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# A tale of two cities: Communication, innovation, and divergence

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**Abstract**

We present a two-area endogenous growth model where abstract knowledge flows at no cost across space but tacit knowledge arises from the interaction among researchers and is hampered by distance. Digital communication reduces this "cost of distance" and reinforces productive specialization, leading to an increase in the system-wide growth rate but at the cost of more inequality within and across areas. These results are consistent with evidences on the rise in the concentration of innovative activities, income inequality, and skills and income divergence across US urban areas.

**KEYWORDS**

agglomeration, digital communication, inequality, patents, specialization

**JEL CLASSIFICATION**

J24, O31, O41, R12

## 1 | INTRODUCTION

The idea of a network allowing users to communicate through their personal computers dates back to the 1950s; in 1969, the first message was sent over the Advanced Research Projects Agency Network from a laboratory at the University of California to a second network node at the Stanford Research Institute. Commercial service providers emerged in 1989, marking the beginning of the transition to the modern Internet, whose volume of traffic has doubled approximately every 18 months; its popularity became massive during the 1990s, thanks to the introduction of the World Wide Web and the rise in near-instant communication, through for example, electronic mail, instant messaging, voice over Internet Protocol telephone calls, and videoconferencing. This changed the way people lived and worked over the last decades, but it is likely that a disproportionally strong impact was felt in all those activities in which knowledge and information sharing are fundamental for production, like research and innovation. Likewise, in the world that will emerge when the pandemic is eventually over, digital communication in general, and videoconferencing

**Abbreviations:** DOI, Department of Interior; GDP, gross domestic product; HDR, highest density region; IPUMS, Integrated Public Use Micro Samples; MSA, metropolitan statistical area; NHGIS, National Historical Geographic Information System; R&D, research and development; US, United States; USDA, United States Department of Agriculture; USPTO, United States Patents and Trademarks Office.

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in particular, will most probably be integral part of daily working to a much higher extent than before. How does a boost to digital communication change the relative productivity of researchers and their ability to innovate? Which impact does it have on the spatial distribution of these activities and their contribution to growth? What are the repercussions on income and inequality?

To investigate these questions, we construct an endogenous growth model with different urban areas and various knowledge spillovers. The economy features two urban areas, each with three sectors: a research sector producing patents using knowledge and skilled labor, an intermediate sector producing differentiated inputs using patents, and a manufacturing sector using skilled labor, unskilled labor, and intermediate inputs. Workers are free to move across areas, and skilled workers can also decide in which sector to work; location and sector decisions are evaluated solely in terms of wage rates. Knowledge takes two forms in the model: abstract and tacit. As in the endogenous growth literature originating from Romer (1986), the former represents codifiable knowledge created during the research effort, which spreads freely throughout the system enhancing the productivity of every researcher. Tacit knowledge is instead all that body of knowledge that cannot be codified, being the non-written heritage of individuals or groups (Polanyi, 1967). This form of knowledge can be transmitted and positively affects the productivity of the researchers, but the flows of tacit knowledge occur essentially through direct, face-to-face, contacts rather than through impersonal means such as patent documents or scientific papers. This introduces a distinction between system-wide and bounded external spillovers on the basis of the type of knowledge being transmitted.

We assume that one urban area is endowed with a more productive research sector, which may parsimoniously reflect a more developed absorptive capacity, that is, a higher ability to assimilate new knowledge, recognize its value, and apply it to commercial use (Cohen & Levinthal, 1990), or a richer network capital, defined as an area's capacity and capability to access economically beneficial knowledge (Huggins & Thompson, 2014). As a consequence of this productivity gap, geographical specialization arises in equilibrium: the more productive research sector attracts a larger share of researchers and thus the related area specializes in research activities; conversely, the composition of the workforce of the area with a less productive research sector leans toward skilled and unskilled workers producing the final good. Since skilled workers command a higher wage than unskilled ones, the area with a more productive research sector (and thus a relative specialization in research activities) is characterized by higher income per capita; if skilled workers are relatively scarce in the entire population, this area also exhibits a more unequal income distribution. However, the growth rate is the same across areas, since the presence of spillovers means that this only depends on the aggregate flows of new knowledge generated in a period.

We then model a boost to near-instant communication technologies as a fall in the "cost of distance," that is, a facilitation of the informal interactions among researchers. First, this has a positive effect on the growth rate of the entire economy, since both areas benefit from an increase in the effectiveness of their research effort. Second, a skilled worker becomes relatively more productive if employed in the research sector than in the manufacturing sector, causing a reallocation of skilled workers from manufacturing to research activities. Third, since the more productive research sector is better equipped to exploit these additional interactions (consistently with the interpretation of the productivity of a research sector as its absorptive capacity or network capital), it attracts a larger share of these new researchers, strengthening the previously existing patterns of specialization. As a consequence, this shock increases the previously existing disparities in income per capita and Gini coefficients between areas, as well as the Gini coefficient of the entire system.

Our model is consistent with a series of well-known empirical evidences on innovation and inequality that we recast at the level of metropolitan areas for the United States. In particular, we highlight that, starting from the 1990s, patents have become increasingly spatially concentrated, and there has been increasing divergence in terms of average hourly wages, skills, and patents per capita across metropolitan areas. We also examine the evolution of the cross-sectional distribution of patents per capita using a distribution dynamics approach. We provide evidences supporting the existence of convergence clubs: the polarization identified in the evolution of the unconditional distribution of patents per capita is partly explained by a measure of topography of the area (corrected for natural amenities), which is a commonly used instrument for broadband expansion.

The remainder of this paper is organized as follows. Section 2 reviews previous literature, whereas Section 3 presents some basic facts on patents concentration, inequality, and divergence across metropolitan areas in the United States. Section 4 formalizes the model and Section 5 describes its balanced growth path. Section 6 carries out the comparative statics and presents a numerical example, whereas Section 7 presents some empirical evidences on the evolution over time of the cross-sectional distribution of patents per capita across metropolitan areas. Section 8 concludes.

## 2 | PREVIOUS LITERATURE

Our paper is connected to several strands of literature. First, our model is based on the endogenous growth literature originating from Romer (1986), that stresses the role of knowledge as a key driver of productivity and economic growth. In particular, we provide an expanding variety model with knowledge spillovers à la Romer (1990b), where current researchers "stands on the shoulders of past giants." However, we allow for different areas, so that the growth rate of the entire economy results from the research and development (R&D) decisions of all areas. In terms of modeling, our paper is similar to models of endogenous technological change with knowledge spillovers across countries (such as Acemoglu et al., 2017; Howitt, 2000), but we take a more regional perspective and allow our researchers to move freely across areas and sectors, thus endogenizing the spatial distribution of human capital.[1]

Second, we relate to the new economic geography literature. Its canonical setting is the so-called core-periphery model introduced by Krugman (1991), showing the link between agglomeration and economic integration, and an early analytically solvable version with exogenous size asymmetries or asymmetric trade costs is provided by Forslid and Ottaviano (2003). In particular, we are close to those papers embedding the core-periphery model in an endogenous growth framework; see for example, Martin and Ottaviano (1999), Baldwin and Forslid (2000), Baldwin et al. (2001), and Fujita and Thisse (2003) for some seminal contributions and Bond-Smith and McCann (2014) for a literature review.[2] Among the numerous subsequent core-periphery growth models, we share with Bond-Smith and McCann (2020) a focus on innovation, the presence of multiple sectors, and footloose skilled workers (i.e., freely choosing location in response to wage pressure). One of the main differences between our papers concerns the way in which information flows are modeled, as they parsimoniously capture knowledge spillovers through exogenous parameters. Conversely, we introduce endogenous spillovers based on the endogenous allocation of workers across sectors and areas, thus highlighting the feedback effects among technology, knowledge, agglomeration, and inequality; moreover, we focus on the consequences for specialization, growth, and inequalities of the introduction of new communication and information technologies.

Third, this paper connects to the literature on innovation and agglomeration, which studies how they relate to economic performance and growth (see Carlino & Kerr, 2015, for a literature review). This literature suggests that population and economic activity are spatially concentrated, and that R&D activities are more concentrated than manufacturing activities (e.g., Audretsch & Feldman, 1996; Buzard et al., 2017). One of the underlying explanation, which dates back to Marshall (1890), is that geographic proximity facilitates the transfer of knowledge, especially through serendipitous interactions among workers and firms.[3] However, there is a growing base of evidence suggesting that knowledge is increasingly being shared across geographic clusters, but through more selective routes that require conscious investments, absorptive capacity, and network capital (see Huggins & Thompson, 2014, for a review). In this paper, we take as given that one area is endowed with a research sector relatively more effective at exploiting the knowledge spillovers and analyze theoretically the resulting spatial allocation of innovative activities.

Finally, our paper also belongs to the literature studying the effects of new communication and information technologies on inequality across regions and skill levels (e.g., Duranton & Puga, 2005; Fujita & Thisse, 2006; Glaeser & Ponzetto, 2010; Potlogea, 2018), where the progress of communication technology is often modeled as an exogenous decrease in communication costs. We focus on the spatial reallocation of skilled and unskilled labor between research and manufacturing activities and across areas following a positive permanent shock to communication technologies that facilitates the sharing of information across innovation activities, whereas this literature studies the increased feasibility of separating managerial activities from labor-intensive production activities.

## 3 | SOME EMPIRICAL FACTS

We report some empirical facts regarding innovation and inequality in the United States in the last decades. Our unit of geography is the metropolitan statistical area (MSA) that is, "a region consisting of a large urban core together with surrounding communities that have a high degree of economic and social integration with the urban core" (Ruggles et al., 2020). We pick MSAs as our geographic entities for various reasons. First, MSAs represent economic spatial units and so are considered more appropriate to study income convergence than states, regions, or even counties (e.g., Drennan, 2005); moreover, they are more consistent with our theoretical model. Second, innovation is mainly an urban phenomenon.[4] Third, there is large heterogeneity across MSAs in terms of wages, wage disparities, and capacity to innovate.

We measure innovation with the number of patents granted by the United States Patents and Trademarks Office (USPTO).[5] We locate each patent according to the US location in which the inventor of the innovation resides, which is extracted from patent text and used to determine latitude and longitude; then, we assign that location to its current MSA.[6] When a patent is coauthored by more than one inventor, we split it equally among them.

