Reproducing scientists’ mobility: A data-driven model

Giacomo Vaccario\textsuperscript{1*}, Luca Verginer\textsuperscript{2}, Frank Schweitzer\textsuperscript{1}

\textsuperscript{1}ETH Zürich, Chair of Systems Design, Department of Management, Technology and Economics, Weinbergstrasse 56/58, CH-8092 Zürich, Switzerland
\textsuperscript{2}IMT School for Advanced Studies Lucca, AXES Lab, piazza S. Francesco 19, IT-55100 Lucca, Italy

*Corresponding author: gvaccario@ethz.ch

Abstract

This paper makes two important contributions to understand the mobility patterns of scientists. First, by combining two large-scale data sets covering the publications of 3.5 mio scientists over 60 years, we are able to reveal the geographical “career paths” of scientists. Each path contains, on the individual level, information about the cities (resolved on real geographical space) and the time (in years) spent there. A statistical analysis gives empirical insights into the geographical distance scientists move for a new affiliation and their age when moving. From the individual career paths, we further reconstruct the world network of movements of scientists, where the nodes represent cities and the links in- and outflow of scientists between cities. We analyze the topological properties of this network with respect to degree distribution, local clustering coefficients, path lengths and assortativity.

The second important contribution is an agent-based model that allows to reproduce the empirical findings, both on the level of scientists and of the network. The model considers that agents have a fitness and consider potential new locations if they allow to increase this fitness. Locations on the other hand rank agents against their fitness and consider them only if they still have a capacity for them. This leads to a matching problem which is solved algorithmically. Using empirical data to calibrate our model and to determine its initial conditions, we are able to validate the model against the measured distributions. This allows to interpret the model assumptions as microbased decision rules that explain the observed mobility patterns of scientists.

1 Introduction

Migration of high-skill labour is an important economic and political issue of our time. Modern economies rely on high skill labour to keep their competitive advantage (Bahar et al. 2012; Beechler and Woodward 2009; Beine et al. 2001). For this reason, attracting and retaining scientists is becoming an important concern for migration policy (Boucher and Cerna 2014). In this work we investigate the migration of scientists by studying several forces that arguably drive their relocation choice. We propose an agent-based model that we calibrate and validate against real data. With this data driven approach, we test if a set of minimal decision rules can explain observed mobility patterns of scientists.
Scientists are highly mobile individuals, a fact that has been true in the past and is becoming ever more important (Geuna, 2015). There is an expanding literature on the mobility of scientists. Many works have been focusing on the relationship between movements and scientific impact (Scellato et al., 2017; Franzoni et al., 2014; Fernandez-Zubieta et al., 2015). Other works analyzed scientists mobility across countries to determine the effects of policy (Czaika and Parsons, 2017) and to investigate aspects of the brain circulation phenomenon (Bénassy and Brezis, 2013; Saxenian, 2005; Agrawal et al., 2011; Verginer and Riccaboni, 2018).

Most works address scientist mobility at an aggregated level, i.e. they focus on bilateral flows between countries. At the same time, the need to understand the basic forces at scientist level underlying academic mobility has been highlighted by Appelt et al. (2015); Fortunato et al. (2018). This need has been approached both empirically (Franzoni et al., 2015; Gibson and McKenzie, 2014; Veugels and Bouwel, 2015) and theoretically (Mahroum, 2000). Empirical works are traditionally based on survey data that provide only a small coverage of the global mobility of scientists and usually aggregated a country level. While theoretical works are rarely validated against data.

In order to go beyond speculation in what drives the global academic mobility, we start by reconstructing the global mobility network of scientists. We use the approach of Verginer and Riccaboni (2018) that allows to extract geographical career paths of scientists using bibliographic data. For this work, we use the MEDLINE databases, the largest open access bibliographic database in the life sciences (see Sect. 2). After reconstructing the mobility network, we propose an agent-based model to reproduce this network and other scientists-level properties. The model together with its calibration and validation procedure are explained in the Sect. 3 and follow the data-driven approach of Tomasello et al. (2014, 2017); Vaccario et al. (2018). Finally, in Sect. 4 we further discuss the results from our simulations, analyze the limitation of the model and provide some outlooks.

