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INTERNAL MIGRATION OF SCIENTISTS IN RUSSIA AND THE USA: THE CASE OF APPLIED PHYSICS

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INTERNAL MIGRATION OF SCIENTISTS IN RUSSIA AND THE USA: THE CASE OF APPLIED PHYSICS[2]

When scientists change jobs they bring to their new workplace the experience, tacit knowledge and social ties they acquired at their previous workplace. Not only is the level of mobility important when discussing knowledge transfer between academic organizations or between regions, but the topology of mobility network is also of crucial importance. This study presents a comparison of the structure of internal migration networks for Russian and American physicists, more specifically for scholars working in the field of applied physics. To build a migration network, we selected physicists who had changed their city of affiliation between 2009 and 2013/2014. Data on scientists' affiliations were obtained from the Web of Science. After the structures of two networks were compared, we formulated a hypothesis of how the features of the network are connected to the overall scientific productivity of the system.

Keywords: knowledge flows, knowledge transfer, labor mobility, scientific mobility, migrant scientists, network structure

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Introduction

One of the major trends in how science is conducted today is the constant growth of mobility of scientists. This growth is assumed to be one of the factors of scientific and technological progress. Mobility and migration of scientists has been the object of research for decades. There is a shared understanding that migration flow influences a country's scientific performance, which is why both ‘pure scientists’ and policy makers are interested in learning the exact patterns of that influence, the structure of flows, and the predictors of migration scale and directions. Although there are plenty of reports and studies on academic mobility, most of them focus on international migration (for example, look Bauder, 2015; Cañibano et al., 2011; Stephan, 2010; Franzoni et al., 2012; Gaule, 2014). Compared to international migration, which can be considered as the macro-level, inter-regional and inter-organizational mobility – mezo- and micro-levels – seem to be unduly neglected. To learn how national science works and what its strengths and weaknesses are, it is indeed important to know about cross-border flows of scientists, but it is of no less importance to know how mobility is structured within national borders.

There exist different forms of spatial mobility when we speak of scientists. Among them are some forms of short-term mobility, like conferences, summer schools, visits for giving guest lectures, and so on. One could study how professional trips have become easier for researchers and how this ease of travel affects their work. But generally, when scientific mobility is studied the focus is on migration, not travelling. In this paper we will also focus on migration patterns, more precisely on internal labor mobility.

When scientists change jobs they bring to their new workplace the experience, tacit knowledge and social ties acquired at the previous workplace. When we speak of mobility-induced knowledge transfer between academic organizations or between regions, it is not only the level of mobility which is important, but also the topology of mobility network. We can assume that different patterns of mobility have different influences – fostering or inhibiting – on the overall performance of the system. For example, knowledge transfer should occur differently in star-like and in decentralized networks, which influences performance. In this sense, when we consider a mobility network as a feature of the whole system, we can speak of relatively more or relatively less effective mobility. In this study we use the SNA (Social Network Analysis) approach to compare the structure of mobility for Russian and American physicists, specifically for scholars working in the field of applied physics. The tasks set out in this study are, first, to describe the networks of mobility of Russian physicists and to compare these networks with those in the USA, and, second, to formulate a hypothesis of how the features of a network are connected to scientific performance. Both Russia and the USA are major players in the field of applied physics research, with thousands of researchers and large networks of institutions. What is of crucial importance for this study is that in both countries, research institutions are geographically widely dispersed. Apart from these similarities, there are many differences in how science is organized in two countries as well as in internal migration trends, which is why we expect to find considerable differences in the structure of mobility.

The basic idea of SNA is that actors' actions and outcomes depend crucially on their relations with other actors, and more precisely, on their position within the structure of relations. The SNA approach is particularly productive where knowledge transfer is concerned. The common questions SNA deals with are what positions in the network are the most favorable, in the sense of boosting the chances of an actor to generate knowledge-based advantages (Powell et al., 1996; Ruef, 2002; Burt, 2004), and what structure maximizes overall network performance (Llobrera et al., 2000). When applied to academic networks, the approach is generally used to analyze co-authorship and collaboration (Uddin et al., 2012; Abbasi, 2013). In studies of scientific mobility, network instruments are used more often for visualization than for analysis. As Ronald Burt has written, there is a 'structural hole' between the studies of scientific migrations and SNA studies of knowledge transfer, which gives chances for good ideas to emerge [Burt, 2004].

It is worth noting that neither the intensity of mobility nor the specific structure of a mobility network per se can be interpreted as relatively effective or ineffective. A star-like network can be more effective than a decentralized configuration, and vice versa. The part of SNA theory dealing with the overall effectiveness of the system is far from complete, and empirical results are patchy. The study presented here does not aspire to contribute to the debate over which structure is more effective. The goal is to draw hypotheses from empirical data on mobility and the network built on it. It is natural to expect Russia to have a star-like structure of mobility with Moscow as its centre, and for the USA to display a decentralized structure. But a network built on real data may provide further evidence for effectiveness-related hypotheses, or it may refute, at least to some extent, common-sense expectations.

There are different lenses one could use to look at mobility processes. In this study migration is analyzed on the city level – a change in the city of a scientist's affiliation is registered as a data unit. This lens is perhaps not very common in mobility studies, at least as far as scientists and

R&D employees are concerned. One of the mainstream areas of research in this field is international labor mobility, where labor flows are analyzed on the level of countries. Another direction is inter-organizational mobility, where the transfer is registered on the level of institutions and firms. If we accept the concept of localized knowledge flows [Agrawal et al., 2006] it is fair to assume that every lens – the city level among them – provides some unique insights into mobility. At the core of the concept of localized knowledge flows is the idea that knowledge is not distributed evenly across the globe – what you know depends in part on where you are. Among other things, this means that people tend to be more familiar with what is done inside their own organization than inside other organizations, in their city than in other cities (but probably worse than in their organization – an insight which yields the idea of non-permutability of different lenses), and in their country than in other countries. Although one could probably find counter-evidence to this theory, we nonetheless expect that scientists will tend to know how science is conducted in their city better than in other places: "individuals who are co-located are able to meet and exchange ideas at lower cost than those who are geographically separated. At the same time, individuals who are co-located are more likely to experience serendipitous meetings during which useful knowledge exchanges may occur. Finally, co-located individuals are more likely to develop social relationships, which may act as conduits for knowledge flows" [Agrawal et al., 2006]. When such individuals move to another place they take with them, in a figurative sense, not only their organizations, but also their cities. And when they move across a border they take with them the country where they had worked before. By the same logic it is not only an organization which receives new knowledge when a new employee migrates to join it. We assume that the migration of a researcher to new city or country in some sense enriches these places beyond the particular institution [Oettl & Agrawal, 2008]. So when we choose cities and not organizations as the level of analysis, this includes not only technical matters of data aggregation. It reflects consideration that labor mobility is associated with knowledge flows in their broader sense, including both direct transfer and spillover effects.

