High-skilled labour mobility in Europe before and after the 2004 enlargement

Alexander M. Petersen[a,1] and Michelangelo Puliga[2]

[1]*Ernest and Julio Gallo Management Program, School of Engineering, University of California, Merced, CA 95343*
[2]*Laboratory for the Analysis of Complex Economic Systems,*
IMT Lucca School for Advanced Studies, Lucca 55100, Italy

The extent to which international high-skilled mobility channels are forming is a question of great importance in an increasingly global knowledge-based economy. One factor facilitating the growth of high-skilled labor markets is the standardization of certifiable degrees meriting international recognition. Within this context, we analyzed an extensive high-skilled mobility database comprising roughly 382,000 individuals from 5 broad profession groups (Medical, Education, Technical, Science & Engineering, and Business & Legal) over the period 1997–2014, using the 13-country expansion of the European Union (EU) to provide insight into labor market integration. We compare the periods before and after the 2004 enlargement, showing the emergence of a new East-West migration channel between the 13 mostly eastern EU entrants (E) and the rest of the western European countries (W). Indeed, we observe a net directional loss of human capital from $E \rightarrow W$, representing 29% of the total mobility after 2004. Nevertheless, the counter-migration from $W \rightarrow E$ is 7% of the total mobility over the same period, signaling the emergence of brain circulation within the EU. Our analysis of the country-country mobility networks and the country-profession bipartite networks provides timely quantitative evidence for the convergent integration of the EU, and highlights the central role of the UK and Germany as high-skilled labor hubs. We conclude with two data-driven models to explore the structural dynamics of the mobility networks. First, we develop a reconfiguration model to explore the potential ramifications of Brexit and the degree to which redirection of high-skilled laborers away from the UK may impact the integration of the rest of the European mobility network. Second, we use a panel regression model to explain empirical high-skilled mobility rates in terms of various economic 'push-pull' factors, the results of which show that government expenditure on education, per-capita wealth, geographic proximity, and labor force size are significant attractive features of destination countries.

Introduction

Human migration is a topic of increasing interest as data quality and coverage is increasing in our digital age. The digital traces, arising from a wide range of electronic recordings of everyday activities provide new avenues to study movements over various scales, from microscopic daily mobility patterns of individuals [1], to mesoscopic patterns accounting for socioeconomic factors [2–4], to macroscopic pattens of long-term international migration [5–13].

Here we provide a contribution to the macro-scale literature concerning cross-border migration, in the particular context of the integration of European labor markets [6]. Despite major efforts, developing a competitive labor market that keeps the best talent within Europe remains a challenge [14]. This is particularly problematic, as mounting empirical evidence indicates that local economic spillovers are generated by the regional agglomeration of activities – both in innovation-driven industries as well as other service industries that follow hightech [15]. Thus, in order to establish and maintain international competitiveness [16], the retention and subsequent leveraging of human intellectual capital is of fundamental importance for knowledge-based economies.

In the case of our study, it is important to highlight two important and inextricable features of European labor markets. First, Europe is among the global leaders in the production of high-skilled labor. Second, the freedom of movement for European Union (EU) citizens between member states is a profound attribute representing a resounding EU achievement. After all, aside from being convenient for European and international travelers alike, open borders are the starting point for competitive labor markets, providing access to a wealth of career opportunities for jobseekers across the EU [6].

In an effort to improve the openness and competitiveness of the *entire* high-skilled labor market, the EU has developed the "Free movement of professionals" program, which provides individuals the opportunity to have their professional credentials certified in other EU countries. While the growth and evolution of the EU has been ongoing for decades, only recently has this data become readily available, making it possible to measure the impact of the EU's "free movement" policies on mobility rates in Europe, and to use this particular type of cross-border activity to measure the progress towards European unity.

Open borders lure hundreds of thousands of career-minded individuals – from a wide range of professions, e.g. teachers, to doctors, lawyers, architects, electricians, etc – to relocate within Europe. Thus, a better understanding of intra-European migration is key to modeling the supply and demand for high-skilled labor in these different labor markets, for measuring the distribution of human and intellectual capital and its geographic convergence over time, and for evaluating European labor market policies.