2 Individual and global mobility of scientists

2.1 Extracting individual and global career paths of scientists

For the analysis we use two datasets provided by Torvik, namely MapAffil (Torvik, 2015) and Author-ity (Torvik and Smallheiser, 2009). These datasets have been extracted from the MEDLINE corpus of publications, and thus covers research in the life sciences. MapAffil covers MEDLINE up to 2015, and Author-ity covers MEDLINE up to 2009. This discrepancy means that we can only use the years up to 2009, when combining the datasets. MapAffil lists for each MEDLINE paper and each author the disambiguated city names of the listed affiliation (37,396,671 city-name instances). It further gives a unique identifier as well as the geo-coordinates.
of each city. Author-ity contains the disambiguated author names, liking them to their respective publications. By combining the two datasets we can extract for each given author all the cities of her affiliation and the dates of the associated publications. Combining these two sources of information about geo-coordinates and time allows us to construct the “career path” of those scientists that have published in that time, i.e. the sequence of cities they worked in over the time of their active career as a scientist (as witnessed by their publications). An example of such a career path is given in Table 1. The merged dataset contains in total the career paths of $N = 3,740,187$ scientists, which were active in the period between 1950 and 2009, traversing $M = 5,485$ unique cities.

<table>
<thead>
<tr>
<th>Year</th>
<th>Affiliation City</th>
<th>PubMed ID</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Stony Brook, NY, USA</td>
<td>12703729</td>
</tr>
<tr>
<td>2</td>
<td>Stony Brook, NY, USA</td>
<td>12595470</td>
</tr>
<tr>
<td>3</td>
<td>Kansas City, KS, USA</td>
<td>15936007</td>
</tr>
<tr>
<td>4</td>
<td>Stony Brook, NY, USA</td>
<td>15791955</td>
</tr>
<tr>
<td>5</td>
<td>Stony Brook, NY, USA</td>
<td>15944300</td>
</tr>
<tr>
<td>6</td>
<td>Milwaukee, WI, USA</td>
<td>16299285</td>
</tr>
<tr>
<td>7</td>
<td>Milwaukee, WI, USA</td>
<td>17311921</td>
</tr>
<tr>
<td>8</td>
<td>Milwaukee, WI, USA</td>
<td>17490406</td>
</tr>
<tr>
<td>9</td>
<td>Boston, MA, USA</td>
<td>18566416</td>
</tr>
<tr>
<td>10</td>
<td>Stony Brook, NY, USA</td>
<td>18591234</td>
</tr>
</tbody>
</table>

Table 1: Example of career path of a specific author (Zhang Y.). For each record we have the year of publication, the city of the affiliation and the PubMed ID identifying the paper. (The PubMed ID is the unique identifier of the paper within the MEDLINE corpus)

Figure 1: Illustration of procedure to extract movements

Formally we denote a career path of author $i \in N$ as a sequence $p_i$, for example $p_i = \{A_{t_0}, A_{t_1}, A_{t_2}, B_{t_3}, B_{t_4}, C_{t_5}, C_{t_6}, B_{t_7}\}$. $A$ denotes the city as defined by its geo-location $R_A = (X, Y)$ where $X$ gives the latitude and $Y$ the longitude according to the data from MapAffil. The subscript $t_0$ refers to the time measured in years, author $i$ was based in the respective city, according to the career path data obtained. An illustration is shown in Figure 1. Note that due to the time resolution of one year, an author may have multiple publications as well as multiple
locations in the same year. This can be seen in Figure 1 at $t_2$ where both $A$ and $B$ are observed simultaneously.

2.2 Statistics of geographical career paths

The information about the consecutive cities a scientist was based during her career allows us to analyze the distance she moved when changing her affiliation. For this we use the Haversine formula to compute the geodesic distance over the geo-locations of the respective cities, measured in kilometers. The distribution obtained from 62465 scientists moving between 2000 and 2008 is shown in Figure 2(a). We note that it is a left-skew distribution with the median of 1000 km. I.e. most scientists find a new affiliation in cities within a radius of 1000 km around their current affiliation. However, movements of more that 6000 km toward distant cities are also quite frequent.