It is possible to distinguish two main lines in the field of migration and mobility studies. One consists of studies dealing with the factors of mobility and another consists of studies concerning the effects of mobility. The studies of the first type seek to explain and predict the configuration of migration flows [Appelt et al., 2015]. The methodology of such studies ranges from micro-level investigations, like those in which researchers are interviewed about the reasons for their migration decisions, to macro-level investigations, in which countries are the units of analysis. The studies of the second type deal with the consequences of migration for the migrants themselves, or for the organizations and regions where they work or worked previously. The study presented in this paper falls into the second type, as its driving idea is that the structure of internal mobility flows matters for the overall productivity of national science.

One should note that the overall productivity of the whole system is not a common target function in mobility studies, in the same way that cities are not the most common choice of data aggregation level. One can easily find studies dealing with the effect of mobility on the careers of workers, researchers among them [Cañibano et al., 2008; Jonkers & Tijssen, 2008; Scellato et al., 2015]. Apart from these, there are many studies on how labor mobility affects organizations. It is quite obvious that organizations generally benefit from newcomers, although the relation of this benefit to the quality and quantity of newcomers is complicated. What is less obvious is that an organization can benefit not only from those who join it, but also from those who leave it. The benefit comes from the knowledge flow established between the mover's previous organization and the new one. While sometimes the knowledge is transferred directly by the mover who stays in touch with former colleagues, in other cases the mover's direct participation is not even necessary – it is enough for former colleagues to be curious about the mover's new work. Empirical evidence of such backward knowledge flow was obtained, for example, in research based on citation analysis of patents [Agrawal et al., 2006].

When we look at studies of migration macro-effects – effects on the whole system – most often we see studies of international migration. In the case of scientists' migration there are a number of works discussing what countries end up winning and losing from migration (the so-called "brain drain/brain gain" perspective). Other literature considers the overall effects of migration deals with technological clusters. Silicon Valley is classic example of such a cluster. Intensive interfirm labor mobility in the high-tech sector was found to be one of the drivers of innovation, in the end fostering the whole sector. The paper presented here does not fit either of the two mainstream literatures. It does not focus on the winner/loser dichotomy common for international migration studies, and is closer to studies of technological clusters, although as we consider nationwide mobility we cannot fully rest upon cluster studies.

Another important distinction is that we consider here the nonprofit research sector. How labor mobility is related to knowledge flows and how this relation affects researchers, institutions and countries, has been studied for both the academic and R&D sectors. Apart from studies concerning mobility either in the academic or in the R&D sector, there are works dealing with inter-sector mobility, such as labor flows from academia to business [Crespi et al., 2007]. There is a difference between commercial and non-commercial sectors which is important in the context of mobility. If somebody working in the commercial sector has valuable knowledge and leaves for another job, it poses a threat to the original firm, as there is a chance that the former employee could capitalize on inventions the firm had invested in at his or her new workplace. This danger shapes, in part, the economy of labor mobility in the private sector [Kim & Marschke, 2005; Kaiser, 2015] and explains why one cannot easily extrapolate conclusions about academic mobility from the results obtained in the business sector. Here we use publications indexed in the Web of Science to trace the mobility patterns, which places this study in the domain of academic mobility research.

Methodology

In the case of applied physics, we are dealing with a field which has blossomed both in Russia and the USA. For both countries, publications in applied physics constitute a considerable share of national scientific output. In 2009 the USA was the world leader in publishing papers in applied physics, with 20% share of the world output.[3] Russia was in 7th place, with a 4.5% share. In 2014 the position of Russia in the rating remained the same, while the USA yielded first place to China. To build networks of mobility, we compiled samples of scientists who worked in Russian and American institutions in 2009, and checked whether in 2013-2014 they worked in the same cities or had changed their workplace. Data on scientists' affiliations were obtained from the Web of Science (WoS) and aggregated on the level of cities. Samples of scientists were derived from samples of articles indexed in the database.

The Web of Science Core Collection contains records on 2765 papers with Russian authors published in 2009 and assigned in the database to the field of applied physics. From these papers we randomly selected 200 articles, which gave a set of 594 authors working in Russia in 2009. For each author the data were obtained on his/her affiliations from the papers published four to five years later, in 2013-2014.[4] Not all of the authors from the initial sample had 2013-2014 papers in the database. We found 2013-2014 papers indexed in WoS for 371 of the original 594 authors, which means that the authors' "survival rate" was 62%. These 371 physicists constituted the sample out of which the network of mobility was constructed.

[3] All the numbers in this paragraph were obtained from the Web of Science. We used Web of Science subject categories to generate the total number of publications in a certain field.

[4] We used hyperlinks on an author's name, which is an instrument built in by WoS for locating all the papers written by a certain author indexed in the database. This instrument does not always provide a correct result, and sometimes papers indexed in WoS cannot be located.

This survival rate of 62% should be taken as an artefact which is the result of data gathering techniques we used. The 38% of original authors excluded from the mobility analysis consists only in part of authors for whom WoS did not locate 2013-2014 papers. This set also contains authors for whom WoS contains too many papers, in the sense that it contains data on several authors with the same name who cannot be distinguished. For Russian physicists we encountered such uncertainty only for seven authors, while in the case of the USA it occurred more often.

For the identifiable authors who have both 2009 and 2013-2014 papers we gathered data on their city affiliation at these two points. If an author had several papers published in 2013-2014, we used the latest one as the data source. In the Russian sample we detected 64 authors who changed cities between 2009 and 2013-2014, which is about 17% of the 371 for whom we have full data. One should note that we registered any change in in an author’s city affiliations, so the “change” here does not necessarily means “researcher moved from city A to city B,” there was more variability. The affiliations of the 64 physicists who had migrated were used to build networks of mobility with nodes representing cities, and edges representing migrating scientists. The resulting network was visualized and analyzed by means of UCINET software (UCINET 6 for Windows).

