*, we compute the equilibrium path assuming that all international migrants between 1880 and 1920 were unskilled. Hence, the total amount of "bodies" (and hence the share of immigrants) is exactly the same as in the baseline economy, but the supply of "ideas" is reduced. The impact of this counterfactual is shown in green. Even though the share of immigrants actually patenting is quite low, they account for a large part of the adverse effects of immigration restrictions: missing out on this small number of skilled immigrants would have reduced GDP per capita by 5.9% by 1940, accounting for about 75% of the overall effect of migration restrictions.

Second, to highlight the role of *space*, in particular immigrants' sorting toward cities, we consider a counterfactual where we keep both the size and the skill content of international arrivals as in the baseline calibration, but assume that migrants do not have a specific urban bias, that is, the initial spatial distribution of incoming immigrants is the same as that of natives, and migrants do not specifically value urban amenities, $\gamma^I = 0$. Hence, this scenario quantifies the importance of immigration-led urbanization for overall innovation and growth. As seen in the blue line, without migrants' "taste" for cities, overall economic activity would have been lower. Interestingly, for the first three decades, migrants' spatial sorting was as important for US growth as their innate skills. In the longer run, the effects subside because of migrants' spatial mobility within the US.

In Appendix Section A.3.2 we also document the effects on overall innovation activity and urbanization. In the absence of migration, innovation would be lower, reflecting the drop in market size. Recall that immigrants' innovation share is *lower* than that of natives. Hence, one might have thought this composition effect would cause the share of innovators to be *higher* in the absence of immigrants. However, natives' incentives to innovate are lower, given the non-rival nature of idea-creation. As for urbanization, between 1880 and 1920, the share of people living in the most urbanized SEAs increased from 35% to 45%. Without international migration, this increase would have been substantially lower.

Spatial Impacts Because immigrants arrive in a spatially unbalanced way, locations are differentially exposed to the shock. In Figure 8, we depict the change in patent flows (left panel) and local wages (right panel) in the absence of migration inflows, relative to the baseline economy, as a function of the urbanization rate. To highlight the differential dynamic responses, we depict both the short-run effects (in 1890) and the long-run effect (in 1940).

FIGURE 8: SPATIAL IMPACTS



Notes: The left panel shows the change in the flow of patents (I_{rt}) in the absence of migration relative to the baseline economy, $\ln I_{rt} - \ln I_{rt}^{\text{Baseline}}$ as a function of the urbanization rate. The right panel shows $\ln w_{rt} - \ln w_{rt}^{\text{Baseline}}$. We show both the short-run effect in 1890 and the long-run effects in 1940.

The left panel of Figure 8 shows the importance of international migration for innovation, especially in cities. In the absence of international migrants, patent creation would have declined by 15% in the short run and by more than 40% in the long run. The right panel depicts the impact on local wages. Consistent with the overall impact on GDP per capita reported in Figure 7, wages fall by around 3% in the short run and by about 8% in the long run. Interestingly, the wage impact is, if anything, slightly larger in rural areas. The reason is that rural areas are knowledge-scarce. As a consequence, a given decline in innovation has a larger impact on local wages.[17]

5.2 The Immigration Quotas of the Early 20th Century

In our second exercise, we evaluate the effects of the 1921 Emergency Quota Act and the 1924 Johnson–Reed Act, which together imposed the first major restrictions on US immigration. These policies disproportionately targeted Southern and Eastern Europeans and effectively barred all Asian immigration. The 1921 Act capped each nationality's inflow at three percent of its foreign-born population recorded in the 1910 Census. The 1924 Act tightened these quotas to two percent of the observed population in the 1890 Census. Both policies, explicitly chosen to favor Western European source countries that already had a large stock of immigrants in the 1890s, remained in place until the Hart–Celler Act of 1965 dismantled the national-origins framework.

To quantify the impact of these restrictions, we construct a counterfactual immigrant inflow series for the quota period 1930–1960. As we describe in more detail in Appendix

[17] As we show in Figure A.8 in the Appendix, the relative decline in population growth is larger in cities, given immigrants' urban bias.