The data also allows us to relate the frequency of such moves to the age of scientists. Because the physical age of scientists is not recorded, we have to rely on their academic age, $t^a_i$, also measured in years. $t^a_i = 0$ when the scientist publishes her first paper, according to our database (which is a physical age of about 25 years). The frequency of any recorded move irrespective of the distance over the academic age $t^a$ is shown in Figure 2(b). Again, it is a left-skew distribution with a median of 7 years. This matches the known fact that the mobility of scientists drastically decreases with age (Cañibano et al. 2011; Verginer and Riccaboni 2018). But, again, we find frequent moves even at the (physical) age of retirement.
Figure 3: Distributions of (a) inflow of scientists into any city, (b) outflow of scientists out of any city. The x-axis is in log-scale.

2.3 Reconstructing the mobility network of scientists

While the career paths and their statistics refer to individual scientists, we can also analyze the network that results from aggregating all of the career paths of a given year. This moves the discussion to the macro level of movements between cities. For each year, we can calculate the number of scientists $N_K(t)$ in a given city $K$ from their publications, taking unique geo-located authors into account. We can further calculate for each year $t$ the number of scientists $\Delta N_{K\leftarrow L}(t)$ moving into city $K$ from another city $L$, i.e. the inflow, and the number of scientists $\Delta N_{L\leftarrow K}(t)$ moving out of city $K$ to another city $L$, i.e. the outflow.

Figure 3(a,b) show the respective distributions for the aggregated inflow $\Delta N_{K\leftarrow L}^\text{in}(t) = \sum_L \Delta N_{K\leftarrow L}(t)$ of scientists into city $K$ and the aggregated outflow $\Delta N_{K\leftarrow L}^\text{out}(t) = \sum_L \Delta N_{L\leftarrow K}$ of scientists out of city $K$. The aggregate inflow and the outflow are computed during three different time windows centered in 2000, 2002 and 2004, meaning that each city is considered three times (once for every time window). Again, we note the left-skew distribution for both quantities, which indicates the heterogeneous contribution of cities to the global movement of scientists.

For any given pair $(K, L)$ of cities we can then calculate the total flow of scientists between these two cities. This is the total number of scientists exchanged between $K$ and $L$, $\Delta N_{L\leftarrow K} + \Delta N_{K\leftarrow L}$. The total flow allows us to visualize the mobility network of scientists at the world level, as it is shown in Figure 4. The links are undirected, but weighted according to the total flow.

Fitness of a city. The calculated inflow and outflow already makes clear that cities are very different with respect to their attractiveness for scientists. Obviously, a small number of cities
are more attractive, which can be explained to a large extent by the reputation of the academic institutions hosted there. Hence, it makes sense to assign to each city $K \in M$ a fitness value $F_K(t)$ reflecting the quality of their academic institutions. This fitness value is not precisely known, but can be estimated from available data, for example taking different university rankings into account. We will not describe in detail how we measure the city fitness, suffice it to say that we measure it through a citation weighted output metric. We assume that such a measure reflects the scientific attractiveness a scientist associates with that city. The actual values are not relevant, since we are primarily interested in the ranking of cities resulting from this measure, i.e. in the fitness relative to the others. We note that city fitness can change over time.

### 2.4 Topological properties of the mobility network

In order to further characterize the mobility network by means of topological properties, we aggregate the mobility networks for the time period 2000-2008. On this aggregated network, we calculate standard measures that are common in network analysis. This includes the degree distribution $P(d)$, where $d$ is the number of cities scientists in a given city either move to, or come from. Already Figure 4 indicates that this is a very broad distribution. Some cities act as hubs, with a large degree, most cities however only have a small degree. This is confirmed by the degree distribution shown in Figure 5(c).

The distribution of path lengths, shown in Figure 5(b), measures how many stops are needed to reach, on the network, any city from a given starting point. The small number of hops indicates that the network is very dense in a topological sense, not necessarily in a geographical one.
The local clustering coefficient, on the other hand, measures whether three neighboring cities (with respect to their geographical proximity) form closed triangles, i.e. whether there is an exchange of scientists between them. Figure 5(a) shows the distributions of these values and we find that most cities have a small local clustering coefficient.