The set of applied physics papers published in 2009 and assigned to the USA consists of 12854 documents. Randomly selecting 200 articles yields data on 674 authors who worked in American institutions in 2009. After filtering out the authors which do not have 2013-2014 papers indexed in WoS and those who could not be unambiguously matched with papers, the sample was narrowed to 396 physicists (59% of the whole set). In the case of the USA, we saw quite often that the same name relates to several different people. This shows the limits of usefulness of bibliographical data for tracking migration. When one uses survey or CV data, there are other limitations on data completeness, but at least one can be sure that any single piece of data relates to a single person, which is not the case when the data are obtained from publications. The use of bibliographic data will become easier when initiatives like ResearcherID and ORCID, which aim to assign unique identifiers to scientists, become widespread enough to cover the majority of authors. At present this is still not the case, so we chose to use CVs as an additional source of data for distinguishing between authors with the same names.

When the authors of 2009 and 2013-2014 papers were affiliated with the same institution, we could be quite sure that we were dealing with the same person. When the institutions were different – which happened in the cases of 95 authors in our USA sample – we used CVs and information on institutional web-sites to determine whether it was the same person or not. For 71 of the 95 authors, the data from CVs confirmed the mobility data derived from publications. We found only 4 authors for whom CV data refuted the data on mobility obtained from publications. In the remaining 20 cases we could not find data which could either confirm or deny that migration had occurred. It should be noted that for Russian physicists a CV-based check would be probably be useful in fewer cases, as it is less typical for Russian physicists to publish CVs on the web.

Results

First of all, we should note that Russia and the USA differ significantly in how authors are distributed across cities. In Russia, the 594 authors of 2009 are dispersed across 43 cities. In the USA 674 authors, which is 1.13 times larger than the Russian sample, in 2009 were distributed across 138 cities, which is more than three times larger than the number of cities represented in the Russian sample. Such a difference stems from the difference in size of the Russian and American applied physics research sectors – the latter is larger in terms of the number of researchers and research centers. When the two distributions are compared, however, the two sectors are found to be different not only in scale. The distribution of Russian authors is highly skewed, with Moscow accounting for 27% of the sample, and three leading cities (Moscow, St. Petersburg, Nizhnii Novgorod)[5] accounting for more than half. American authors are distributed more evenly. There is no city home to more than 5% of the authors. Table 1 shows the top ten cities of both countries which are home to the largest number of authors of 2009 papers in the sample.

The samples of physicists show quite a stable distribution of scientists across cities in the sense that the distribution according to 2013-2014 affiliations is close to the distribution in 2009, despite the fact that during the same period a significant number of scientists in both countries changed cities. In the case of Russia there was only one major change in ratings – Nizhnii Novgorod dropped from its third-place position. In the case of the USA the gaps between positions in the ratings were smaller, which tended to make differences in 2009 and 2013-2014 ratings trivial.

[5] We use Web of Science spelling.

Table 1. Cities in Russia and the USA with the largest number of authors in the sample.

N	City (Russia)	Number of authors, 2009	% of total (of 594)	City, state (USA)	Number of authors, 2009	% of total (of 674)
1	Moscow	161	27.1%	Berkeley, CA	29	4.3%
2	St Petersburg	97	16.3%	Cambridge, MA	27	4.0%
3	Nizhnii Novgorod	70	11.8%	Austin, TX	19	2.8%
4	Novosibirsk	33	5.6%	Atlanta, GA	16	2.4%
5	Ekaterinburg	25	4.2%	Evanston, IL	16	2.4%
6	Tomsk	24	4.0%	Richland, WA	15	2.2%
7	Rostov Na Donu	18	3.0%	Santa Clara, CA	15	2.2%
8	Chernogolovka	14	2.4%	Washington, DC	15	2.2%
9	Saratov	13	2.2%	Albuquerque, NM	13	1.9%
10	Troitsk	11	1.9%	Argonne, IL	12	1.8%

Of 371 scientists from Russia who published papers in both 2009 and 2013-2014, 64 authors changed cities during this period. Figure 1 presents a network of “incoming mobility” for Russian physicists. The edge directed, for example, from Saratov to Tambov means that some physicist who worked in Saratov but not in Tambov in 2009 was found to be working in Tambov in 2013-2014 (although he or she may continue to hold a job in Saratov). Nodes towards which the edges are directed are the cities which people came to. Two cities are close on the map if they have many common partners. The proximity of the nodes connected by an edge does not reflect the scale of migration flow from one city to another. In our case, with the samples modest as they are, we do not observe big variation in scale of migration flows. For Russia almost all flows from one city to another were of more or less the same size, from 1 to 3 people. The flows which stand out are those from Moscow outside the country[6] (six authors), from St. Petersburg outside the country (four authors), and from Nizhnii Novgorod to Moscow (five authors). For the USA, the maps for which will be presented further, all flows fall into the range from 1 to 3 authors. Such moderate variance of the scale of the flows makes needless its depiction on the maps, by regulating the thickness of edges for example.

[6] On the map the node marked ‘out’ is reserved for foreign affiliations.