To provide some anecdotal evidence on inequality, we draw data from the Census Integrated Public Use Micro Samples (IPUMS, Ruggles et al., 2020), which reports for each decade between 1950 and 2010 individual-level information on demographic and socio-economic indicators, including data on wage received and education; moreover, it also provides the metropolitan area of residence of each individual.

## 3.1 | Innovation

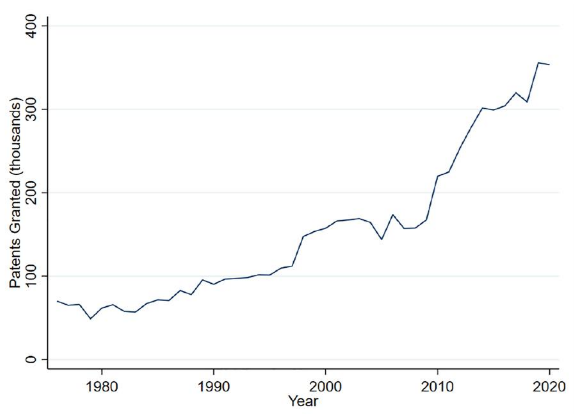
It is well known that the number of patents issued by the USPTO annually has steadily increased since the 1990s, as shown for example, in Figure 1a. But what about the spatial distribution of these innovating activities? In general, R&D activities are more concentrated than manufacturing activities (e.g., Buzard et al., 2017); moreover, both Andrews and Whalley (2021) and Forman and Goldfarb (2021) report a particularly pronounced increase in the geographic concentration of patenting at the US county level starting from the 1990s.

Following Andrews and Whalley (2021), we measure concentration using Ellison and Glaeser's (1997) "dartboard approach." This consists in calculating an index of the spatial concentration of innovation intensity by comparing the observed spatial distribution of patents to what it would have been if it was proportional to population distribution.[7] In particular, for each year $t$ and all MSAs $n \in N$, our dartboard innovation intensity concentration index is

$$Concentration_t = \frac{\sum_{n=1}^{N}(SharePat_{nt} - SharePop_{nt})^2}{1 - \sum_{n=1}^{N} SharePop_{nt}^2}, \tag{1}$$

where $SharePat_{nt}$ and $SharePop_{nt}$ are, respectively, the shares of patents granted and of population living in area $n$ in year $t$. The scale of this index is such that a value of zero can be interpreted as indicating a complete lack of agglomerative forces, whereas a value of one would indicate that all patenting occurs in one geographic area.

The evolution of this index is reported in Figure 1b, which shows a decline in concentration across MSAs between 1976 and the beginning of the 1990s, followed by a sharp increase in patenting concentration.




**(a)** Number of Patents


**(b)** Patenting Concentration

**FIGURE 1** Innovation in the United States. The first panel shows the number of utility patents granted by USPTO in any given year between 1976 and 2020. The second panel shows the dartboard innovation intensity concentration index across metropolitan statistical areas in the United States between 1976 and 2020. Own elaborations using data from USPTO. USPTO, United States Patents and Trademarks Office.

## 3.2 | Inequality

As documented by for example, Piketty and Saez (2003) and Atkinson et al. (2011), following several decades of wage compression and increasing equality, starting around 1980 income inequality has risen sharply in the United States. This trend, which has been named "great divergence" by Paul Krugman, is evident in Figure 2a, which shows the evolution of the US Gini coefficient over the last hundred years. However, the same term has been used by Moretti (2012) to describe a different process, whereby there has been, approximately from the same time, increasing divergence between leading cities and poorer cities (see also Berry & Glaeser, 2005; Giannone, 2021). Figure 2b provides a first look at this divergence across MSAs: by plotting the distributions of the average hourly wages across the set of MSAs in 1990 and 2010, it shows a spreading out over this time period.

Moretti (2012) argues that one reason for the increasing divergence across cities is due to a divergence of skills. Using education as a proxy for skills (like e.g., Acemoglu & Autor, 2011), Figure 2c,d show the relationship between the growth rate in the ratio between the number of highly and less educated workers living in a MSA and the value of this

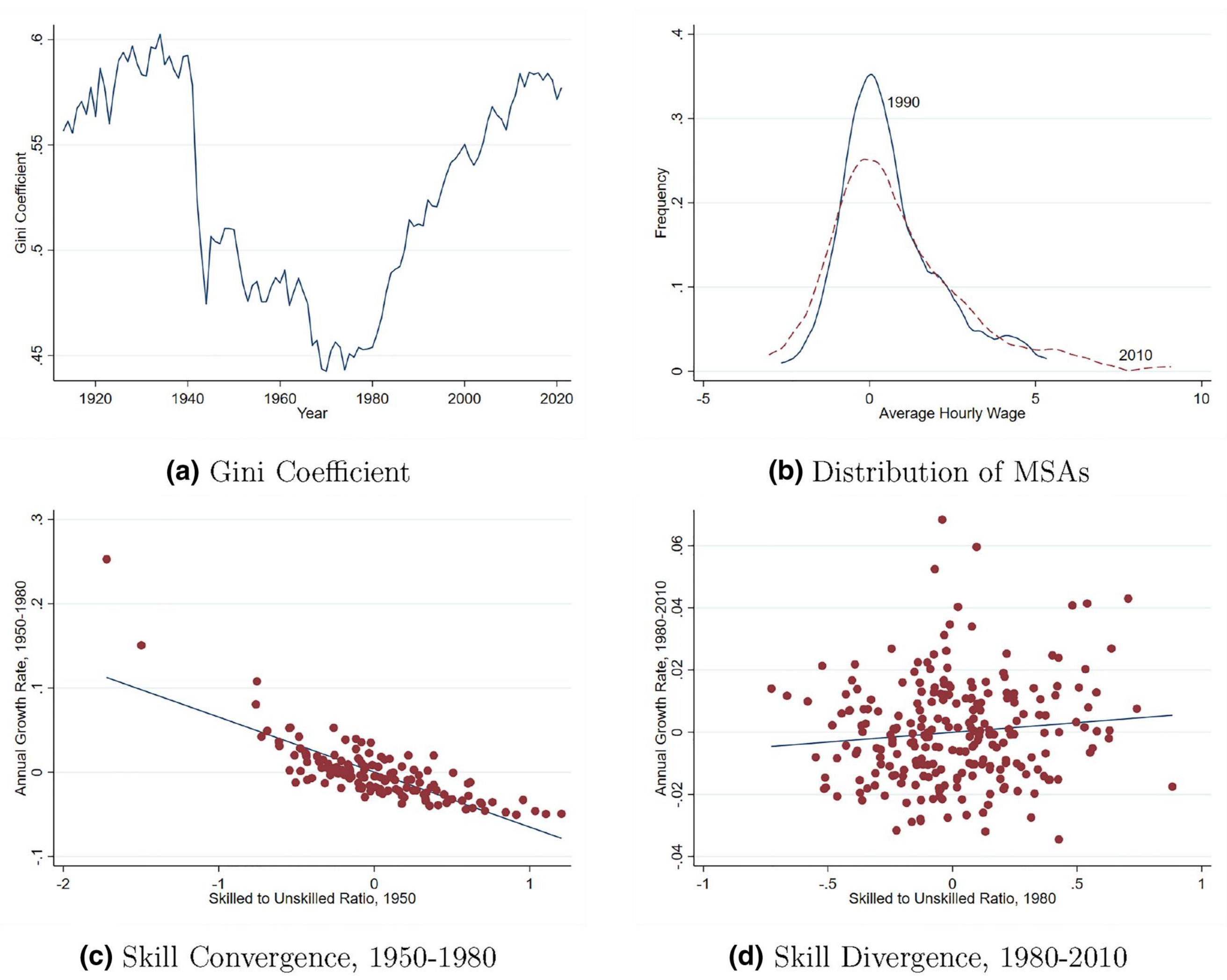



FIGURE 2 Divergence in the United States. The first panel reports the Gini coefficient calculated using pre-tax national income (from labor and capital) of US adults between 1913 and 2019 (*Source*: World Inequality Database). The second panel provides kernel estimations of the distributions of (a balanced panel of) MSAs according to the (demeaned) average hourly wages (at constant 1999 prices) in 1990 and 2010 (note that data may be censored, with amounts higher than a certain time-changing top code value expressed as the state medians of values above it). The third and fourth panels show each MSA's annual average growth (demeaned) against its (demeaned and in natural logarithm) initial level of the ratio between highly educated (at least 4 years of college) and less educated (everyone else) respondents; lines are linear fit. Own elaboration using data from IPUMS (Ruggles et al., 2020). IPUMS, Integrated Public Use Micro Samples; MSA, metropolitan statistical area.

ratio in the initial period, respectively for 1950–1980 and 1980–2010. As already observed by Giannone (2021), before 1980 there was convergence in the skill ratio across MSAs, whereas afterward skills diverged over space (as reported by e.g., Moretti, 2004).

## 4 | THE MODEL

We consider an infinite-horizon economy in continuous time. This is inhabited by a continuum of infinitely-lived agents comprising a constant mass $H$ of skilled workers and a constant mass $L$ of unskilled workers. The economy features two urban areas, $i$ and $j$. Each area has three sectors: a research sector which produces patents using knowledge and skilled labor, an intermediate sector producing differentiated intermediate inputs using forgone final good and patents, and a manufacturing sector producing a homogeneous good using skilled labor, unskilled labor, and intermediate inputs.

Agents are footloose. This means that unskilled workers, employed in the manufacturing sectors, are free to move across areas; likewise, a skilled worker is employed in either the research sector or the manufacturing sector, and can freely move across areas and sectors. Locations and sectors are evaluated solely in terms of wage rates. Moreover, we also abstract from transportation costs for goods across areas. We take these assumptions not only for simplicity but also to focus exclusively on the effects of the knowledge spillovers on the relative allocation of research and production activities.

### 4.1 | The agents

Agents, indexed by $z$, are infinitely-lived and have an instantaneous constant relative risk aversion utility function, meaning that they each maximize, subject to a budget constraint,

$$\int_{t=0}^{\infty} e^{-\rho t} \frac{c_z(t)^{1-\sigma} - 1}{1-\sigma} dt, \tag{2}$$

where $c_z(t)$ is the consumption of agent $z$ at time $t$, $\rho > 0$ is the subjective discount rate, and $1/\sigma > 0$ measures the willingness to substitute intertemporally. Agents inelastically supply one unit of labor and own equal shares of all the area's firms.