To this end, recent studies focusing on intra-European networks of cross-border collaboration in publications, patents, and researcher and inventor mobility [17–19] have addressed

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[a] Send correspondence to: petersen.xander@gmail.com

the stagnating progress towards the development of a unified R&D innovation system in Europe [20–22]. Researchers in R&D, however, have traditionally been internationally mobile, and are not necessarily representative of all high-skilled professions. Nevertheless, international mobility is becoming increasingly the norm in other high-skilled professions. Indeed, a recent study shows that the growth of high-skilled migration is outpacing the growth of low-skilled migration, to the point that in 2010 the net levels of each were remarkably similar, thereby illustrating how the international migration of high-skilled labor is an increasingly important topic [5, 13].

Here we contribute to these research streams by performing a large-scale analysis of the dyadic (country-country) and bipartite (country-profession) European high-skilled mobility networks over the period 1997-2014. While the literature on high-skilled labor mobility has traditionally focused on zero-sum perspectives – i.e. 'brain drain' versus 'brain gain' [23–28], we proceed, instead, with an alternative focus by measuring the emergence of European brain circulation – a dynamic cross-border configuration with long-term benefits for individuals and institutions across Europe [29]. We conclude with two data-driven models that leverage the longitudinal and network aspects of the mobility data. In the first model, we develop a heuristic redistribution model to estimate how the potential strength of 'Brexit' may impact the community structure and country centrality within future European mobility networks. In the second model, we use a lagged panel regression framework to identify the strength and sign of various economic "push-pull" factors which best explain the patterns of cross-border mobility over the last two decades.

Methods

We analyzed extensive records from the official EU Commission "Professionals moving abroad (Establishment)" program as documented in The EU Single Market Regulated professionals database. More specifically, this database aggregates records for (certified) professionals who applied for official recognition of their professional certification in a particular host country (destination country) from a given country of qualification (source country) [30]. 32 European countries are included in the database over the 18-year period 1997-2014: Austria (AT), Belgium (BE), Bulgaria (BG**), Croatia (HR***), Cyprus (CY*), Czech Republic (CZ*), Denmark (DK), Estonia (EE*), Finland (FI), France (FR), Germany (DE), Greece (GR), Hungary (HU*), Iceland (IS), Ireland (IE), Italy (IT), Latvia (LV*), Liechtenstein (LI), Lithuania (LT*), Luxembourg (LU), Malta (MT*), Netherlands (NL), Norway (NO), Poland (PL*), Portugal (PT), Romania (RO**), Slovakia (SK*), Slovenia (SI*), Spain (ES), Sweden (SE), Switzerland (CH), United Kingdom (UK). The asterisks indicate the entry year for the new EU member states: *2004,**2007, ***2013. The four countries that are not members of the EU are CH, IS, LI, and NO, however they each maintain close economic agreements; Iceland, Liechtenstein and Norway are members of the European Economic Area (EEA), European Free Trade Association (EFTA) agreements,

and have accepted the Schengen Agreement affording "Free of Movement of Persons" to EU member citizens.

The database also provides the profession ("Recognition Regime") of each high-skilled professional. For example, according to the number of observations, the top-5 mobile professions from 1997–2014 are "Doctor of Medicine" ($N_{obs} = 75,567$), "Nurse" ($N_{obs} = 64,945$), "Secondary school teacher" ($N_{obs} = 43,479$),"Physiotherapist" ($N_{obs} = 18,184$), "Second level nurse" ($N_{obs} = 13,949$). According to the database description at the *The EU Single Market Regulated professionals database* web portal, individual countries are responsible for procuring and providing information, and so variation due to reporting procedures may exist, but to what extent it is not possible to determine. As such, we note that a limitation to our study is the lack of detailed documentation specifying the nuances of the data collection procedure. As such, it is possible that country-level and profession-level reporting bias may exist. We continue under the assumption that the European Commission standards for data collection and reporting are of sufficiently high quality that their use in statistical analysis is warranted.