Section A.3.2, we hold the total number of immigrants constant at the 1910–1920 average and apportion the additional inflow equally between the two restricted groups: Southern and Eastern Europeans and Asians. While Europeans dominated pre-WWII immigration, given the rapid growth of Asian immigration at the time and the policies' explicit intent to block Asian inflows, we treat this as a reasonable baseline. We also estimate the skill levels of Southern and Eastern Europeans and Asian immigrants, finding that both groups had substantially lower skills than natives in 1920 (see Table A.10 in the Appendix).

Figure 9 summarizes the economic impact of the immigration quotas of the 1920s. Compared to a situation where immigrant inflows had continued at the same pace as in the early 20th century, GDP per capita could have been 1.7% higher by 2000. The main reason why this effect is relatively modest is that the additional immigrant inflow is large in absolute numbers, yet its effect on the overall population and the immigrant share is limited given the size of the US population; see panel B of Figure 9, which shows that the overall immigrant share does not dramatically differ from the actual data.

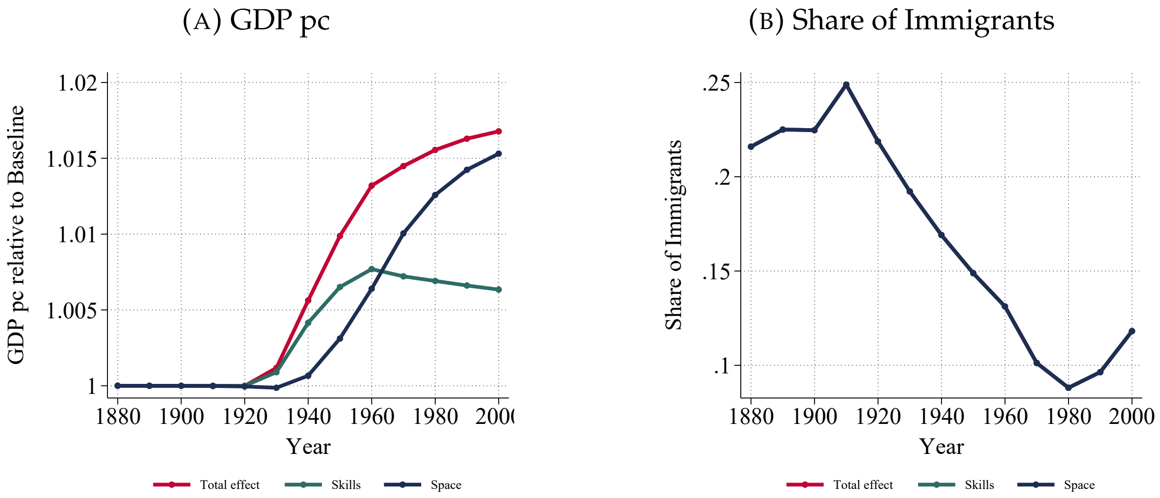
As before, we also decompose the overall effect into the role of skills (where we assume that all additional immigrants are unskilled) and the role of space (where we assume that all additional immigrants feature no specific urban bias). Figure 9 shows again that migrants' innovative skills played an important role: if all immigrants had been unskilled, the effect on GDP per capita in 1960 would only have been half as large and, if anything, slightly declining after 1960 once the quota was lifted. Interestingly, migrants' spatial allocation plays an important role in the short run. If the new immigrants had arrived without an urban bias, GDP per capita would not have risen until the 1940s. Over time, people reallocate spatially, and the gap relative to the full counterfactual becomes smaller.

6. ROBUSTNESS

While most of the structural parameters of our model are directly estimated, we calibrate some externally. In this section, we discuss the robustness of our main results with respect to these choices; the results are summarized in Table 8. For each alternative specification, we recalibrate our model and conduct both counterfactuals reported in Section 5. We always report the estimated rate of exogenous technological progress (g_A), the effects of international arrivals between 1880 and 1920 on GDP per capita by 1940, both the overall effect and the respective roles of *space* and *skills*, and the overall GDP impact of removing the 1920s immigration quotas. For comparison, we report our baseline results in the first row.