Agents consume a unique final good that can be transported between the two areas at no cost; therefore, all consumption arising from the system can be aggregated in the system-wide variable $C(t)$. The maximization problem of the agents results in the usual consumption Euler's equation, which relates the interest rate $r(t)$ to the rate of growth of consumption according to

$$\frac{\dot{C}(t)}{C(t)} = \frac{r(t) - \rho}{\sigma}. \tag{3}$$

Here, we concentrate on the case in which the growth rate of consumption is positive, which implies $r(t) > \rho$. To ensure that the integral in Equation (2) converges, the rate of growth of current utility is assumed to be smaller than the rate of time preference, that is,

**Assumption 1.** $(1-\sigma)\dot{C}(t)/C(t) < \rho$.

### 4.2 | The manufacturing sector

The final good is produced competitively by a representative firm using unskilled labor, skilled labor, and a set of intermediate inputs. The available variety of intermediate inputs in a urban area at any point in time is taken as given by the firm and consists of the sum of inputs produced in the same area and inputs imported from the other area (as in e.g., Rivera-Batiz & Romer, 1991; Rivera-Batiz & Xie, 1993). The intermediate inputs depreciate fully after use.[8] Below and in the next subsections, we describe $i$'s sectors, but the same applies to $j$'s; for ease of reading, we drop the time index.

Define $A_i$ and $A_j$ as the number of intermediate inputs designed and produced in $i$ and $j$, respectively. Let the quantity of any intermediate input produced in $i$ and employed in the same urban area be $x_i(a_i)$, with $a_i \in A_i$; analogously, the quantity of any intermediate input produced in $j$ and employed in $i$ is $x_i(a_j)$, with $a_j \in A_j$. The overall production structure in $i$'s final sector is represented by the following additively separable function:

$$M_i = L_i^{\alpha} H_{m,i}^{\beta} \left[ \int_0^{A_i} x_i(a_i)^{\gamma} da + \int_0^{A_j} x_i(a_j)^{\gamma} da \right] S_{m,i}, \tag{4}$$

where $M_i$ is the final good produced in $i$, $H_{m,i}$ represents skilled labor employed in $i$'s manufacturing sector, and $S_{m,i}$ reflects the size of spillovers arising from the interaction between skilled workers employed within the same urban area. Formally, these intra-area spillovers are parametrized through the following equation,

$$S_{m,i} = H_{r,i}^{\phi_r} H_{m,i}^{\phi_m}, \tag{5}$$

where $H_{r,i}$ represents skilled labor employed in $i$'s research sector, while $\phi_r$ and $\phi_m$ measure spillover elasticities.[9] In the remaining of this paper, we focus on the more interesting case by taking the following assumption:

**Assumption 2.** $(\phi_r + \phi_m)/\phi_m \geq 0$.

Note that Assumption 2 is quite weak. Indeed, it is automatically satisfied in the perhaps more natural case of agglomeration effects due to local human capital (i.e., both elasticities are positive), a type of local spillovers with a long tradition in economics (since at least Jacobs, 1970). A special case satisfying Assumption 2 which is consistent with this interpretation is $\phi_r = \phi_m \geq 0$, in which case the intra-area spillovers in manufacturing are parametrized according to the gravity-type equation $S_{m,i} = \left(H_{r,i} H_{m,i}\right)^{\phi}$, and Assumption 2 simply requires that the economies arising from the agglomeration of skilled workers are non-negative, $\phi \geq 0$. However, it is also satisfied if both elasticities are negative (i.e., with congestion effects in human capital). Finally, it also accommodates the case in which signs differ, for example, if intra-area spillovers positively depends on the proportion of researchers out of all skilled workers in an area (like in Abel et al., 2012). Only in this case this assumption imposes a bound on one of these two elasticities and ensures specialization across areas in equilibrium.

The Cobb-Douglas formulation of the production function in Equation (4) leads to iso-elastic demand curves; in particular, the demands of intermediate inputs by the final good producer in area $i$ are

$$x_i(a_i) = \gamma^{\frac{1}{1-\gamma}} L_i^{\frac{\alpha}{1-\gamma}} H_{m,i}^{\frac{\beta}{1-\gamma}} S_{m,i}^{\frac{1}{1-\gamma}} p_i(a_i)^{-\frac{1}{1-\gamma}} \tag{6a}$$

$$x_i(a_j) = \gamma^{\frac{1}{1-\gamma}} L_i^{\frac{\alpha}{1-\gamma}} H_{m,i}^{\frac{\beta}{1-\gamma}} S_{m,i}^{\frac{1}{1-\gamma}} p_i(a_j)^{-\frac{1}{1-\gamma}}, \tag{6b}$$

where $p_i(a_i)$ and $p_i(a_j)$ are the prices of an intermediate good sold in $i$ but produced in $i$ and $j$, respectively.

The final sector operates in a perfectly competitive setting, hence $\alpha + \beta + \gamma = 1$. To ensure that the wage rate earned by skilled workers is higher than the wage rate earned by unskilled workers, we assume

**Assumption 3.** $H_{m,i}/L_i < \beta/\alpha$.

We assume that the final good is traded freely within the system in the absence of any transportation cost; as a consequence, in equilibrium its price must be the same in both urban areas, and we normalize it to one.

## 4.3 | The research sector

Following the large literature originated from Romer (1990a, 1990b), the research sector produces knowledge in the form of designs for new intermediate inputs, using skilled labor and existing knowledge. Formally, the flow of new knowledge, that is, the number of new designs, created in urban area $i$ at any point in time is given by:

$$\dot{A}_i = \delta_i H_{r,i}^{\eta} S_{r,ij} A, \tag{7}$$

where $H_{r,i}$ is the number of *researchers* in $i$, $0 \leq \eta < 1$ is a parameter inducing decreasing private returns in its stock (similarly to Jones, 1995; Kortum, 1993), $\delta_i > 0$ is an exogenous parameter characterizing the productivity of the local research system, $A$ is an index of the economy technology frontier (which will be endogenized below), and $S_{r,ij}$ reflects inter-area spillovers in research. This form of the innovation possibility frontier implies that new knowledge in $i$ results from the effort of the researchers in the area, but the effectiveness of these efforts more generally depends on the research done in the entire economy.[10]

Indeed, Equation (7) introduces two types of spillovers. First, there is a positive a-spatial spillover coming through the economy technology frontier, $A$. This is assumed to be given by

$$A \equiv A_i + A_j, \tag{8}$$

meaning that $A$ simply represents the aggregate number of designs already existing, or, equivalently, the overall level of abstract knowledge created so far and available to all researchers.[11] Second, there is a positive network effect between the researchers in the two areas; this represents the flow of tacit knowledge, which occurs essentially through informal interactions and exchange of ideas. We assume that these inter-area spillovers have the following representation:

$$S_{r,ij} = H_{r,i}^{\psi_1} H_{r,j}^{\psi_2} \nu_i^{\psi}, \tag{9}$$

with the function $\nu_i$ expressing the effectiveness of the interaction to the benefit of $i$ and the parameters $\psi_1$, $\psi_2$, and $\psi$ governing the strength of the impact of each component (i.e., researchers in the area, researchers in the other area, and the effectiveness, respectively). We take the following assumption:

**Assumption 4.** $\psi_2 > \psi_1 + \eta - 1$.

As clarified in Appendix A.1, this assumption is a sufficient condition for the stability of the (interior) equilibrium allocation of researchers across areas. In our setting, as typical in endogenous growth models, there can be socially increasing returns to local research activity (if $\psi_1 + \eta - 1 > 0$) even if the private returns are decreasing (since $\eta < 1$): this assumption imposes an upper bound on these spillover effects so that we can focus on the interior equilibrium in which research is done in both areas.

It is well-known that any sort of distance, $d$, between the researchers of the two areas, being geographical or technological, may make these informal interactions more difficult (see e.g., Jaffe et al., 1993; Storper & Venables, 2004); however, a natural assumption is that a higher productivity of the local research system, which may partly be intended as its absorptive capacity (Cohen & Levinthal, 1990) or its network capital (Huggins & Thompson, 2014), may not only facilitate the exploitation of these interactions but also (partly) compensate for the distance.[12] As a consequence, we let $\nu_i \equiv \nu(\delta_i, d)$ and $\nu_j \equiv \nu(\delta_j, d)$ and we take the following assumption:

**Assumption 5.** The function $\nu(\delta, d)$ is twice differentiable in $\delta$ and $d$, and satisfies

$$\frac{\partial \nu(\delta, d)}{\partial \delta} \geq 0, \quad \frac{\partial \nu(\delta, d)}{\partial d} \leq 0, \quad \frac{\partial^2 \nu(\delta, d)}{\partial d \partial \delta} \leq 0, \quad \frac{\partial}{\partial \delta} \left| \frac{d}{\nu(\delta, d)} \frac{\partial \nu(\delta, d)}{\partial d} \right| > 0,$$

where the last condition ensures that the $d$-elasticity of $\nu(\delta, d)$ increases with $\delta$.

## 4.4 | The intermediate sector

The intermediate sector in area $i$ is composed of an infinite number of firms on the interval $[0, A_i]$. Each of these firms has purchased a patent from the research sector and can then produce the related intermediate input at marginal cost equal to $\varkappa > 0$ units of the final good. We assume that this marginal cost is strictly higher if the intermediate input is manufactured in the other area, thus excluding the existence of an inter-area trade of patents.[13]

In line with the endogenous technological change literature, an intermediate producer acts as a monopolist in the production of its particular intermediate input. An intermediate firm in $i$ faces the demand $x_i(a_i)$ in Equation (6a) from the final producer in $i$ with the corresponding price $p_i(a_i)$ and the demand $x_j(a_i)$ at price $p_j(a_i)$ from the final producer in $j$; let aggregate demand faced by an intermediate firm in $i$ be $X(a_i) \equiv x_i(a_i) + x_j(a_i)$. Since demands are iso-elastic, the monopoly price is a constant mark-up over marginal cost. Without loss of generality, we normalize the marginal cost of machine production to $\kappa \equiv \gamma$, so that

$$p \equiv p_i(a_i) = p_j(a_i) = \kappa\gamma^{-1} = 1. \tag{10}$$

Intermediate inputs all have the same price across intermediate firms and areas, since the marginal cost is the same. Intermediate inputs depreciate fully after use, and so $p$ can also be interpreted as a rental price or the user cost of the input. For simplicity, we are assuming the absence of transportation costs for intermediate goods across areas, but we show in Appendix A.3.2 that results are qualitatively the same with symmetric costs.