In order to reduce the dimensionality of this large dataset, we manually categorized the professions into 5 groups: (i) Medical, (ii) Education, (iii) Technical, (iv) Science & Engineering and (v) Business & Legal. Figure 1(a,b) show the frequency of each profession and profession group in our dataset, which is dominated by the Medical and Education profession groups, which account for roughly 62% and 16% of the total mobility, respectively.

We grouped the mobility data according to 13 periods indexed here by $t = 1...13$ corresponding to 1997/1998, 1999/2000, 2001/2002, 2003/2004, 2005/2006, 2007, 2008, 2009, 2010, 2011, 2012, 2013, 2014. For each period indexed by t we recorded $M_{ij,t}$, the total number of high-skilled migrations ("Total positive decisions") from country i ("Country of qualification") to country j ("Host country").

In addition to analyzing the annual mobility matrices $M_{ij,t}$, we also aggregated the first 4 and the final 9 periods into two subsets in order to study the net mobility patterns before and after the 2004 expansion. Figure 2 shows the mobility network after the 2004 enlargement, characterized by the substantial cross-linking in all directions, indicative of the substantial progress towards European labor-market integration. In all, the total mobility (head counts) for a given aggregate time period $M_t = \sum_{ij} M_{ij,t}$ are 381,757 (1997–2014), 43,010 (1997–2004), and 338,747 (2005–2014). Comparing these two periods, before and after 2004, these numbers indicate a 530% increase in the annual mobility of high-skilled labor within Europe.

Results

Regional brain-circulation by profession group. Intra-EU mobility data provides a wealth of new insights into the re-organization of high-skilled labor following the 2004 EU enlargement. In addition to a sharp increase in the total amount of high-skilled mobility, the 2004 EU expansion facilitated a

new mode of high-skilled mobility: East to West (E→W) and West to East (W→E). Here we define "East" as the group of thirteen 2004/2007/2013 EU entrant countries, and "West" as the complementary set of European countries (including non-EU countries CH, IS, LI, and NO).

While the within-region mobility E→E and W→W was dominant before 2004, after the expansion, we observe 29% of the total mobility going from E→W and 6.8% going from W→E. Figure 1(c) shows the breakdown of mobility within and across East-West borders, before and after the 2004 expansion and by profession group. Interestingly, within the Education, Sci&Eng, and Business & Legal profession groups, there was a substantial W→E mobility after 2004.

Figure 1(d) shows the annual dynamics of the intra- and inter-regional mobility flow. The juxtaposition of the Medical profession and the Sci&Eng profession illustrates the non-uniform patterns of mobility. While in the Medical profession the E→W mode has stabilized since 2004 around 30% of the net flow, for Sci&Eng this mode has actually decreased since 2004, from around 26% to roughly 6%. Interestingly, for Sci&Eng there has been a significant shift of mobility towards the E→E mode. The Education profession group also mimics this pattern, although less substantially. Overall, the Medical, Technical, and Business&Legal professions exhibit common dynamic patterns, with the E→W mode being substantial, while Education and Sci&Eng form a second group wherein E→E has been growing over time.

Relative comparative advantage in the import/export of high-skilled labor. In order to measure each country's relative strength as an exporter and importer of high-skilled labor by profession group, we calculated the revealed comparative advantage (RCA) [31, 32] for each country and profession. The scalar quantity $RCA_{i,p}$ measures to what extent the share of the total export (imports) by country i of profession group p is above or below the global share for the same profession.

First some basic definitions. At the aggregate country level, the total incoming mobility is given by $I_{j,t} = \sum_{i,t} M_{ij,t}$ and the total outgoing mobility is given by $O_{i,t} = \sum_{j,t} M_{ij,t}$, serving as 'brain gain' ('brain drain') indicators. We define the relative difference, $B_{i,t} = (O_{i,t} - I_{i,t})/(O_{i,t} + I_{i,t}) \in [-1, 1]$, as a standardized measure of brain drain. We choose this convention for $B_{i,t}$ (i.e. positive values corresponding to $O_{i,t} > I_{i,t}$) in order to be consistent with ref. [19].