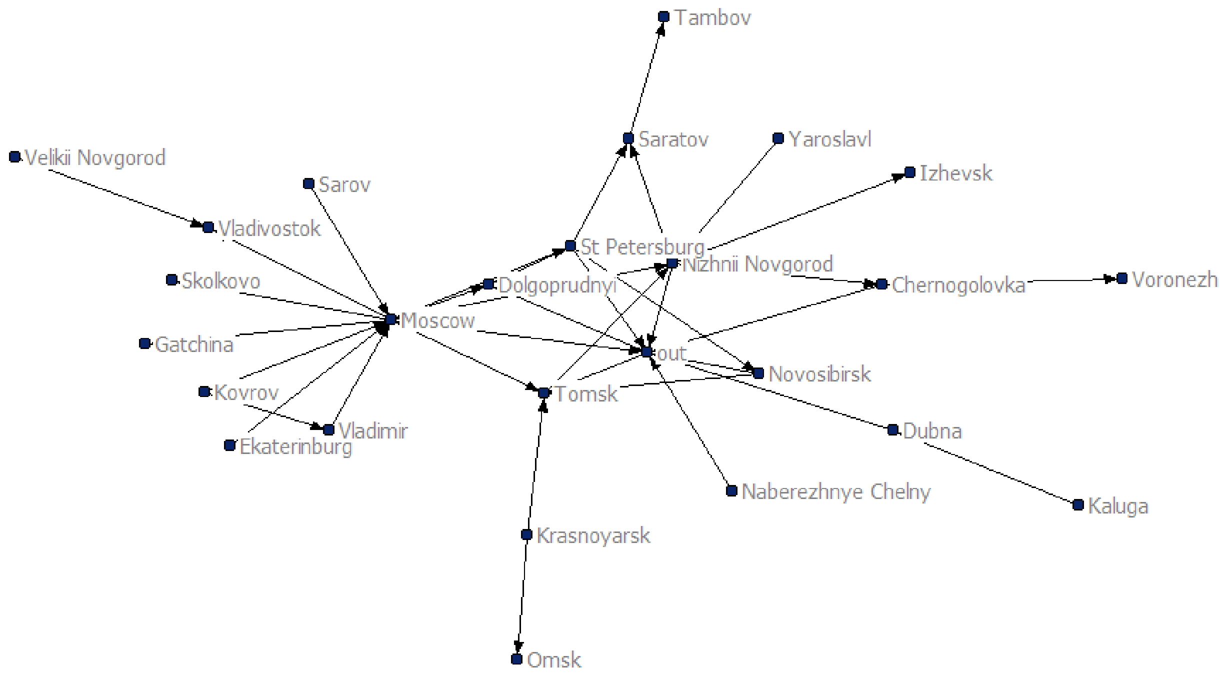


Figure 1. Network of incoming mobility of Russian physicists.

The problem with mapping scientist migration is that, in the present day, more and more scientists have multiple affiliations, which makes it difficult to build a map which is intuitive and comprehensible at first sight. It is easy enough to read a map where an edge between two nodes represents those who **left** one node to move to another. If we want to include all data on authors' multiple affiliations, though, maps become somewhat intricate, and should be read with reservations. For the map presented in Figure 1, one should understand that this is a map showing gain, not loss. A node on such a map that has, for example, only outgoing edges, does not necessarily represent the city that lost any researchers due to labor mobility.

For the purpose of comparison with the network of incoming mobility, we present in Figure 2 a network of outgoing mobility built with the same data. On this map the edge directed, for example, from Krasnoyarsk to Omsk means that some physicist who worked in Krasnoyarsk (probably while also working in Omsk) in 2009 was found working in Omsk and not in Krasnoyarsk in 2013-2014. The nodes with edges directed away from them are the cities **left** by the physicists. In a "ideal world" where each scientist has a job in only one city, the maps of incoming mobility and outgoing mobility would be exactly the same. In reality we see that, because scientists have multiple affiliations, the maps are not identical. If, for example, we look at Krasnoyarsk in these two maps, we can see that mobility flows associated with this city are different. There is an edge from Krasnoyarsk to Tomsk on the map on the Figure 1, and no such edge on the map in Figure 2. This means that we have scientists in the sample – one or several – who in 2009 worked in Krasnoyarsk and not in Tomsk, and who by 2014 had moved to Tomsk, but had not left their jobs at Krasnoyarsk.

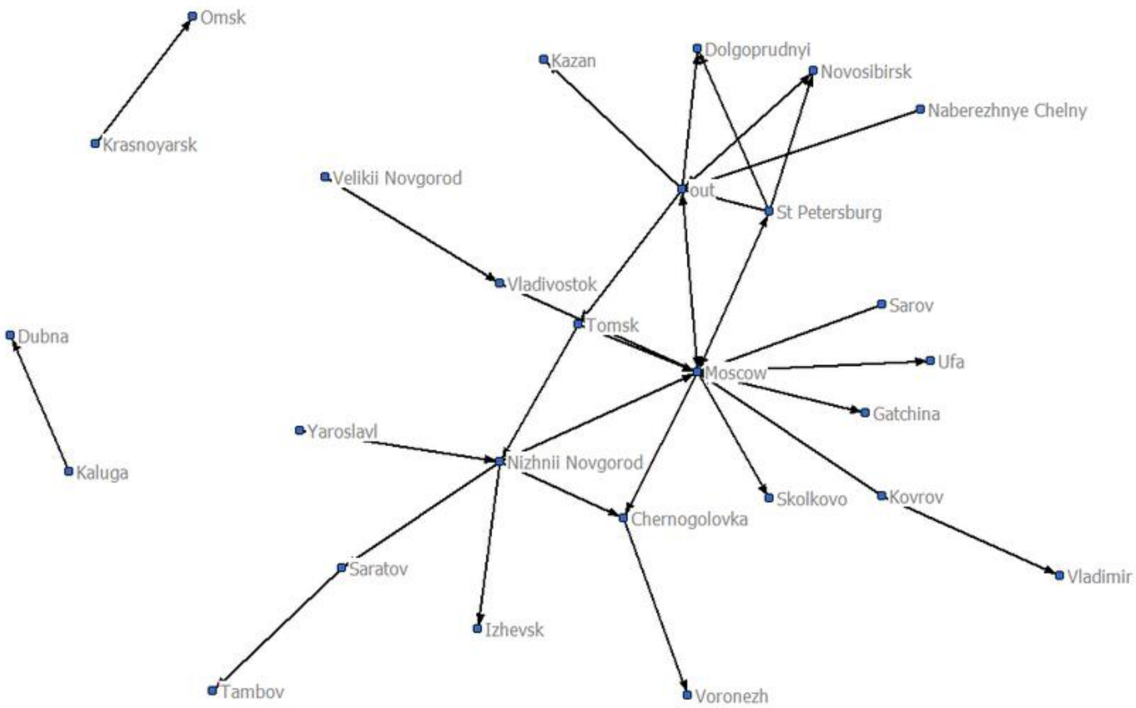


Figure 2. Network of outgoing mobility of Russian physicists.