In rows two and three, we analyze the importance of aggregate knowledge spillovers. In our baseline model, we assumed that innovators only build on local knowledge, N_{rt-1}. Now we assume that $\psi_{rt} = \zeta_r N_{rt-1}^{\vartheta} (\sum_j N_{jt-1})^{\gamma}$. The higher γ, the less exogenous growth is "required" to match the overall growth experience of the US, and the larger the impact

FIGURE 9: THE AGGREGATE IMPACT OF THE 1920S MIGRATION RESTRICTIONS



Notes: The figure shows the change in aggregate income per capita relative to the baseline economy (Panel A) and the aggregate share of immigrants (Panel B). We depict the counterfactual of removing the 1920s immigration restrictions in red, the counterfactual in which the additional immigrants generated by removing the restrictions are assumed to be unskilled in green, and the counterfactual in which the additional immigrants have no urban bias in blue.

TABLE 8: ROBUSTNESS

Specification	g_A	Mass Migration 1880-1920			1920s
		Full effect	Space	Skills	Quotas
Baseline	0.086	0.918	0.990	0.941	1.007
Agg. spillover ($\gamma = 0.15$)	0.071	0.904	0.988	0.929	1.009
Agg. spillover ($\gamma = 0.30$)	0.023	0.882	0.985	0.913	1.015
EoS ($\sigma = 4$)	0.053	0.893	0.988	0.922	1.010
EoS ($\sigma = 7$)	0.121	0.944	0.993	0.961	1.005
Myopic capitalists ($\beta = 0$)	0.087	0.917	0.990	0.939	1.007
Dynamic migration	0.088	0.918	0.991	0.941	1.007

Notes: This table reports the estimated g_A (row 2), the aggregate impact of international arrivals between 1880 and 1920 on GDP per capita in 1940 (rows 3–5), and the impact of the 1920s immigration quotas (row 6). See text for the details on these respective counterfactuals.

of immigrants on growth. If $\gamma = 0.3$, the impact would be roughly 30% higher than in our baseline estimation (a decline of 11.8% as opposed to 8.2%). In rows four and five, we explore different values of the elasticity of substitution σ, which determines the strength of variety gains. The lower σ, the stronger the link between immigration and growth. Quantitatively, if σ were four as opposed to five, the impact on GDP would increase from 8.2% to 10.7%. In row six, we present the results from a calibration where capitalists are myopic and only pay researchers one-period profits. Doing so leaves our results essentially unchanged. Finally, we also estimate a version of our model where workers solve a dynamic migration problem (see Appendix Section OA.4 for details). Again, this does not change the impact of immigrants on growth once the model is recalibrated.

7. Conclusion

Between 1880 and 1920, more than 20 million immigrants made the United States their home. In this paper, we evaluate the impact of this large immigration wave on US innovation and growth.

Using our data on individual patent behavior, we document that immigrants played an important role in US innovation and show that spatial sorting played a key role in immigrants' innovativeness. Much like today, immigrants were overrepresented in urban innovation hubs, where patent intensity was five times larger than in rural areas.

Motivated by this evidence, we propose a model of spatial growth by incorporating the insights of idea-based, semi-endogenous growth theory into a canonical spatial model. Our theory emphasizes the local supply of innovative human capital as the main determinant of local productivity, admits a balanced growth path with a stationary distribution of economic activity, yet is still sufficiently tractable to analyze the transitional dynamics. As such, our framework is useful to quantify the importance of immigrants in a realistic setting featuring many locations, trade costs, and frictional population mobility.

For the historical episode, we find that without the inflow of international migrants between 1880 and 1920, income per capita by 1940 would have been 8.2% lower. Turning from history to policy, we apply the same framework to the immigration quotas of the 1920s and find that lifting these restrictions would have raised US income per capita by a further 1.7% by 2000—a modest effect, because the excluded migrants were both demographically small relative to the US population and predominantly low-skilled. In both exercises, immigrants' innate innovative skills and their bias to arrive in and move to urban locations are quantitatively important determinants of the productivity gains from migration.

We view our paper as a natural starting point for further research at the intersection of mobility, migration, innovation, and long-run growth. We hope the tools introduced here, together with the growing availability of historical microdata, will enable a deeper understanding of how immigration shapes innovation, regional development, and long-run growth in both historical and contemporary settings.

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