Substituting Equation (10) into Equation (6) shows that a manufacturing firm demands the same quantity of each intermediate input, irrespective of their origin,

$$x_i = \gamma^{\frac{1}{1-\gamma}} L_i^{\frac{\alpha}{1-\gamma}} H_{m,i}^{\frac{\beta}{1-\gamma}} S_{m,i}^{\frac{1}{1-\gamma}}. \tag{11}$$

As a consequence, the intermediate input producers located in the two different areas all face the same aggregate demand, $X = x_i + x_j$, and enjoy the same instant profits, $\pi = X(1-\gamma)$. Hence, final good production simplifies to

$$M_i = AL_i^{\alpha} H_{m,i}^{\beta} x_i^{\gamma} S_{m,i}. \tag{12}$$

The decision about undertaking the production of a new intermediate input is taken comparing the discounted value of the flow of future profits to the cost of the initial investment in acquiring a patent from the research sector. With this knowledge, the monopolistically competitive research sector sets the price of a patent equal to the present value of the stream of future profits of the intermediate sector's monopolist. Therefore, the cost of a patent, irrespective of its location, is $P = \int_{t=0}^{\infty} \pi(t) e^{-rt} dt$. Patents are infinitely lived; hence, if the interest rate is constant,

$$P = \frac{X(1-\gamma)}{r}. \tag{13}$$

## 5 | THE EQUILIBRIUM

We now characterize the equilibrium; when necessary to avoid confusion, we reintroduce time indexes. An allocation is defined by time paths of consumption levels $[C(t)]_{t=0}^{\infty}$, aggregate spending on intermediate inputs $\left[X_i(t), X_j(t)\right]_{t=0}^{\infty}$, labor allocations $\left[H_{m,i}(t), H_{m,j}(t), H_{r,i}(t), H_{r,j}(t), L_i(t), L_j(t)\right]_{t=0}^{\infty}$, available intermediate input varieties $\left[A_i(t), A_j(t)\right]_{t=0}^{\infty}$, and time paths of interest rates $[r(t)]_{t=0}^{\infty}$, wage rates in the research sectors $\left[w_{r,i}(t), w_{r,j}(t)\right]_{t=0}^{\infty}$, wage rates for skilled and unskilled workers in the manufacturing sectors $\left[w_{m,i}(t), w_{m,j}(t), w_{l,i}(t), w_{l,j}(t)\right]_{t=0}^{\infty}$, quantities of each intermediate input $\left[x_i(t), x_j(t)\right]_{t=0}^{\infty}$, and patent costs $[P(t)]_{t=0}^{\infty}$. An equilibrium is an allocation in which final good producers, research firms, and intermediate good producers choose, respectively, $\left[H_{m,i}(t), H_{m,j}(t), L_i(t), L_j(t), x_i(t), x_j(t)\right]_{t=0}^{\infty}$, $\left[H_{r,i}(t), H_{r,j}(t), P(t)\right]_{t=0}^{\infty}$, and $\left[x_i(t), x_j(t)\right]_{t=0}^{\infty}$ as to maximize (the discounted value of) profits, the evolution of wages and interest rate is consistent with market clearing, agents make labor and consumption decisions as to maximize their lifetime utility, and the evolution of $\left[A_i(t), A_j(t)\right]_{t=0}^{\infty}$ is determined by free entry.

In particular, we focus on a balanced growth path, that is, an equilibrium in which aggregate variables, like consumption $C(t)$ and output $M(t)$, grow at the same constant rate as system-wide abstract knowledge, $g \equiv \dot{A}(t)/A(t)$ for all $t$. This is possible, from Equation (3), only if the interest rate is constant: we thus look for an equilibrium in which $r(t) = r$ for all $t$.

Assuming for a moment that the labor market is characterized by a stable allocation of both unskilled and skilled labor across areas and sectors, then it is clear from Equation (11) that the equilibrium demands of intermediate inputs would also be constant, $x_i(t) = x_i$ and $x_j(t) = x_j$ for all $t$; as implied by Equation (13), in such an equilibrium, also the price of a patent is constant over time, $P(t) = P$ for all $t$. Under such a constant allocation of resources, Equation (12) ensures that the output in both urban areas, $M_i(t)$ and $M_j(t)$, grows at the same rate as system-wide abstract knowledge, $g$. As a consequence, aggregate output, $M(t)$, also grows at $g$. Therefore, in an economy characterized by a constant allocation of unskilled and skilled labor across areas and sectors, a balanced growth path allocation exists in which

$$\frac{\dot{M}(t)}{M(t)} = \frac{\dot{M}_i(t)}{M_i(t)} = \frac{\dot{M}_j(t)}{M_j(t)} = \frac{\dot{C}(t)}{C(t)} = \frac{\dot{A}(t)}{A(t)} \equiv g.$$

To solve the model for this balanced growth equilibrium it is therefore necessary to determine the equilibrium allocation of workers across areas and sectors, and to verify that this allocation is consistent with a constant interest rate.

## 5.1 | The equilibrium allocation of workers

In this section, we characterize the allocation of skilled and unskilled workers across areas and sectors.

### 5.1.1 | The inter-area allocation of researchers

We first take the aggregate number of researchers, $H_r \equiv H_{r,i} + H_{r,j}$, as given; this will be endogenized below. From the maximization problem of a firm in the research sector, the wage rate for a researcher in urban area $i$, $w_{r,i}$, must satisfy the first order condition $w_{r,i} = \partial(P\dot{A}_i)/\partial H_{r,i}$. Using Equations (7) and (13), this wage rate is

$$w_{r,i} = AX\eta\delta_i H_{r,i}^{\eta-1} S_{r,ij} \frac{1-\gamma}{r}. \tag{14}$$

Any skilled worker is free to enter either research sector: in equilibrium, researchers must receive the same compensation across the two areas, that is, $w_{r,i} = w_{r,j} \equiv w_r$. The following equilibrium allocation ensues:

$$\frac{H_{r,i}}{H_{r,j}} = \left(\frac{\delta_i}{\delta_j}\right)^{\frac{1}{1-\eta-\psi_1+\psi_2}} \left(\frac{\nu_i}{\nu_j}\right)^{\frac{\psi}{1-\eta-\psi_1+\psi_2}}. \tag{15}$$

For given distance and research productivities, the equilibrium spatial allocation of skilled labor in research is thus constant. Moreover, by Assumptions 4 and 5, there is a positive relationship between productivity in research and the relative concentration of research activities: an urban area characterized by a relatively higher productivity of the research sector will attract a larger share of researchers.

### 5.1.2 | The allocation of workers in the manufacturing sector

The manufacturing sectors are competitive, hence the wage rate of unskilled and skilled workers employed in area $i$ are, respectively

$$w_{l,i} = \frac{\partial M_i}{\partial L_i} = \alpha L_i^{\alpha-1} H_{m,i}^{\beta} A x_i^{\gamma} S_{m,i} \tag{16a}$$

$$w_{m,i} = \frac{\partial M_i}{\partial H_{m,i}} = \beta L_i^{\alpha} H_{m,i}^{\beta-1} A x_i^{\gamma} S_{m,i}. \tag{16b}$$

Since workers can freely move between the two manufacturing sectors, in equilibrium unskilled and skilled workers must receive the same compensation across areas, that is, $w_{l,i} = w_{l,j} \equiv w_l$ and $w_{m,i} = w_{m,j} \equiv w_m$. This implies

$L_i/L_j = H_{m,i}/H_{m,j}$; consequently, $H_{m,i}/L_i = H_{m,j}/L_j = H_m/L$, where $H_m \equiv H_{m,i} + H_{m,j}$ is the aggregate number of skilled workers employed in the manufacturing sector. Moreover, by combining this result with Equation (11), we prove in Appendix A.1 that $L_i/L_j = x_i/x_j$ and that the external effects are endogenously equalized, $S_{m,j} = S_{m,i}$. In turn, this implies that, in equilibrium,

$$\left(\frac{H_{r,j}}{H_{r,i}}\right)^{\frac{\phi_r}{\phi_m}} = \frac{H_{m,i}}{H_{m,j}} = \frac{L_i}{L_j} = \frac{x_i}{x_j}. \tag{17}$$

These ratios are constant along the balanced growth path given (15).

### 5.1.3 | The inter-sector allocation of skilled workers

Finally, the intra-area equilibrium requires inter-sectoral wage equalization for skilled workers, $w_{m,i} = w_{r,i}$ and $w_{m,j} = w_{r,j}$. Given the inter-area equilibrium allocation of researchers, these conditions become $w_m = w_r \equiv w_h$, where $w_h$ is the unique wage paid to a skilled worker across sectors and areas. We show in Appendix A.1 that this condition is met when

$$\frac{H_r}{H_m} = \frac{\eta(1-\gamma)\gamma}{\beta}\left(\frac{r-\rho}{r\sigma}\right). \tag{18}$$

Condition (18) maintains that the equilibrium allocation of the given stock of skilled labor depends on parameters and the endogenous interest rate. Since the interest rate must be constant along the balanced growth path, the proportional allocation of skilled workers in the research sector and in the final good sector also remains constant.

## 5.2 | The equilibrium growth rate

We showed in Section 5.1 that the system is characterized by a constant allocation of workers across sectors and urban areas. Given that such a constant allocation exists, the economy exhibits a balanced growth path. To complete the characterization of the balanced growth path, note that free entry into research implies

$$\eta\delta_i S_{r,ij} A H_{r,i}^{\eta-1} \frac{X(1-\gamma)}{r} = w_h, \tag{19}$$

where the left hand side is the private return from hiring one more researcher and the right hand side is the related flow cost. Together with Equation (16b), this implies that the equilibrium interest rate must be $r = \eta(1-\gamma)\delta_i\gamma\beta^{-1}S_{r,ij}H_{r,i}^{\eta-1}H_m$, which is constant under the constant allocation of workers.