The neighbor connectivity, eventually, measures to what extent cities with a certain degree are connected to other cities with a similar degree. Figure 5(d) shows a non-monotonous dependency. Cities with a low degree tend to show an assortative pattern, i.e. they are connected to cities that have a similar number of neighbors. Cities with a high degree, which are characterized as hubs above, are rather connected to cities with a lower degree, i.e. they are dissortative. This gives us already on the topological level important information about the origin of scientists coming to the hubs and the destination of scientists leaving the hubs. Obviously, they do not hop between hubs - which would have been indicated by a clearly assortative pattern for hubs.
3 Modeling the mobility of scientists

3.1 Overview of the agent-based model

In this section we propose and define a model, which is able to reproduce the characteristic empirical properties of the scientists’ mobility network discussed above. Precisely, we want to reproduce features both at scientists and network level. These are, on the scientists’ level, (1) the distribution of move distances, Figure 2(a) and (2) the “age at move” distributions, Figure 2(b).

And at the network level we want to reproduce (3) the distributions of the topological features shown in Figure 5 i.e. local clustering coefficients, path lengths, degrees and degrees of neighbors.

We note that this is quite an ambitious goal, since our model needs to correctly reproduce several very different system dimensions (i.e. scientists (micro), intercity (macro)). If the model is able to reproduced the described distributions, we have a strong indication that the interaction rules governing scientist and city interactions, capture a relevant aspect of the real mobility of scientists. The information available to the model during fitting does not imply the more complex validation measures. If we find that the simulated results agree with the empirical validation metrics it means that the interaction rules are the reason for the observed patterns and good validation results.

We decide to develop an agent-based model because we want to model the migration of scientists, as opposed to a system dynamics model in which we would merely reproduce the flows between different cities, on the aggregated level. This implies that macroscopic features describing the system or network level, such as the topological properties already discussed, have to be emergent properties arising from the agent dynamics.

Our model is composed of two entities, agents and locations. Agents represent scientists. Each agent $i$ is characterized by three properties that change over time: its position, $r_i(t)$, its fitness, $f_i(t)$, and its years of activity $y_i(t)$. Time is measured in discrete simulation steps, each representing one year. When we start our simulations at time $t = 0$, which is chosen as the year 2000 below, we cannot assume that all agents also start to become active only then. Instead, agents have already been publishing before, which is included in $y_i(t)$. An agent that published its first paper in 1995, will have a $y_i(2000) = 5$ in this case. This becomes of importance when measuring the fitness of agents, $f_i(t = 0)$, as determined below.

Locations represent cities and host agents. In agreement with the dataset, we have $M = 5,485$ different locations. Each location $K$ is characterized by three properties that can also partly change over time: its position $R_K$ defined in real geographical space by means of longitude and latitude (see Sect. 2.1), its fitness, $F_K(t)$ (see Sect. 2.3), and the number of agents it hosts, $N_K(t)$ (see Sect. 2.3). Note that $R_K$ and $N_K(t)$ are taken from the available empirical data.

For the fitness of a location, however, we do not take accumulated ranking values of institutions into account. Instead, we choose a different proxy for fitness, which is more consistent with our model: the fitness $F_K(t)$ is equal to the average fitness of all agents hosted in location $K$. This
relates the problem back to defining the fitness of agents. But at the same time, it is in line with the ranking of academic institutions, which in essence is also determined by the fitness, or quality, of the scientists working there. In our model, we assume that the $F_K(t)$ are public information, just as the rankings are.

For the position $r_i(t)$ of an agent, we assume that at each time step the agent can be found in one of the available locations. So $r_i(t) = R_K$ where $K$ is the number of the location, agent $i$ is based at time $t$.

**Movement preferences.** Our main modeling assumption is that agents prefer to work in locations that provide a higher fitness than the one they are currently based. These locations, however, can be very distant from the current place, which incurs larger switching costs. Therefore, agents do not only take the fitness $F_K(t)$ of locations into account, but also the geodesic distance $\Delta_{i,K}(t)$ between the current location of $i$ and any other location $K$. They combine this information in an re-scaled fitness score $\tilde{F}_{i,K}(t) = F_K(t)/(\Delta_{i,K}(t))^b$ for each location $K$. $b$ is a model parameter, used to weight the impact of spatial distances. The bigger $b$, the more important any spatial distance becomes.

Ranking the values $\tilde{F}_{i,K}(t)$ from high to low, each agent then obtains an individual ranking that reflects its preferences where to move next. Agents in $L$ will consider only those locations where $F_K(t) > F_L(t)$, i.e. where the average fitness of scientists is larger than the average fitness of scientists in their city.