There are 26 nodes on the map of incoming mobility and 27 nodes on the map of outgoing mobility. Seventeen cities were the destinations for incoming mobility, and fourteen cities were left by one or more physicists. Moscow and the node ‘out’, which represents all foreign affiliations, are two centers of the network on each map. The overall centralization of the network in Figure 1 counted by in-degree is 0.61. A simple core/periphery model characterizes Moscow, Tomsk and ‘out’ as the core of the network. The overall centralization of the network in Figure 2, counted by out-degree, is 0.64. A simple core/periphery model characterizes Moscow and ‘out’ – but not Tomsk – as the core of the network.

On the whole we see that two maps are not completely different. In part, this is because in our sample there are not so many cases of authors with affiliations in different cities. We have 16 such cases in a broad sample of 594 researchers, which is 2.7% of the authors. If multiple affiliations were more common, the maps of incoming and outgoing mobility would be more divergent, and the choice of which map to analyze would be of more importance than in our case. Still, the focus of our study makes it more appropriate to analyze the maps of incoming mobility, because we discuss migration in context of knowledge transfer, or, so to speak, knowledge cross-pollination.

When one analyzes academic migration, multiple affiliations could be not only of methodological but substantive importance as well. Of sixteen Russian physicists who combined jobs in different cities in 2009, fourteen were included in our mobility analysis (i.e., they published papers in 2013-2014). Eleven of these fourteen proved to be mobile, meaning that they had changed cities between 2009 and 2013-2014, which makes the concentration of those combining much higher in the subset of mobile scientists than in the non-mobile subset. This leads us to the rather natural hypothesis that those who combine jobs in several cities are more prone to migration than those who work in one city. There is another structural resemblance between the geographical distribution of mobile scientists and of those combining jobs in several cities. In both cases Moscow and institutions outside the country (aggregated to the node 'out' on the map) play central roles. Of the sixteen researchers who combined jobs in several cities in 2009, ten combined jobs in Russia with jobs abroad, and ten had affiliations in Moscow. At the same time the corresponding nodes – 'out' and 'Moscow' – are two centers of the network of incoming mobility.

In Figure 3 one can find the network of incoming mobility for cities in the USA. In order to make the structure of the network clearer, we present it in two ways – with and without node labels. First of all, the network is much larger than in the Russian case. The difference in the scale of the networks is not only due to wider dispersal of American physicists across cities compared to Russian physicists, but also due to the higher level of mobility in the USA. Russian physicists for whom we have data on both 2009 and 2013-2014 affiliations represent 40 different cities. Because we do not show isolates on the maps, only cities where the mobile researchers worked are displayed. There are 24 cities on the map for Russia, which means that 63% of the 40 represented cities are involved in the migration network. The remaining sixteen cities could be displayed on the map as isolates. American physicists from the sample with full data have affiliations in 133 cities, of which 93 (70%) are involved in the migration network.

Figure 3. Network of incoming mobility of American physicists.

In the Russian case the node 'out' has the most diverse incoming migration flow – researchers from seven cities migrated abroad between 2009 and 2014. This flow is larger than any of the flows inside Russia. In a similar manner, migrations to outside the USA outnumber migrations to any city inside the country. The node 'out' received a flow of 39 researchers from 28 different cities and occupies the central position in the network. Still, there is major difference in how this node shapes the two respective networks. If we build networks of internal mobility, which do not show migrations outside of the country, the structure of the mobility network will change slightly for Russia (compare Figure 1 and Figure 4), while in the case of the USA the map will look quite different (compare Figure 3 and Figure 5).

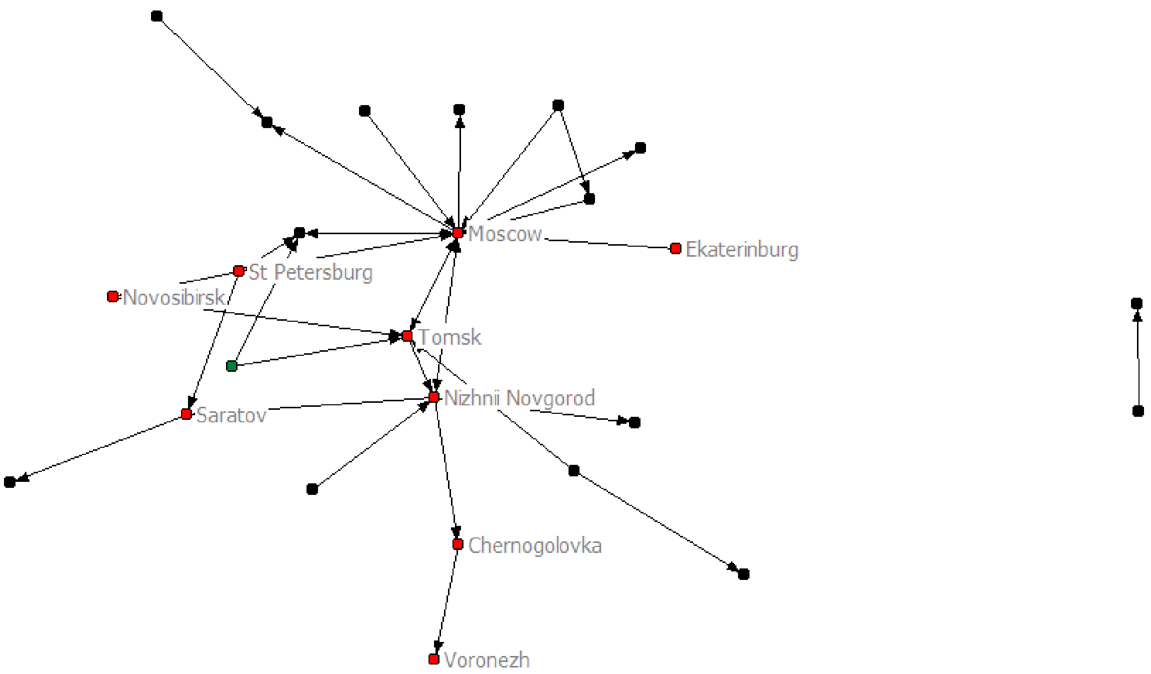


Figure 4. Network of internal incoming mobility of Russian physicists (migrations outside the country excluded).