**Proposition 1.** *The system exhibits a globally stable balanced growth path equilibrium in which output, consumption, physical capital, aggregate abstract knowledge, abstract knowledge in each area, and wages grow at the same constant rate given by*

$$g = \delta_j S_{r,ji} H_{r,j}^{\eta-1} H_r = \delta_i S_{r,ij} H_{r,i}^{\eta-1} H_r. \tag{20}$$

*Along the balanced growth path, the price of a patent, the price of each intermediate input, the price of the final good, the interest rate, and the labor allocations across sectors and areas are constant.*

*Proof.* See Appendix A.1 □

## 5.3 | Income, inequality, and growth in urban areas

In this section, we evaluate whether differences in income per capita levels and growth rates arise between the two urban areas along the balanced growth path. Without loss of generality, we assume that area $i$ is endowed with a more productive research sector,[14] that is,

**Assumption 6.** $\delta_i > \delta_j$.

Our first result characterizes the relative specialization of skilled labor between the two areas.

**Proposition 2.** *Along the balanced growth path, the urban area with a relatively more productive research sector is characterized by a relative specialization in research activities, i.e.* $H_{r,i}/H_{r,j} > H_{m,i}/H_{m,j} = L_i/L_j$.

*Proof.* Condition (15) and Assumptions 4, 5, and 6 imply $H_{r,i} > H_{r,j}$; the rest follows from condition (17) and Assumption 2. □

Having established the relative productive specialization of the urban areas, we can turn our attention to disparities in income levels within and across areas. The level of income in each area, its gross domestic product (GDP), is calculated as the summation of the wages of its workers, since profits are driven down to zero by competition or free entry. Thus, the overall GDP level in $i$ can be expressed as

$$Y_i = w_l L_i + w_h H_{m,i} + w_h H_{r,i}. \tag{21a}$$

**Corollary 2.1.** *Along the balanced growth path, the area with a relative specialization in research activities has a constantly higher level of GDP per worker.*

*Proof.* See Appendix A.1 □

Since skilled agents command a higher wage than unskilled ones, the area with the more productive research sector, and thus a relative specialization in research activities, is characterized by a higher income per capita. Conversely, the area where the workforce leans toward manufacturing activities is on average poorer.

In area $i$, there are $H_{r,i} + H_{m,i}$ skilled workers earning $w_h$ and $L_i$ unskilled workers earning a lower wage $w_l$. With two income levels, the Gini coefficient, $G_i$, is simply the difference between the proportion of all income accruing to the high income group and the proportion of agents in the high income group, that is,

$$G_i = \frac{(H_{r,i} + H_{m,i})w_h}{Y_i} - \frac{H_{r,i} + H_{m,i}}{L_i + H_{r,i} + H_{m,i}}. \tag{22}$$

**Corollary 2.2.** *If skilled workers are relatively scarce in the entire population, the area with a relative specialization in research activities has a constantly higher Gini coefficient.*

*Proof.* See Appendix A.1 □

When skilled workers are relatively few in the entire population (the precise condition is in Appendix A.1), a minority of agents (researchers and skilled workers) earn the majority of total income produced, both across the entire system and within each area. In equilibrium, since the proportion of skilled agents is higher in the area specialized in research, this area is also more unequal.

Finally, we consider the effect of the relative specialization of the urban areas on the growth rates of their income levels.

**Corollary 2.3.** *Along the balanced growth path, GDP per worker grows in both urban areas at the constant rate g, irrespective of the areas' specialization.*

*Proof.* Along the balanced growth path, wages grow at $g$ whereas labor allocations are constant. Thus, the areas' GDP levels in Equation (21) must also grow at rate g. Since labor allocations are constant, GDP per worker also grows at $g$ in both areas. □

Summarizing, we find that the urban area whose research system is more productive features a relative specialization in research activities compared to the other urban area and enjoys a permanently higher level of GDP per worker but, possibly, a more unequal society. However, the growth rates are the same.

Several empirical papers report a positive relationship between metro size and inequality (e.g., Baum-Snow & Pavan, 2013; Florida & Mellander, 2016). This empirical prediction is matched by our theoretical model if we further impose $\phi_r/\phi_m < 0$. This is the case if, for example, intra-area spillovers positively depends on the proportion of skilled workers employed in research in an area; that urban productivity may relate to the density of researchers is well-established in the literature (e.g., Abel et al., 2012).

## 6 | COMMUNICATION, PRODUCTIVITY, AND SPECIALIZATION

In this section, we focus on a positive technology shock, intended as a boost to near-instant communication technologies, that in terms of the model translates into a reduction in the distance involved in inter-urban relations among researchers, $d$.[15] We show that this shock increases the previously existing disparities in income per capita and Gini coefficients between areas, as well as the Gini coefficient of the entire system. Appendix A.2 presents results following a relative change in the productivity of research, that could be either specific to an area, for example, on the parameters $\delta_i$ or $\delta_j$, or common to the system, for example, on $\psi$.

### 6.1 | A positive technology shock

A firm in the research sector needs knowledge and information, in addition to labor: the flow of tacit knowledge, which occurs through informal interactions and exchange of ideas, not only allows to keep up with scientific and technological advancements, but also to gain timely access to problems, needs, and requests that may direct its activity. In this regard, the diffusion of near-instant communication technologies and videoconferencing certainly plays an important role. Their importance, however, is likely to depend on the features of the network of relations in which they are employed: their effectiveness is probably stronger when these tools are adopted within an already established network (Cohen & Levinthal, 1990; Huggins & Thompson, 2014).[16]

Consistently with this interpretation, we assume that it is within the inter-area networks of relations that these tools are more likely to be successful in reducing distances, possibly giving a boost to the pre-existing phenomenon toward a digitalization of communications. In terms of the model, this takes the form of a permanent fall in the cost of distance between the two areas $d$, which implies a strengthening of inter-area spillovers between researchers that the more productive area is more able to exploit. This has the following long-term effects on the balanced growth path:

**Proposition 3.** *A permanent reduction in the distance between areas, d, results in an increase in the growth rate of the system along the balanced growth path, an increase in the total number of researchers, and a strengthening of the previously existing pattern of specialization.*

*Proof.* See Appendix A.1 □

Not surprisingly, an improvement in the flow of tacit knowledge has a positive effect on the growth rate of the economy, since both areas essentially benefit from an increase in the effectiveness of their own research efforts. At the same time, this shock increases the relative productivity of a skilled worker employed in the research sector as compared to one in the manufacturing sector. This causes a reallocation of skilled workers from manufacturing to research, which is necessary to equalize once again the skilled wage across sectors. However, the relatively more research-intensive area is better equipped to exploit these increased interactions (consistently with the interpretation of the productivity of a research sector as its absorptive capacity or network capital) and thus is able to accommodate a larger share of these added researchers. To keep with equilibrium condition (17), this same area must also experience a relatively greater reduction of skilled workers in the manufacturing sector and an outflow of unskilled workers toward the relatively more manufacturing-intensive area. As a consequences, this reallocation of workers across sectors and areas following the positive technology shock strengthens the previously existing patterns of specialization in research and manufacturing, with important repercussions in terms of inter-area inequality.

**Corollary 3.1.** *A permanent reduction in the distance between areas, d, increases the previously existing differences in the levels of GDP per worker.*

*Proof.* This follows directly from Corollary 2.1 and Proposition 3. □

**Corollary 3.2.** *If skilled workers are relatively scarce in the entire population, a permanent reduction in the distance between areas, d, increases the previously existing differences in the areas' Gini coefficients.*

*Proof.* This follows directly from Corollary 2.2 and Proposition 3. □

Finally, we look at the overall level of inequality, as measured by the Gini coefficient of the entire system,

$$G = \frac{Hw_h}{Y} - \frac{H}{L+H} = \frac{H}{wL+H} - \frac{H}{L+H}, \tag{23}$$

where $w \equiv w_l/w_h = (\alpha/\beta)(H_m/L)$. As explained above, the permanent reduction in the distance between the areas modifies the relative marginal productivity of the workers in the different sectors to the advantage of the researchers (and thus, in the equilibrium that follows, of the skilled workers in general). Together with the strengthening of the previously existing patterns of specialization, this also implies that an even larger share of total income is now in the hands of the same proportion of agents:

**Corollary 3.3.** *A permanent reduction in the distance between areas, d, increases the Gini coefficient of the entire system.*

*Proof of Corollary* 3.3. The Gini coefficient in Equation (23) is clearly decreasing in $w \equiv w_l/w_h = (\alpha/\beta)(H_m/L)$. From Proposition 3, $\partial H_m/\partial d > 0$ and thus $\partial G/\partial d < 0$. □

## 6.2 | A numerical example

We now report the results of a simple quantitative example to highlight the effects of the shock analyzed above on the equilibrium allocation, rather than providing a comprehensive quantitative evaluation. Appendix A.2 presents results following changes in the relative productivity of a research area.

### 6.2.1 | Parameter choices

A period in our model corresponds to 1 year. We take $\alpha = \beta = 1/3$, so that the shares of unskilled and skilled labor in production are approximately 33% and the share of income spent on machines is approximately equal to the share of capital (see Appendix A.3.3 for some robustness checks). The constant relative risk aversion parameter is taken to be $\sigma = 2$ (see e.g., Kaplow, 2005) and the concavity parameter of the innovation production function is $\eta = 0.5$ (Hall & Ziedonis, 2001). We set $\psi = \psi_1 = \psi_2 = 1 - \eta = 0.5$, which respects Assumption 4. The fraction of skilled workers is chosen such that it equals the percentage of individuals in the U.S. with at least a postgraduate degrees that is, $H/L = 13\%$ (U.S. Census, 2018). We normalize the size of the entire population to one and $d = 1$. We calibrate the function $\nu_i = d^{-\delta_i/\delta_j}$, which respects Assumption 5 but makes it explicit that what matters is the relative productivity of a research sector rather than its absolute productivity.[17] We set $\delta_i$ as to target a long-run annual growth rate equal to 2%; by setting the annual subjective discount rate equal to $\rho = 0.01$, we obtain a long-run annual interest rate equal to $r = 5\%$. Finally, we set $\delta_j$ so that the productivity gap between the two research sectors equals 12%.[18]

### 6.2.2 | Results

The balanced growth path values resulting from the above parametrization are shown in the first column of Table 1. Consistently with the results from the theoretical model, area $i$, endowed with a relatively more productive research

**TABLE 1** Balanced growth path values.

| | Baseline | $\Delta d = -25\%$ |
|---|---|---|
| $g$ | 2.00% | 2.41% |
| $H_{r,i}/H_{r,j}$ | 129.13% | 139.02% |
| $H_r/H$ | 11.76% | 12.13% |
| $H_{r,i}/H_r$ | 56.36% | 58.16% |
| $L_i/L$ | 43.64% | 41.84% |
| $y_i/y_j$ | 102.56% | 103.44% |
| $G_i/G_j$ | 103.34% | 104.47% |
| $G$ | 0.416 | 0.417 |

sector, hosts a larger share of researchers than area $j$ (approximately 1.3 times as much), which is instead specialized on manufacturing. As a consequence, area $i$ enjoys a higher level of output per capita but a relatively more unequal society.