Using these conventions, it is then straightforward to calculate each $RCA_{i,p}$ as

$$RCA_{i,p}^{out} = \frac{(O_{i,p}/O_i)}{(O_p/O_{total})} \text{ and } RCA_{i,p}^{in} = \frac{(I_{i,p}/I_i)}{(I_p/I_{total})} . \quad (1)$$

In other words, for exported mobility, the within-country share is given by $(O_{i,p}/O_i)$, and this share is normalized by the net share of mobility in p across all countries, (O_p/O_{total}). As such, the threshold for being above or below the global baseline is $RCA_{i,p} = 1$. By definition, the net export and import shares by profession group are equal, $S_p \equiv (O_p/O_{total}) = (I_p/I_{total})$.

Figure 3(a) shows S_p separated into three sub-periods:

the pre-enlargement period 1997–2004, the pre-crisis period 2005-2007 and the post–crisis period 2008–2014. Figure 3(b) shows the export and import $RCA_{i,p}$ for these same three sub-periods. Since $RCA_{i,p}$ is principally a within-country comparisons, by construction a country can have a relatively large $RCA_{i,p}$ in at most just one or two different p. Conversely, it is possible that several countries have large $RCA_{i,p}$ for the same p group.

By way of example, Poland (PO) appears as significant exporter of Technical professions and Spain (ES) a significant exporter of Education and a significant importer of Sci&Eng in each sub-period. Germany (DE) is closer to baseline levels in all categories during each sub-period. The principal export profession for the United Kingdom (UK) is Business & Legal, with Education being its principal import profession.

Between-country migration and brain drain. The dyadic country-to-country relations provide insight into the high-skilled export and import capacity of each country as well as the role of topology in the mobility network. In general, the network $M_{ij,t}$ is defined by aggregating the mobility data over an arbitrary time interval indexed by t and a given profession group. Figure 4 shows the mobility matrices for all the profession groups after the 2004 enlargement (i.e. $t = [2005, 2014]$).

An important summary variable derived from $M_{ij,t}$ is the net mobility polarization, $B_{i,t}$, with minimum value $B_{i,t} = -1$ corresponding to entirely incoming mobility, and maximum value $B_{i,t} = 1$ corresponding to entirely outgoing mobility. Figure 4 also shows the mobility metrics $O_{i,t}$, $I_{i,t}$ and $B_{i,t}$ for each country and profession. In all, the countries with the largest absolute brain gain $I_{i,t}$ – corresponding to the columns of $M_{ij,t}$ (shown in Fig. 4) with the largest total counts – are DE, BE, UK, CH, and NO. Similarly, the countries with the largest absolute brain drain – corresponding to the rows of $M_{ij,t}$ with the largest total counts – are RO, PL, GR, ES, SE, and DE. Thus, $B_{i,t}$ combines the absolute measures $O_{i,t}$ and $I_{i,t}$, and is useful as a relative measure to compare countries with total mobility rates that differ across several orders of magnitude. For consistency, in Figs. 3 and 4 we ordered the countries in each mobility matrix and bar chart in decreasing order of the $B_{i,t}$ value calculated over the entire period 1997–2014.

Mobility rates and network structure vary by profession, with the Medical professions dominating with the least sparse mobility matrix. The UK dominates most mobility matrices in terms of the largest incoming mobility as well as the broadest distribution of source countries, except for in case of Technical professions. Instead, for Technical professions, the countries with the largest brain-gain are DK, BE, and NO.

In order to provide a quantitative comparison by professions, Fig. 4b shows a matrix with entries representing the Pearson cross-correlation coefficient value calculated between any given pair of mobility matrices. Interestingly, we find that Sci. & Eng. is the least-correlated profession, possibly a result of directed EU R&D policies aimed at establishing an integrated European innovation system [17, 20–22], which results in more distinct mobility patterns. The Medical and Education

mobility matrices are the most highly correlated (Pearson correlation = 0.82).

In order to compress the information contained in Fig. 4, Figs. S1 and S2 visualize the country-profession bipartite networks. We summarize just a few of the most prominent trends. UK has the largest brain gain of Medical professionals and DE and RO have the largest brain drain of Medical professionals; PL shows a relatively large brain drain in Medical, Education, and Technical professions and a small brain gain in Science & Engineering professions.