In case of Russia the removal of the edges representing migrations abroad made the network lose one of its centers. But the other central node, 'Moscow,' did not allow the network to dissipate. All the nodes except two are included in the connected component of the graph. The network definitely has a center-periphery structure which means that the network has a few nodes with many ties, and a majority of nodes with a few ties. This means that there are a few cities – Moscow, Tomsk, Nizhnii Novgorod, Dolgoprudnyi[7] – which have a diverse incoming flow of migrating researchers while the majority of cities either do not accept migrants at all or have a sparse incoming migration flow.

[7] This city is shown without a label in Figure 4, because labels are shown for the largest cities only.

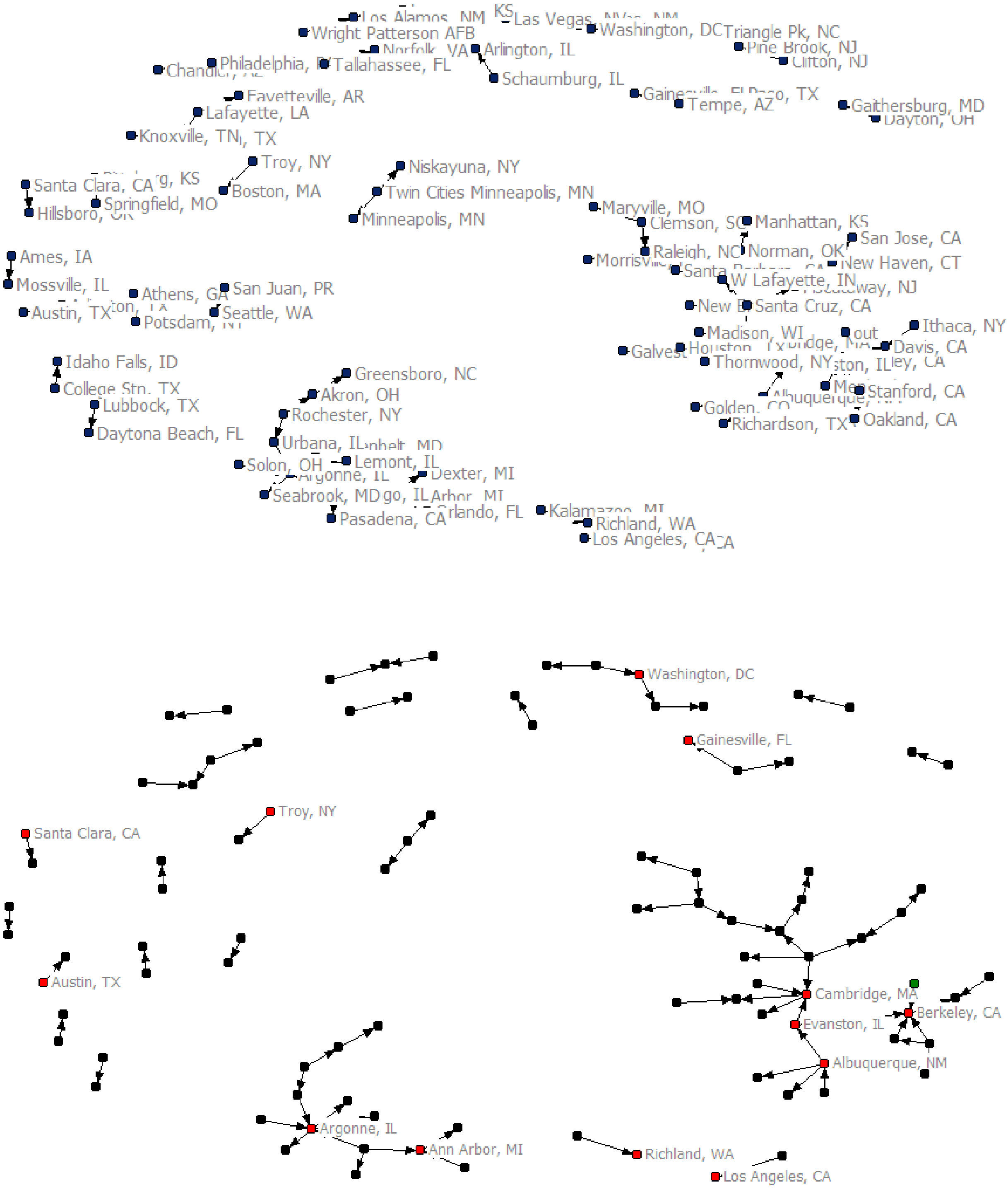
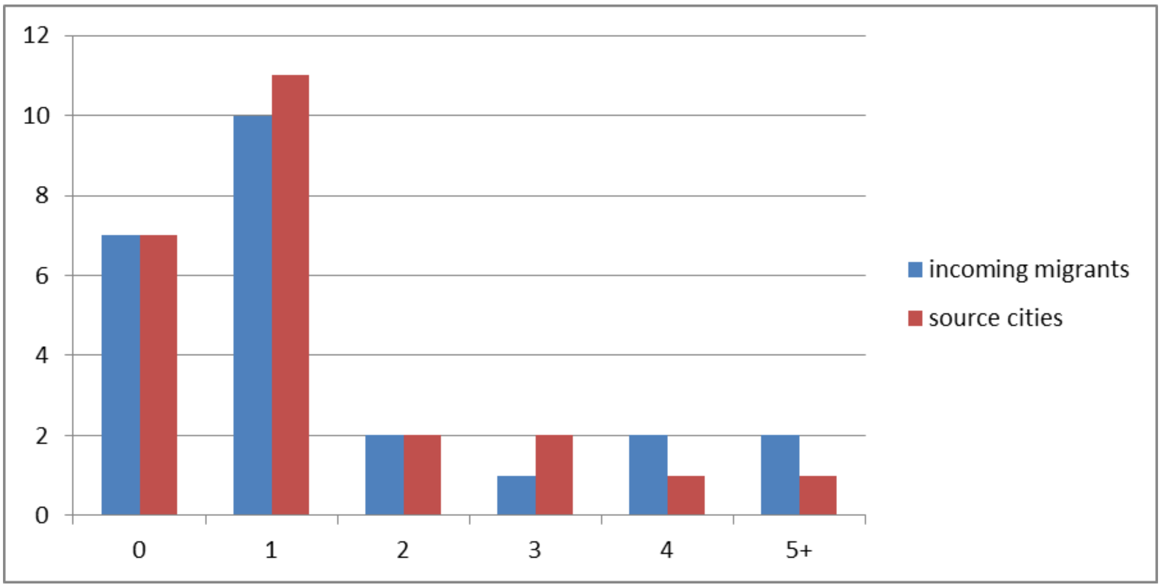