In the second column, we show how the balanced growth path values change after a permanent negative shock to $d$, such that the cost of distance between the two areas is reduced by one fourth. Consistently with the theoretical results above, the annual growth rate grows by 20%, since both areas benefit from an increase in the effectiveness of their own research efforts. The shock means that researchers are now relatively more productive than before, and thus the percentage of skilled workers employed in research increases by half a percentage point. However, area $i$ is more equipped to take advantage of this increase, and this strengthens the pre-existing agglomeration dynamics: the share of researchers employed in area $i$ sharply increases, whereas the reverse happens for skilled and unskilled workers in the manufacturing sector. The mass of unskilled workers moving from the research-intensive area to the manufacturing-intensive area is relatively bigger than the mass of skilled workers moving in the opposite direction, causing a relative increase in the level of GDP per worker and the Gini coefficient in area $i$ with respect to area $j$, and a rise in inequality in the economy at large.

### 6.2.3 | Transitional dynamics

It is straightforward to see that our expanding variety model does not exhibit transitional dynamics, as the economy always grows at the constant rate given in Proposition 1. Therefore, following an exogenous shock as the one considered in this section, the economy immediately moves to the new balanced growth path. We introduce transitional dynamics into this numerical example by assuming that workers relocate across sectors and areas according to a logistic function.[19]

In particular, we assume that, following a shock, the stock of workers in a given sector, say $H_{r,i}$, evolves according to

$$H_{r,i}(t) = \frac{H^{\star\star}_{r,i} - H^{\star}_{r,i}}{1 + e^{a_{r,i} - t}} + \min\left(H^{\star\star}_{r,i} - H^{\star}_{r,i}\right), \tag{24}$$

where $H^{\star}_{r,i}$ is the old balanced growth path value, $H^{\star\star}_{r,i}$ is the new balanced growth path value (the *carrying capacity* of the sector), and $a_{r,i}$ is a parameter defining the sigmoid's midpoint. Whereas the initial and final values for each sector correspond to the different balanced growth paths from the numerical examples above, the parameters $a$ remain to be set. To facilitate the interpretation of the results, we assume only two possible values for this parameter: $a_h = 0.3$ for skilled workers and $a_l = 0.4$ for unskilled workers, thus assuming that unskilled workers move more sluggishly in response to shocks (see e.g., Notowidigdo, 2020; Wozniak, 2010). We assume that, along these dynamic paths between balanced growth equilibria, the remaining endogenous variables evolves following the changes in labor stocks according to their respective equations in Sections 4 and 5.

Imagine our economy in period $t = 0$ in the balanced growth path described by the first column of Table 1 being hit by a permanent shock such that $\Delta d = -25\%$; as we already know, this economy will converge to the balanced growth path described by the second column of Table 1. The transitional dynamics are given in Figure 3, where panel 3a presents the evolution of the stocks of labor as deviation from their old balanced growth path values (these are s-shaped

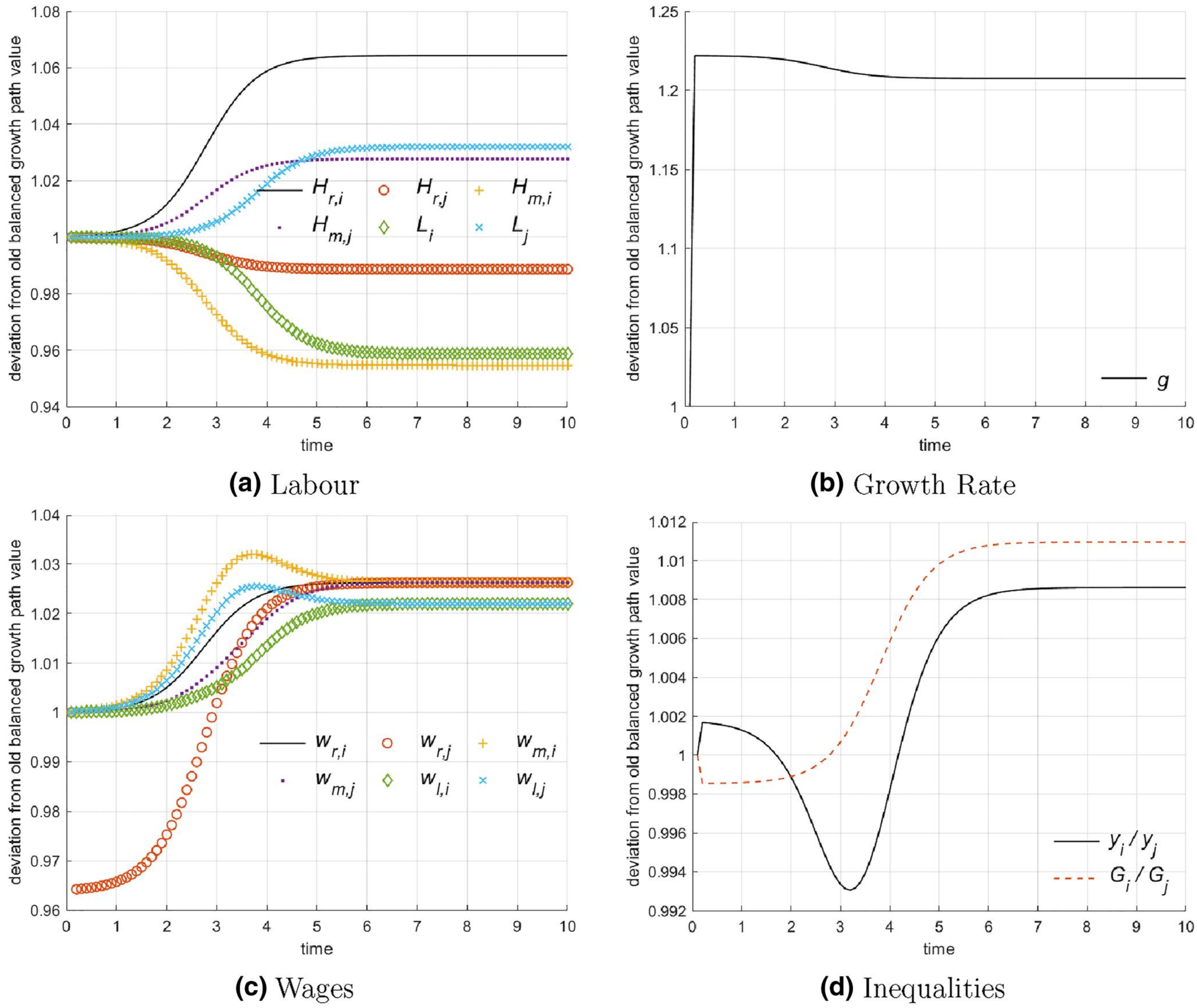



**FIGURE 3** Transitional dynamics following a shock $\Delta d = -25\%$.

as typical of the logistic function). These stocks monotonically converge to their new values, characterized by a strengthening of the previously existing patterns of specialization, but unskilled workers are more sluggish in their response to the shock: by assumption, both $L_i(t)/L_i^\star$ and $L_j(t)/L_j^\star$ take longer to converge to their new balanced growth path values than the curves for skilled workers. Panel 3b shows the resulting evolution of the growth rate of the economy, with a discontinuous jump at the time of the shock and a subsequent smooth descent toward its new value.

Panel 3c shows the evolution of wages: the stocks of labor adjusts to the shock at different speed and the composition of the workforce in each area changes between periods during the transition. This is reflected in wage transitions that are not necessarily monotonic. Adjusting workforce composition and non-monotonic wages translate in inequality dynamics that may exhibit cycles, as shown in panel 3d.

## 7 | CONVERGENCE DYNAMICS IN PATENTING

As shown in Section 6, our model predicts that the diffusion of near-instant communication technologies and videoconferencing should have different effects on metropolitan areas characterized by different levels of absorptive capacity or network capital. In particular, our model predicts a sort of club convergence following such a positive technology shock, whereby areas characterized by a less productive research sector will diverge from areas characterized by a more productive research sector. In this section, we present some empirical evidences in support of this theoretical finding.

### 7.1 | The distribution dynamics approach

We use the distribution dynamics approach (Quah, 1993a, 1993b, 1996a, 1996b, 1997), in which the evolution of the cross-sectional distribution is examined directly, using stochastic kernels to describe both the change in the distribution's external shape and the intra-distribution dynamics.[20]

In simple terms, this works as follows. Let $X_t$ represent a random process, and $F_t(x)$ the corresponding distribution evolving in continuous time, with each $F_t$ defined on the real line; further assume that the distribution at time $t$ admits a density $f_t(x)$. Assuming that the dynamics of $f$ can be modeled as a first order process, the density at some future time $t + s$ is given by

$$f_{t+s}(x') = \int_{-\infty}^{\infty} g_s(x'|x) f_t(x) dx, \tag{25}$$

where $g_s(x'|x)$ is the $s$-period ahead density of $x'$ conditional on $x$. Specifically, the conditional density function (25) maps the density at time $t$ into the density at time $t + s$ and therefore provides information both on the evolution of the external shape of the distribution and on intra-distributional dynamics between time $t$ and time $t + s$.