Evolution of the mobility network: 1997–2004. In order to investigate the relative importance of the 32 European countries within the high-skilled mobility network, we applied the Google PageRank algorithm using the standard 0.85 value for the "damping factor" parameter [33]. It is also important to note that we implemented an algorithm variant modified especially for application to weighted directed networks. The algorithm takes as input the mobility network $M_{ij,t}$ and produces a centrality measure $c_{i,t}$ for each country, with normalization $\sum_i c_{i,t} = 1$ for a given t.

This algorithm, among others, is particularly well-suited to measure the relative importance, or "centrality", of a node (country) within $M_{ij,t}$, where links represent individuals migrating from country to country. Thus, the PageRank algorithm measures the likelihood that a synthetic high-skilled migrant traversing the network – modeled as a "random walker" – might be found at country i. The country-to-country transition (migration) probabilities of the random walker are specified by the empirical $M_{ij,t}$. Thus, this algorithm also incorporates the direction of the network links into the calculation of $c_{i,t}$, which is important here due to the emergence of the new $W \rightarrow E$ mobility channels after 2004.

The baseline centrality value is $c^* = 1/dim(M) = 1/32 = 0.03125$, corresponding to a uniform network where $M_{ij} = $ constant for all ij and $dim(M)$ is the dimension of M, i.e. the total number of countries. Figures 5(a,b) show the evolution of each $c_{i,t}$ over time, including the average within the set of 2004 countries that were already EU members, and the complementary set of non-EU countries. Interestingly, the centrality of Switzerland (CH) has significantly increased, demonstrating the positive externalities of the 2004 expansion on even some non-EU members.

One of our main results follows from the comparison of the average values – $\bar{c}_{EU,t}$ in Fig. 5(a) and $\bar{c}_{non-EU,t}$ in Fig. 5(b) – which together signal the convergence of the EU high-skilled mobility network towards a more uniform network. Specifically, after 2004, $\bar{c}_{EU,t}$ decreased by 14% while $\bar{c}_{nonEU,t}$ increased by 53%. Figure 5(c) compares the networks before -vs- after 2004, identifying the individual countries whose centrality has significantly increased (CH, CY, DK, FR, PO, SE) and decreased (ES, IE, IS, LI, LU, NL).

Estimating the impact of Brexit using a network redirection model. It is unclear how current events may impact these convergent trends. In order to estimate the potential impact of 'Brexit' on the structure of the high-skilled mobility network, we used the $M_{ij,t}$ for $t = 2005-2014$ to simulate what would

happen if a certain fraction q of the observed mobility into the UK, $M_{i \rightarrow UK,t}$, were redirected to other countries as a result of new immigration policies. For a given q, capturing the degree to which the UK limits the freedom of movement – i.e. the 'hardness' of Brexit – we modeled this scenario by redistributing the incoming mobility $M_{iUK,t}$ to other countries instead. For $q = 0$ the mobility network represents the empirical $M_{ij,t}$ and for $q = 1$ represents an extreme scenario where no high-skilled migrants are able to enter the UK.

We operationalized the range of hypothetical 'Brexit' scenarios by defining a reconfigured mobility matrix

$$M_{ij,t}^H \equiv M_{ij,t} + \Delta M_{ij,t} \tag{2}$$

where

$$\Delta M_{ij,t} \equiv q M_{iUK,t} M_{ij,t}/(O_{i,t} - M_{iUK,t}) \text{ for } j \neq UK \tag{3}$$

and $\Delta M_{iUK,t} \equiv -q M_{iUK,t}$ for $j = UK$. Importantly, this redirection scheme conserves the total observed mobility $M_t = \sum_i O_{i,t} = 338,747$ for all q over the period 2005–2014. To illustrate by way of example, consider a country i with outgoing mobility O_i divided between just three countries, UK, A, and B. The mobility to country A is $M_{iA}^H = M_{iA} + q M_{iUK} M_{iA}/(M_{iA} + M_{iB})$, and similarly, the mobility to country B is $M_{iB}^H = M_{iB} + q M_{iUK} M_{iB}/(M_{iA} + M_{iB})$; then it follows that $M_{iA}^H + M_{iB}^H + M_{iUK}^H = O_i$, and so the total outgoing mobility is conserved for each country i, and thus for the entire system.