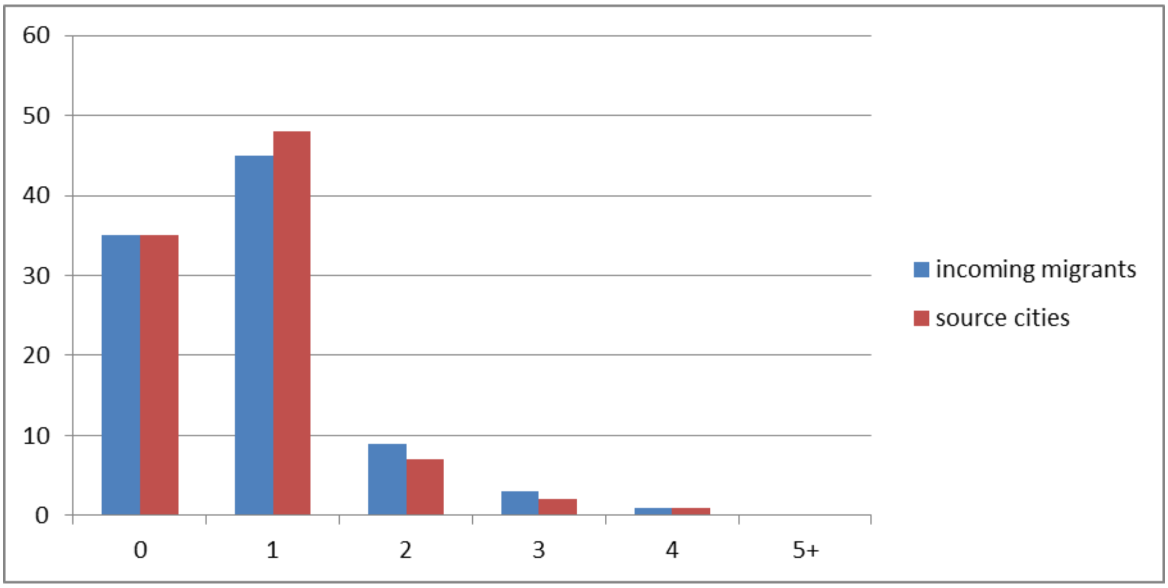
Figure 5. Network of internal incoming mobility of American physicists (migrations outside the country are excluded).

In case of the USA, the node ‘out’ was the single center of the network, and after filtering out the edges representing migrations abroad, the network broke apart into many unconnected components. Two of these components are quite large, but the majority of nodes are beyond them. There is some similarity with Russian network, as only a few cities in the USA are characterized by diverse incoming migration (Cambridge, Argonne, Berkeley), while the majority have fewer than three sources of migrants. But if we look at the number of migrants attracted by the central cities in each country – 24 in the case of Russia, which is 38% of those who changed cities, and 10 in case of the USA, which is only 8% of mobile American physicists – it will become clear that these centers play quite different roles in the two networks.

In Figure 6 one can see frequency bar charts of in-degree, counted by the number of incoming migrants and number of the source cities, for the Russian and American mobility networks. For example, blue bars marked by 1 on the X-axis of Figures 6A and 6B show the number of cities in each network which received only one migrant according our data – there are 10 such cities in Russia and 43 in the USA. A red bar next to the blue bar shows how many cities received migrants only from one other city – 11 in Russia and 48 in the USA. We see that the absolute numbers vary greatly for Russia and the USA, but this difference to a large extent is explained by the difference in the scale of the networks. Another difference may be important when one considers how the network structure influences the performance of the system – namely, the difference in uniformity of mobility. By "more uniform network" we understand a network where the nodes are characterized by closer values of in-degree.



A) In-degree frequencies for nodes of the Russian mobility network



B) In-degree frequencies for nodes of the American mobility network

Figure 6. In-degree frequencies for Russian (A) and American (B) mobility networks.

The charts in Figure 6 show that for both countries, the majority of cities are characterized by minimal in-degree values (0 or 1). What seems important is that in the American case, there is no long tail adjoining this majority. The ‘periphery’ comprises the network almost in its entirety. In the Russian case there is a long tail of cities with higher in-degrees, which means that we see the core/periphery structure not only on the map, where the core is presented by the central nodes, but also in the distribution of the scale of incoming flows. This distribution shows that cities in Russia are unequal in terms of how many migrants they accept and from how many cities, more unequal than American cities.

On the maps in Figures 4 and 5, the biggest cities (i.e., cities home to more than 10 physicists in the full samples) are colored red for both Russia and the USA. Although the Russian sample of physicists is scattered across fewer cities than the American sample, meaning that the population of Russian physicists is more concentrated, we see that more cities in the USA than in Russia qualify as ‘big cities’ according to our definition, which is more evidence of less-skewed distribution of authors across cities in the USA. When we look at the positions in the network taken by the big cities, we see that in the case of Russia most of these cities take more or less central positions, and almost all central positions are taken by big cities. Still, some big cities are found on the periphery (Ekaterinburg, Voronezh), and some are not involved in migration network at all (Rostov na Donu, Troitsk). In case of the USA, it is harder to tell how central big cities are for the network, because the network is much more decentralized than for Russia (the undirected centralization score is 0.76 for Russia and 0.06 for the USA). For the USA, about one third of the big cities are included in the two biggest components of the network, and they take central positions in these components, while the rest are on the periphery or are not involved in the network. We can conclude that in both Russia and the USA, big cities play an adhesive role in the network of labor mobility, but in both cases being 'big' does not guarantee a central position on the network.