**Movement decisions.** Agents only come up with a ranked list of possible locations they would consider to move to (and we can assume that they send applications to the academic institutions in these locations). But agents do not decide where to move. This decision, whether or nor to accept the agent, is taken at the location.

A location $K$ will accept new agents only if it’s capacity allows so, which is defined by $N_K(t)$, the number of scientists empirically observed at a given location. External factors, such as the growth of academic institutions, are implicitly considered in the observed change of $N_K(t)$. As we found out, the $N_K(t)$ are rather stable over time. This implies that, after some transient periods in our simulations, locations have the capacity to accept incoming agents only if agents at $K$ have been accepted somewhere else and move there.

Because, dependent on the individual ranking of agents, some locations obtain more applications than the capacity allows them to accept, each location ranks the qualified agents according to their fitness $f_i(t)$. Available slots are filled starting from agents with higher fitness values until the capacity $N_K(t)$ is reached. Precisely, if $f_i(t) > F_K(t)$, location $K$ considers agent $i$ with probability $p = 1$ because this allows location $K$ to increase its fitness $F_K(t)$. If $f_i(t) \leq F_K(t)$, location $K$ considers agent $i$ only with a probability $p = (f_i(t)/F_K)^{s}$ where $s$ is our second
model parameter. Note that for big value of $s$, locations becomes more selective. In Figure 6 we visualize the basic rules of our model.

![Diagram](image)

Figure 6: The Agents ($a_1, a_2, a_3$ and $a_4$) are all hosted in three locations, $A$, $B$ or $C$, that represent respectively London, Paris and Berlin. Each location has a maximum number of available positions illustrated by some small slots, $N_A = 2$, $N_B = 4$ and $N_C = 3$. In this image, agents $a_1$ and $a_2$ compute the rescaled fitness of the available locations ($A$ and $C$) and rank these location accordingly. Here, we have assumed that $A$ and $C$ have the same fitness ($F_A(t) = F_C(t)$), but $A$ is closer to $B$ than $C$ is ($\Delta_i,A < \Delta_i,C$ for $i = 1,2$). For this reason both $a_1$ and $a_2$ express a preference for $A$ over $C$. Since location $A$ has $N_A = 2$ and one position is already taken, $A$ must decide to host either $a_1$ or $a_2$. Location $A$ will decide depending on the fitness of $a_1$ and $a_2$.

**Matching problem.** In our model agents rank locations, while locations rank agents. To match locations and agents, we have to solve a matching problem similar to the stable marriage problem. However our problem is slightly different as a location can accept more than one agent until the capacity $N_K(t)$ is reached. To solve this matching problem, we use the established NRMP-algorithm developed by the National Resident Matching Program (NRMP) for matching medical students to U.S. training programs. After the matching is completed, only the agents that have been matched to a location will move. If an agent $i$ has moved to a new location $K$, we update its position vector, $r_i(t + 1) = R_K$, and keep its fitness constant, $f_i(t + 1) = f_i(t)$.

**Fitness dynamics.** This leaves us to decide what happens to all those agents that are not accepted at a new location. Here, we consider that the agent stays at its current location, i.e. $r_i(t + 1) = r_i(t)$, and uses the time step to further improve its fitness, $f_i(t)$. For this we assume a stochastic dynamics, precisely an additive stochastic process with a variance proportional to
the fitness of the current location. This implies that it is not guaranteed that agents will increase their fitness for sure, they can also loose.

At the end of each time step, we update the fitness of locations, $F_K(t)$, by averaging over the fitness $f_i(t)$ of all those agents that are currently based there.

**A data driven model.** We use the empirical data not only as an input to our model, but also for calibrating and validating it. As input, we take six observed quantities: three at the city level and three at the scientist level, to determine the initial conditions of our model. As the starting year $t = 0$, we take 2000.

From each city we take its geographical position and the number of scientists in year 2000. We assign these quantities to locations to characterize their $R_K$ and $N_K(t = 0)$. The initial fitness value of a location, $F_K(t = 0)$, is determined by averaging over the fitness values of those agents based in the given city in 2000.