Using this redirection scheme, we start by considering an extreme example corresponding to the $q = 1$ extremely 'hard brexit' scenario where *all* incoming high-skilled mobility to the UK is redirected to alternative countries. The scatter-plot in Fig. 5(d) compares the centralities calculated for the real $M_{ij,t}$ and this extreme scenario $M_{ij,t}^H(q = 1)$, showing that most countries are above the diagonal equivalence line indicating a more central position within the mobility network, with the exception of CY, IE, and the UK, with each experiencing a dramatic decline in $c_{i,t}$.

Because the $q = 1$ scenario is unrealistically extreme, we also calculated the country centralities for hypothetical matrices across the entire range of $q \in [0, 1]$. Then, for a given q and country i, we calculated each country's percent change relative to the baseline (empirical) $q = 0$ scenario,

$$\%_i(q) = 100[c_{i,t}(q) - c_{i,t}(q = 0)]/c_{i,t}(q = 0) . \tag{4}$$

Figure 5(e) shows the range of $\%_i(q)$ across all the countries analyzed for the $q = 0.8$ ("harder Brexit") and $q = 0.2$ ("softer Brexit") scenario. Interestingly, for both of these q values, most countries increase their centrality with the exception of CY, IE, RO, and UK. Thus, in addition to demonstrating the magnitude of UK decline (-97.5% for $q = 1.0$, -78.4% for $q = 0.8$, and -15.8% for $q = 0.2$), we also demonstrate the negative externalities associated with the countries most connected with the UK in the high-skilled mobility network.

In order to further explore the dependence on q, Fig. 5(f,g) shows $\%_i(q)$ for each country. Remarkably, each $\%_i(q)$ ex-

hibits a roughly monotonic progression between the $q = 0$ (real) and the $q = 1$ scenario. As initially suggested by comparing the results in Fig. 5(e), and because the progression between $q = 0$ and $q = 1$ is nearly linear, we find that the distribution of $\%_i(q)$ differ by nearly a constant factor. A corollary of this feature is that the mobility network demonstrate convergent integration – independent of q.

We also considered a generalized redirection model, $\Delta M_{ij,t} \equiv q M_{iUK,t} w_{j,k}$, in which a country's "attraction" $w_{j,k} = (F_{j,k}/F_{total})$ is defined according to a generic variable k, where $F_{total} = (\sum_j F_{j,t,k}) - F_{UK,t,k}$ is a normalization factor to conserve the total mobility. In order to demonstrate the robustness of the results reported in Fig. 5(f,g), we repeated the redirection model analysis using three different economic variables to define $F_{j,t,k}$: (i) government expenditure on education, (ii) GDP per capita, and (iii) labor force size. Specifically, for each country we define $F_{j,t,k}$ as the mean value over the period 2009-2014; we averaged over this period because World Bank data for several countries and variables are not yet available for the most recent years. Figure S3 shows that the UK, IE, and CY each show significant negative $\%_i(q)$ regardless of the choice of the variable k; also, the nearly linear progression of each curve as a function of q is a feature that also appears to be independent of k. However, the ordering of the countries according to the magnitude of $\%_i(q)$ is k-dependent, because basing $w_{j,k}$ on just a single variable neglects the other factors that may play, in concert, important roles underlying mobility decisions. Thus, the results in Fig. 5(f,g) calculated using the empirical mobility $F_{j,t,k} \equiv M_{ij,t}$ produce more inclusive estimates for $\Delta M_{ij,t}$.

To further illustrate the reorganization of the high-skilled mobility networks, we also calculated the community structure of $M_{ij,t}$ and $M_{ij,t}^H$ using the weighted Louvain modularity maximization algorithm [34, 35]. In the empirical network shown in Fig. 6(a), the UK is mainly a brain-gain hub dominating the community composed of Mediterranean countries (ES, IT, PT), new entrants (RO, MT, BG) and its close geographic neighbor Ireland (IE). Meanwhile, DE is the community hub among its geographic neighbors, and NO serves as the community hub for the northern countries. However, in the hypothetical $q = 1$ "hard Brexit" network shown in Fig. 6(b), the number of communities decreases, with the DE community maintaining its constituency; moreover, the entrants CY, GR, PL, and RO are redistributed across the 3 remaining communities, and the incumbents ES, IT, and PT join the France-Benelux community. Altogether, this reorganization indicates a more geographically mediated community structure, consistent with those recently observed for cross-border R&D networks [17].