To analyze the role an external variable might have on the evolution of the distribution, Quah (1996a, 1997) proposes a conditioning scheme. In particular, given a set of economies $\mathcal{I}$, the scheme is a collection of triples, one for each economy $i \in \mathcal{I}$ at $t$, where each triple is made of (i) an integer lag $\tau$, with $\tau \geq 0$, (ii) a subset $C_i(t)$ of $\mathcal{I}$, identifying the collection of economies which are in some form of functional association at time $t - \tau$ with economy $i$, and (iii) a set of probability weights $\omega_i(t)$ for each subset $C_i(t)$. Observations in the conditioned version of the analyzed variable $z$ are obtained normalizing each unit's observation by the weighted average of values in functionally related units. Consequently, the effect of a theoretically motivated factor on the dynamics observed between $t$ and $t + s$ is studied comparing the estimate of the conditional density mapping $f_t(x)$ in $f_{t+s}(x')$ with the estimate of the conditional density mapping $f_t(x)$ in $f_{t+s}(z')$, where $z'$ is the conditioned version of $x'$. Differences in the estimated densities are attributed to the role of the conditioning factor.

### 7.2 | Dynamics in patenting activities

Our model predicts increasing differences in the innovative activities of the two areas following a positive technology shock; thus, here we investigate the evolution of patents per capita across MSAs in the last 50 years.

The dynamics of the distribution of patents per capita among MSAs between 1979 and 2000 are presented in Figure 4a, whereas Figure 4b focuses on the 2000–2019 period. The upper panels show how the cross-sectional distribution at time $t$ evolves into that at time $t + s$, as in Quah (1997). Indeed, the dynamics of the distribution can be analyzed directly from the shape of a plot of the conditional density estimate. When most of the mass is distributed along the 45-degree line, the distribution exhibits persistence; conversely, clockwise (cf. counter-clockwise) rotations highlight a tendency toward convergence (cf. divergence). The lower panels provide a complementary analysis by showing the corresponding highest density region (HDR) plot (Hyndman, 1996): once again, the 45-degree line highlights persistence properties, whereas a counter-clockwise (cf. clockwise) rotation of the estimated probability mass from the diagonal indicates that divergence (cf. convergence) occurs.

Figure 4a indicates the existence of a tendency toward convergence over the first period, through an evident clockwise rotation with respect to the main diagonal. On the contrary, there seems to be a switch toward divergence in the new century, as illustrated in Figure 4b where an evident counter-clockwise rotation is observable for MSAs at almost all initial levels of patents per capita.

However, our aim is to detect the influence of each area's ability to access and share information over the evolution of its relative position: we thus now resort to a condition scheme. To characterize metropolitan areas in terms of their ability to exploit the positive technology shocks, one likely candidate would be broadband availability, since broadband and related technologies lower the cost of sending and receiving information. Yet, this would raise the specter of endogeneity, as broadband availability and economic growth are likely to influence each other. We thus follow Kolko (2012) and instrument broadband availability with the topography of the area. In particular, we use the topography scale by the National Atlas of the United States of America of the U.S. Department of Interior: this classifies

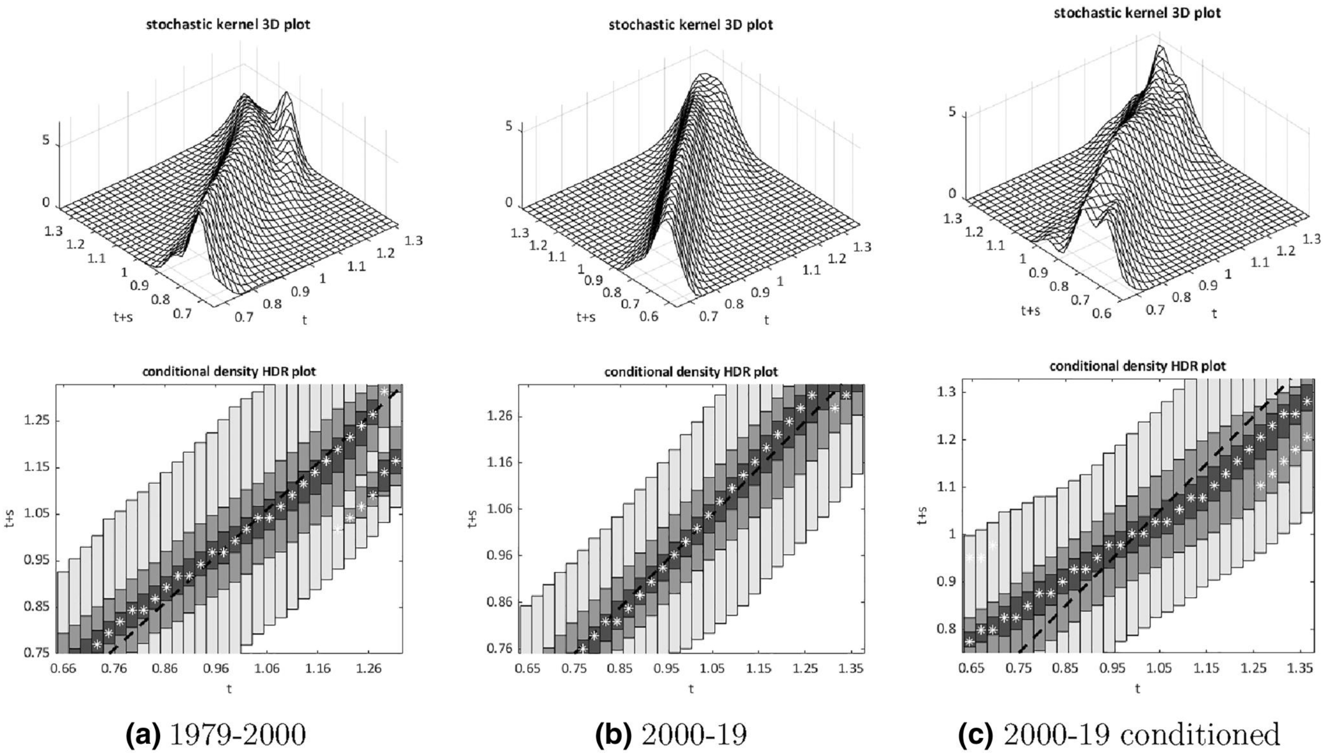



**FIGURE 4** Distribution of patents per capita across MSAs. Each upper panel shows the evolution of the cross-sectional distribution of patents per capita across MSAs between the initial and the final period; the lower panels show the corresponding highest density region plots (Hyndman, 1996) where vertical bands represent the projection of the conditional density of patents per capita at time $t+s$ on patents per capita at time $t$. In each band the 25% (the darkest-shaded region), 75%, 99% HDRs are reported. The dashed line is the 45-degree line and the asterisks represent the modes. Data are normalized as to have mean one. Own elaborations using data from USPTO, DOI, and USDA. Only MSAs for which we observe patents, population, topography scale, and amenities scale are included (for a total of 344 MSAs per year). HDR, highest density region; MSA, metropolitan statistical area; USDA, United States Department of Agriculture; USPTO, United States Patents and Trademarks Office.

areas according to the twenty-one land-form units specified by Hammond (1964), which are based on the slope of the terrain, the difference between its maximum and minimum elevation, and its profile type (i.e., the percentage of gently sloping terrain laying below or above the window's average elevation).[21]

To be a good instrument, the topography scale should be correlated with broadband, and indeed Kolko (2012) shows that broadband availability is strongly negatively correlated with slope of terrain, likely because infrastructure is more expensive to deploy in areas with steeper terrain. At the same time, topography should not be independently correlated with patenting activity, which might not be satisfied (e.g., Rosenthal & Strange, 2008; Saiz, 2010). For example, steeper areas might enjoy lower wages and higher employment if skilled workers value steeper terrains for recreational activities or as an amenity offering views. To partially control for this, we divide the topography scale by the natural amenities scale provided by the U.S. Department of Agriculture,[22] which provides a measure of the physical characteristics of an area that enhance the location as a place to live (e.g., temperatures and humidity in winter and summer and percentage of surface covered in water). Our conditioning scheme is then as follows: we first measure the maximum distance in terms of our modified scale of topography in 1990 between any two MSAs in our dataset, and then, for each MSA $i \in \mathcal{I}$, we let $C_i(t)$ be the set of MSAs within 10% of this maximum distance to $i$; on average, a MSA has 35 "neighbors". We then weight MSAs in $C_i(t)$ uniformly.

The panels of Figure 4c display the cross-section distribution and the HDR plot between observed values of patents per capita in 2000 and topography-conditioned values of patents per capita in 2019. These differ markedly from the unconditioned plots in Figure 4b, since now they exhibit a strong clockwise rotation. This supports the existence of convergence clubs on the basis of the conditioning factor: it appears that the polarization earlier identified in the unconditional distribution-dynamics of patents per capita across MSAs is partly explained by our measure of topography (corrected for natural amenities).

## 8 | CONCLUSIONS

Broadband technology and high-speed connections have steadily changed the way people lived and worked over the last decades. We proposed an endogenous growth model with two areas to investigate how this could have changed the spatial distribution of research activities and their contribution to growth, and the subsequent repercussions on per capita income and inequality levels. We showed that, when one area is endowed with an higher ability to assimilate new knowledge and apply it to commercial use, relative specialization arises in equilibrium, as this area attracts a larger share of researchers; conversely, the other area specializes in manufacturing activities. Since researchers are scarcer in the entire population and command a higher wage than the average manufacturing worker, relative specialization in research translates into a higher income per capita level but a more unequal income distribution.

In this context, a boost toward a digitalization of communications increases the growth rate of the overall economy, but also strengthens the previously existing patterns of specialization, thus increasing disparities in income per capita and Gini coefficients between areas, as well as the Gini coefficient of the entire system. These results are consistent with empirical evidences pointing to increases in the concentration of innovative activities, economy-wide income inequality, and skills and income divergence across urban areas experienced by the United States in the last decades. This may also have important implications for the post-pandemic future, as digital communication will most probably be integral part of daily working to a much higher extent than before.[23] Our results suggest that this may lead to a further rise of specialization, agglomeration, and inequalities across areas.