From each scientist we take its geographical position (in a given city), its academic impact and the years of activity already passed until 2000. We assign these quantities to agents to characterize their $r_i(t = 0)$, $f_i(t = 0)$ and $y_i(t = 0)$. The academic impact is proxied by the papers that a scientist has co-authored in during the last two years of activity. Precisely, we assign to each paper a score equal to the impact factor of the journal where it was published divided by the number of co-authors. Then, for each scientist we sum the scores of the papers he/she has co-authored between 1998 and 2000. This defines the starting fitness of agents, i.e. $f_i(t = 0)$.

We then run the agent-based model using parallel updates of all agents per time step, taking as evolving quantities only the values of $N_K(t)$ into account. To do so, we still have to determine the two free parameters of our model, $b$, which weights the impact of spatial distances for the individual rankings of agents, and $s$, which weights the flexibility of locations to still accept agents with a fitness less than the fitness of the location. Determining $b$ and $s$ is done during the model calibration.

### 3.2 The calibration procedure

To calibrate the model, we use two empirical distributions: the inflow and the outflow distributions shown in Figure 7(a,b). Note that for this manuscript, we calibrate our model considering only cities and scientists present in three countries: France, Germany and United Kingdom. To determine the model parameters $b$, $s$ from that, we use an established approach in agent-based modeling ([Vaccario et al., 2018](#))

2The Journal impact scores are taken from Scimago.
Figure 7: Distributions of (a) inflow of scientists into any city, (b) outflow of scientists out of any city. (red) indicates the empirical distributions, (blue) the (optimally) simulated distributions obtained from the calibration of our agent-based model.

The grid search consists of an exploration of the (low dimensional) parameter space by means of computer simulations. For $b$ the values $\{0.005, 0.01, 0.05, 0.1, 0.5, 1.0, 5.0\}$ are considered, for $s$ the values $\{0.05, 0.1, 0.5, 1.0, 5.0, 10.0\}$. For each parameter combination, we obtain from our agent-based simulations two distributions for the inflow and outflow as shown in Figure 7(a,b). We now have to determine the optimal combination of $(b, s)$ that matches the empirical distributions best. For this, we use a performance score based on the Kolmogorov-Smirnov (KS) statistic [Kolmogorov 1933]. Precisely, for each combination of parameters $(b, s)$, we compute the KS-statistic between the empirical and simulated distributions of inflow, $D_1(b, s)$, and of outflow $D_2(b, s)$. We then define the performance score as $1/(D_1(b, s) \times D_2(b, s))$, such that the optimal combination $(b^{opt}, s^{opt})$ maximizes this score.

From the calibration procedure, we find optimal parameters $(s^{opt}, b^{opt}) = (0.5, 0.5)$. The comparison between the empirical and the simulated distributions is shown in Fig. 7(a,b). The close match demonstrates that our model is correctly calibrated. Some smaller differences are discussed in Sect. 4.

### 3.3 Results of the agent-based simulations

The calibrated agent-based model has to prove its evidence in that it is able to reproduce also the whole set of empirical findings that have not been used during the calibration procedure. If that is the case, the model has been validated. As already mentioned, we will verify this for two distributions on the level of scientists and four distributions on the level of the movement network.
Figure 8: (a) Distribution of movement distances of scientists. (b) Distribution of moves dependent on the (academic) age of scientists. (red) indicates the empirical distribution, (blue) the distributions that are obtained from our agent-based simulations. The distributions are obtained from the frequencies using a kernel density estimation.

Figure 9: Distributions of (a) local clustering coefficients, (b) path lengths, (c) degrees, and (d) degrees of neighbors. (red) indicates the empirical distribution, (blue) the distributions that are obtained from our agent-based simulations. The error bars correspond to the standard deviations of the measures computed on the 10 different realizations of the simulated mobility network.
The results of the validation are shown in Figure 8 and 9. To allow for a direct comparison we plot the empirical data in red and the simulation in blue. We can report a very good match of all distributions both on the level of scientists and on the network level. Specifically, on the scientists’ level, we are able to reproduce the two distributions of movement distances and of age when moving, see Figure 8(a,b).

On the network level, we are able to reproduce the four distributions of clustering coefficients, path lengths, degree and neighbor degree, see Figures 9(a,b,c,d). We emphasize that these results are far from being trivial. As we start with an agent-based perspective, the results of our simulations refer to career paths of individual agents. From these, we have to reconstruct an aggregated network of mobility as described in Section 2.3. Our simulation results for the network topology are reported for these simulated networks.