The reason why it is worth looking at big cities when analyzing how mobility is related to the effectiveness of the system is that big cities may attract too many migrants. It is natural for big centers like Moscow to attract more scientists than other cities. The question is whether big cities attract more than they should have according to their 'mass,' and how this attraction affects the whole system. It is debatable whether big cities themselves benefit from this surplus, if it exists, but it is highly probable that mobility gravitation leaves the periphery underfed with external labor force. Here the "rich get richer" mechanism, known in the sociology of science as the 'Matthew effect,' is in effect. Robert Merton noted that this mechanism can shape the distribution of attention to scientific results [Merton, 1968]. He used the "rich get richer" principle to describe the situation in which researchers at early stages of career are under-cited, while prominent scientists receive heightened attention because they are famous. When we speak of migration, the Matthew effect can be seen when big cities attract disproportionately large flows of scientists while small cities receive few researchers from the outside. There is an important difference between migration distributions and citation distributions, however. While a paper or an author can only gain citations, a city can gain and lose researchers, which should be taken into account in the analysis and interpretation of the "rich get richer" effect.

The maps of mobility presented above show only those cities which were points of arrival or departure. Those cities where physicists within the sample worked in 2009 or in 2013-2014, but which were neither the point of arrival nor departure, were not shown on the maps. In the case of Russia these were the smallest cities in terms of the number of physicists in the sample.[8] In fact, all cities with one or two authors in the broadest sample (594 authors) are not included in the network. This is not so for the USA, as many cities represented by only one or two authors in the sample are included in the network of mobility. This difference indicates that one is more likely to find the Matthew effect in the distribution of Russian internal migration than in the American distribution.

[8] Here and below we speak of the 'size' of the cities only in this sense.

To measure whether scientists in big cities tend to be more ‘mobile’ than in small cities, and how the two countries are different in this respect, we calculated Spearman correlation coefficients between the sizes of the cities and indicators of mobility level. The results are shown in Table 2. The size of the city is defined as the number of physicists from the broadest sample who worked in the city in 2009. We used four indicators of mobility level for the city: 1) the absolute number of those who came to the city between 2009 and 2013-2014 (incoming migrants), 2) the absolute number of those who left the city, and 3) and 4), arrivals and departures respectively, normalized by city size.

Table 2. Correlation between the sizes of cities and their level of researchers’ mobility.

		Russia	USA
Correlation between the size of the city and	(1) the number of incoming migrants	0.51	0.31
	(2) the number of those who left the city	0.61	0.54
	(3) the number of incoming migrants normalized by the size of the city	0.44	0.22
	(4) the number of those who left the city normalized by the size of the city	0.44	0.37

The correlations between the size of the city and the absolute numbers of those who migrated to or out of the city do not show if the “rich get richer” effect applies in Russian or American mobility distributions. The fact that the related coefficients (lines 1 and 2 in the Table 2) are positive indicate the rather unsurprising result that big cities tend to be the point of arrival or departure for more migrants than do small cities. The coefficients in the first two lines of the table are not very close to 1, which means that the relationship between the two characteristics is far from linear. Both coefficients are slightly higher for Russia than for the USA, which means that for Russia the size of the city is more predictive of the number of migrants.

The coefficients in lines 3 and 4 of Table 2 show how the size of the city is correlated with the relative level of mobility. The fact that coefficients are positive means that researchers working in big cities have more chances to migrate. Coefficients in line 3 can be considered as indicators of the Matthew effect for the two countries. Again we see that the coefficients are higher for Russia than for the USA, but not very close to 1 for either country, which means that in either case we cannot state that big cities tend to attract too many migrant researchers. In the Russian case we might expect that at least Moscow, home to the largest number of researchers and the center of the mobility network, would show this effect. Still, our data on migrations shows that Moscow attracts only about 20% of migrating researchers, which is lower than its 27% share in the 2009 distribution of physicists.

Discussion and conclusion

In this work we have focused on the structure of internal mobility of Russian and American physicists. Interest in this question is driven by the widely-discussed idea that labor migration represents a mechanism of knowledge transfer. The notion that this mechanism cannot be substituted by other mechanisms leads to hypothesis that the structure of internal migration is an important factor affecting performance in knowledge-intensive sectors. In this context, a comparison of two networks of migrations seems particularly interesting in relation to the effectiveness of national science.

Comparing the patterns of mobility in two countries, we found that researchers working in the field of applied physics in the USA are characterized by a higher level of mobility and more equally distributed mobility than physicists in Russia.[9] Our hypothesis is that both these features positively influence the effectiveness of American science. To confirm or reject this hypothesis, as well as to estimate the scale of the effect, further research is needed. One possible way to explore this effect is to regress the effectiveness of national science, represented by some indicators, on characteristics of mobility while controlling for other important factors that could influence scientific performance.

The other question of possible interest, which would be more in line with traditional SNA research, is what positions in the network are associated with better performance. In our case, this line of questioning would focus on how migration profiles of the cities are related to their performance. An economic approach to effectiveness suggests using indicators that show how the results obtained are related to the resources spent. Such an analysis goes beyond the scope of this study. Still, we can offer a preview of this sort of analysis as an illustration. For this illustration we used a surrogate indicator derived from our data and related to effectiveness. Since we started with a 2009 sample of physicists and for each researcher searched for 2013-2014 papers in WoS, we can calculate the proportion of 'survivors' for every city, which could serve as such surrogate indicator of effectiveness.

[9] It is problematic to generalize the results of this study to labor mobility in other disciplines, because the level of mobility may vary across fields [Cañibano et al., 2008; Cañibano et al., 2011].

We checked how the variance in ‘effectiveness’ of the cities is explained by the variance in the size of the city and in city characteristics related to migration – the size of incoming migration, size of outgoing migration, and the number of cities receiving migrants from the city in focus. The simplest linear regression analysis of the proportion of ‘survivors’ among physicists working in particular city using four factors[10] showed no statistically significant linear relation between any factor and the proposed indicator of effectiveness. Still, using similar design and further refining either the model or indicators, one could investigate the relation between scientific performance and migration profile in more depth.

Instruments for network analysis are not widely used in studies of scientific migrations, especially when within-borders migration is in the focus. We are not aware of any studies in which knowledge transfer is analyzed through the lens of mobility networks in order to define how network structure relates to national scientific performance. The study presented here, although it did not establish causal relations, was able to produce some insights from the comparison of two networks and set an agenda for future research. The scope of this study is too narrow to derive policy implications from its results. Still, it was conducted with the hope that existing scientific resources in Russia can be organized more effectively, and that mobilizing (in both senses of the word) regional science could be one of the solutions to this task.

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[10] All characteristics related to mobility were normalized to the size of the city.

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