However stylized, our model predicts that policies aimed at facilitating the diffusion of knowledge across the entire system (e.g., improving broadband access) increase the growth rate of the economy, but the resulting strengthening of the previously existing patterns of specialization leads to more inequality within and across areas. Place-based policies aimed toward increasing the productivity of an area's research system similarly imply a trade-off between growth and equality, but results may be significantly different depending on the targeted area. In particular, policies aimed at the more backward research sector increase the growth rate and the Gini coefficient of the entire system (by widening the wage gap between skilled and unskilled workers) but reduce relative specialization and thus differences in income per capita across areas.

We made many simplifying assumptions to keep the model tractable. For example, we have assumed that one area is exogenously endowed with a more productive research sector; it would also be interesting to analyze the case in which this is the outcome of conscious investments in network capital and absorptive capacity (as suggested by e.g., Huggins & Thompson, 2014). Moreover, to focus primarily on the knowledge externality, we have assumed zero transport costs and no differences in the areas' amenities; however, one could include those to analyze how workers and firms balance these factors in making location decisions (but see Appendix A.3.2, where we added potentially asymmetric iceberg costs to the trade of intermediate goods). Finally, by adding more areas, one could study the effects of reduction in the "cost of distance" on the centrality of a research sector. We leave these extensions to future research.

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### DATA AVAILABILITY STATEMENT

The data that support the findings of this study are openly available in openICPSR at https://doi.org/10.3886/E192071V2, reference number E192071V2 (Magrini & Spiganti, 2023). These data were derived from the following resources available in the public domain: CENSUS, https://www2.census.gov/prod2/statcomp/usac/excel/LND01.xls, https://www.census.gov/geographies/mapping-files/time-series/geo/cartographic-boundary.html, and https://www.census.gov/geographies/mapping-files/time-series/geo/carto-boundary-file.html; IPUMS, https://usa.ipums.org/usa-action/variables/group; NHGIS, https://www.nhgis.org/; USDA, https://www.ers.usda.gov/data-products/natural-amenities-scale/; USPTO, https://patentsview.org/download/data-download-tables.

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## ENDNOTES

[1] Related is also a literature that studies urban dynamics using endogenous growth theory, following the seminal contribution of Black and Henderson (1999), with which we share an interest on the effect of agglomeration on income inequalities (see Desmet & Rossi-Hansberg, 2009; Duranton & Puga, 2019; Rossi-Hansberg & Wright, 2007, for some more recent contributions).

[2] There is a growing empirical literature on agglomeration and knowledge spillovers that specifically studies the impact of transportation improvements on innovation. This literature generally finds a significantly positive effects on patenting, due to a facilitation of interactions among researchers, which is line with the results of our theoretical model. See Agrawal et al. (2017) for the effect of a region's stock of highways, Andersson et al. (2021) for railroad expansions, and Bai et al. (2021) and Pauly and Stipanicic (2022) for the introduction of new airline routes. Relatedly, see Acemoglu et al. (2016) for the role played by the expansion of the United States postal service for innovation in the nineteenth century.

[3] For a different approach, see Davis and Dingel (2019) who propose a model where the exchange of ideas is costly, as time spent interacting with others cannot be used to produce directly. In equilibrium, talented individuals locate in larger cities, which are costlier but also better idea-exchange environments.

[4] For example, the vast majority of innovators in our dataset from the USPTO reside in a metropolitan area (approximately 95%).

[5] A patent is an exclusionary right conferred for a set period to the patent holder, in exchange for sharing the details of the invention. As common in the literature, we restrict our attention to utility patents, which cover the creation of a new or improved product, process or machine; these approximately cover 90% of all patents (they exclude design patents and plant patents).

[6] We use the 2019 Cartographic Boundary Files provided by the United States Census Bureau, https://www.census.gov/geographies/mapping-files/time-series/geo/cartographic-boundary.html. The analysis is run using Stata 16 by StataCorp (2019).

[7] Population data at the county level are provided by Manson et al. (2020); we linearly interpolate population for years between census years (only for years before 2010; afterward data are provided for each year) and then aggregate counties to their current MSA. We use definitions provided by the National Bureau of Economic Research, https://www.nber.org/research/data/census-core-based-statistical-area-cbsa-federal-information-processing-series-fips-county-crosswalk.

[8] This is a standard assumption in the expanding variety models. Indeed, it simplifies the exposition considerably, since the past amounts of these inputs are not additional state variables. However, results without this assumption are identical.

[9] The main findings of the model are qualitatively the same, but more analytically complicated, if the externality effect depends positively on the average level of human capital (similarly to e.g., Black & Henderson, 1999; Lucas, 1988; Moretti, 2004); see Appendix A.3.1.

[10] In what follows, we focus on the balanced growth path and thus, as common in the endogenous growth literature, we abstract from diffusion delays. These, however, are likely to be important (see e.g., Jones & Summers, 2021; Kantor & Whalley, 2019, for some recent contributions).

[11] The qualitative results are unaffected as long as the economy technology frontier is a linearly homogeneous function of the number of intermediate inputs in the two areas, for example, equal to the technology level of the most advanced area or an average of the two.

[12] We do not see the presence of information frictions depending on "distance" incompatible with the absence of migration costs across periods. Indeed our focus is on technological developments easing within-period frictions on the informal interactions between researchers across areas. Nevertheless, we investigate transitional dynamics under frictions to the movement of agents across areas in Section 6.2.3.

[13] Our model is homothetic to one in which both the discovery of a new intermediate good and its production are run by the same firm, but we separate these activities to facilitate the exposition.

[14] Our model lacks any of the differences (in e.g., amenities or endowments) and frictions (to e.g., the flows of agents and goods) that are commonly used in economic geography models to understand the main reasons "*why agents' location relative to one another in geographic space matters*" (Redding & Rossi-Hansberg, 2017, p. 25). Therefore, without this exogenous difference in productivity, there would be no path-dependence or lock-in, and our equilibrium would be symmetric due to the presence of diminishing marginal returns in research and manufacturing. We decided to focus on this single difference to highlight the consequences of this source of heterogeneity without any confounding factors, but in Appendix A.3.2 we show that another potential driver of specialization lies in exogenous differences in transport costs for intermediate goods.

[15] Modeling the introduction of new communication technologies as an exogenous shock in communication costs is common in the literature (see e.g., Glaeser & Ponzetto, 2010; Potlogea, 2018).

[16] The positive effect of the diffusion of communication services on growth is well documented in the literature, at least since Hardy (1980); see Kolko (2012) and Castaldo et al. (2018) for studies focusing on the effect of broadband adoption on growth, Gómez-Barroso and Marbán-Flores (2020) for a literature review on telecommunications more generally, and Xu et al. (2019) who instead focus more specifically on access to the Internet as a determinant of innovation. In line with this paper, Mack and Rey (2014) report a generally positive relationship between broadband adoption and the level of knowledge intensive activities across US metropolitan areas but also that

specialization in traditional manufacturing has a negative impact on this relationship; Chen et al. (2020) find that high-speed Internet significantly increases productivity, but the effect is stronger for the more educated workers (but see Maurseth, 2018, who finds negative growth effects from the Internet between 1990 and 2015).

[17] For what concerns this exercise, which focuses on the *relative* concentration of workers across areas and aims at providing qualitative results, the values of $\phi_r$ and $\phi_m$ are not important, given the endogenous equalization of the external effects in the manufacturing sector. For simplicity, we set $\phi_r = \phi_m = 0$, thus $S_{m,i} = S_{m,j} = 1$; in this case, it is easy to prove that condition (17) simplifies to $H_{r,i}/H_{r,j} = L_j/L_i$. Moreover, we normalize the initial level of the technology frontier to $A = 1$.

[18] This is loosely inspired by Moretti (2021), who finds that an inventor in the computer science field moving from the median cluster (i.e., a combination of city and research field) in 2007 to the cluster at the seventy-fifth percentile would experience a 12% increase in the number of patents produced in a year.

[19] Logistic functions are commonly used to model for example, population growth (since Verhurst, 1845), migration patterns (e.g., à la Bass, 1969, even if the Bass model was originally built to study the diffusion of new durable products), and the diffusion of innovations (e.g., Griliches, 1957).

[20] There are two main approaches to the analysis of convergence, namely the regression approach and the distribution dynamics approach. We opt for the latter because the former does not provide information about what happens to the entire cross-sectional distribution of economies, in terms of both external shape and intra-distributional dynamics. For the relative merits of the two approaches, see for example, Durlauf and Quah (1999), Temple (1999), Islam (2003), Magrini (2004, 2009), Abreu et al. (2005), Durlauf et al. (2005).

[21] The topography scale is available at the county level. We thus calculate the topography scale of each MSA as a weighted average of the topography scale of its current counties, where the weights are the relative land area in square miles as provided by the 1990 U.S. Census. We use definitions provided by the National Bureau of Economic Research, https://www.nber.org/research/data/census-core-based-statistical-area-cbsa-federal-information-processing-series-fips-county-crosswalk.

[22] See USDA, Economic Research Service, available at https://www.ers.usda.gov/data-products/natural-amenities-scale/. This is provided for counties, so we aggregate it at the MSA level using relative land surfaces as for the topography scale.

[23] For example, the proportion of US employees who primarily work from home tripled from 0.75% in 1980 to 2.4% in 2010 (Bloom et al., 2015), but this number was an order of magnitude larger in March 2020, when 42% of respondents to a survey of American adults who earned at least $20,000 in labor income in 2019 were working from home (see https://voxeu.org/article/covid-19-and-labour-real-location-evidence-us). Even if some of these jobs will go back to be performed in offices, it is likely that working remotely will still be part of the new reality: for example, Dingel and Neiman (2020) estimate that 37% of jobs in the US can be performed entirely at home, many tech giants have already made working from home a permanent option for employees (see the article on Business Insider by Aaron Holmes, https://www.businessinsider.com/how-tech-companies-plan-to-reopen-facebook-google-microsoft-amazon-2020-5?IR=T) and the share of working days spent at home is expected to triple after the Covid-19 crisis ends compared to before the pandemic hit (see Barrero et al., 2021, and the article by Altig et al. for the Federal Reserve Bank of Atlanta's Policy Hub: Macroblog, https://www.frbatlanta.org/blogs/macroblog/2020/05/28/firms-expect-working-from-home-to-triple).

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## SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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