In conclusion, we report that our agent-based model captures the different features of the empirical data very well, both on the scientists’ and the network level, without using direct information from these for the calibration.

4 Discussion and outlook

This paper contains a number of important results, both on the empirical and the theoretical level. Regarding the empirics, we are able to reveal the patterns of scientists’ mobility on two levels: the level of individual scientists (age, movement distance) and the level of cities that form a global network of scientists’ mobility.

Regarding the theoretical contributions, we introduce the concept of a geographical career path of an individual scientist, which can be extracted from data. Using records of 3.5 mio scientists, we provide a statistical analysis of such career paths, that later forms the basis for comparison with our model, on the scientists’ level. Aggregating over these career paths, we are further able to reconstruct the world network of scientists’ mobility, with cities as nodes and influx/outflux of scientists as links, which is a new empirical insight.

The most important theoretical contribution, however, is an agent-based model that allows to reproduce these empirical findings, both on the level of scientists and the level of cities. In our model we assume as most relevant factors geographical distances, academic importance and selectiveness of cities. This model uses as input only variables that can be proxied by the available data. This extends in particular to the notion of academic importance, denoted as “fitness”, assigned to agents, which is proxied initially from the available publications. The “fitness” of locations, another ingredient of the model, can be then obtained by averaging over the fitness of agents at the particular location.

The agent-based model further uses only very simple assumptions as rules to determine the movement of agents. Agents rank all locations according to their fitness and their distance to the current location. But they do not decide about the movement. This is done by the locations using
Figures 10: Empirical and simulated mobility networks for France, Germany, and UK. The empirical network (a) depicts the flows between cities, the thickness of links indicates their magnitude. The map in (b) depicts one realization of the ABM with optimal parameters.

Information about the fitness of the agents and capacity constraints for the hiring of new agents. In essence, this poses a matching problem and can be related to similar problems discussed in the literature.

Our agent-based model only considers two free parameters, which need to be calibrated against the available data: $b$ weights the spatial distance between the current location of an agent and any other location, $s$ weights the selectiveness of locations when accepting agents that have a fitness below the average obtained for that location. We find as optimal parameters $(s^{opt}, b^{opt}) = (0.5, 0.5)$. This means that both selectiveness and distances better reproduce the empirical data when they give a sub-linear contribution.

Using the model calibrated with the optimal parameters, we are able to reproduce the available empirical data very well. Some minor differences between the simulated and the empirical distributions will be further quantified in a subsequent version of this paper. In a nutshell, they are also due to the fact that the simulations are only done with 22,100 agents, while the data are obtained from 3.5 mio scientists. These discrepancies become noticeable if we plot the network of scientists’ mobility on the European scale, only, as it is shown in Figure 10. We observe that the empirical network in Figure 10 (a) shows more pronounced hubs than the simulated network shown in Figure 10 (b). Specifically, in the empirical network significantly more French cities are linked to Paris compared to the simulated one.

Finally, we stress that there are more factors influencing the relocation choices of scientists than
explicitly covered in our model. For example quality of life, better networking opportunities or higher salaries might be relevant factor here. The more remarkable is the fact, that our model even at this level of detail works considerably well.

Going forward, we want to understand how the empirical core-periphery structure might be explained by other factors. Accounting for this in the simulation might help to recreate more subtle mobility patterns (i.e. a very central Paris). Moreover, we could replace the geographical distance between locations by travel time between cities, since this is most likely how humans estimate travel effort. Additionally we find in Verginer and Riccaboni (2018) that mobility is marked by national borders and cultural/language similarity. This would be an interesting features to further reproduce. Last, but not least, we have currently centered our analysis around France, Germany and United Kingdom, but will spend further effort on the global mobility network.

In summary, with our research, we have provided the first agent-based model reproducing the mobility of scientists. In a data-driven approach, our model has been calibrated and validated against data, and we have found an extremely good match between simulations and empirics. With this, we show that minimal decision rules capture many complex features of the observed mobility of scientists. In addition, we have quantified the relative importance between geographical distances and academic attractiveness from the perspective of a scientist trying to relocate.

References