Multi-factor "push-pull" mobility model. Given the panel nature of the mobility data, we investigated various economic factors, for both the source and the destination country, that may influence high-skilled mobility decisions. As such, this model falls into the class of "push-pull" models [36] which are particularly useful for modeling international migration and estimating long-term population projections [5, 12]. Hence,

we define a 1-period lagged model given by the equation

$$M_{ij,t+1} = \exp[\vec{\beta} \cdot \vec{x}] \prod_k f_{ij,t,k}^{\beta_k} , \qquad (5)$$

where on the left-hand-side is the observed mobility in year $t + 1$, and on the right-hand-side are factors observed in year t; additional lags, for $t - 1$ etc., could also be implemented, but for the sake of brevity we keep the model simple in form. The model is multiplicative, with individual factors $f_{ij,t,k} = F_{j,t,k}/F_{i,t,k}$ measuring the relative difference in the variable $F_{t,k}$ between the source (i) and destination (j) countries.

We collected 7 country-level macro-economic variables from the World Bank Open Data Catalog [37], that could impact high-skilled mobility decisions: (i) $F_{t,H}$ is the total health expenditure (sum of public and private) as a percentage of GDP; (ii) $F_{t,E}$ is the total expenditure on education as a percentage of government expenditure on all sectors; (iii) $F_{t,R}$ is the number of researchers in R&D per million people (i.e. per capita); (iv) $F_{t,U}$ is the total unemployment rate reported as a percentage of the total available labor force that is without work; (v) $F_{t,L}$ is the total labor force size, reported as the economically active population size including individuals 15 years or older; (vi) $F_{t,G}$ is the gross domestic product per capita; and (vii) $F_{t,P}$ is the percent of the total population living in urban areas.

We then constructed a time and country panel dataset and used ordinary linear regression (OLS) to estimate the parameters of the corresponding linearized panel model with 1-period lags, specified by

$$\log_{10} M_{ij,t+1} = [\vec{\beta} \cdot \vec{x}] + \sum_k \beta_k \log_{10} f_{ij,t,k} + \epsilon \qquad (6)$$
$$= [\beta_0 + \beta_D \log_{10} D_{ij} + \beta_N N_{ij} + \vec{\beta}_{i \to j} \cdot E\vec{W}_{ij}]$$
$$+ \beta_H \log_{10} f_{ij,t,H} + \beta_E \log_{10} f_{ij,t,E} + \beta_R \log_{10} f_{ij,t,R}$$
$$+ \beta_U \log_{10} f_{ij,t,U} + \beta_L \log_{10} f_{ij,t,L}$$
$$+ \beta_G \log_{10} f_{ij,t,G} + \beta_P \log_{10} f_{ij,t,P} + \epsilon .$$

which follows from taking the logarithm of Eq. 5; we excluded LI and LU from this analysis because they lacked complete World Bank data. The variables represented by $\vec{\beta} \cdot \vec{x}$ capture time-independent dyadic information: D_{ij} is the distance between the capitals of the two countries, N_{ij} is a dummy variable for neighboring countries ($= 1$ if sharing a land border and 0 otherwise), and $\vec{\beta}_{i \to j} \cdot E\vec{W}_{ij}$ is a set of dummy variables accounting for the four types of regional mobility: $W \to W$, $W \to E$, $E \to E$, and $E \to W$; and ϵ is residual normally-distributed noise. For standard summary statistics and cross-correlations between pairwise sets of variables see Fig. S4.

Of principal interest is the relation between the dependent variable and each of the economic variables, captured by the elasticity β_k, which measure the percent change in $M_{ij,t+1}$ corresponding to a 1% change in the ratio $f_{ij,t,k}$. Moreover, if $\beta > 0$ then there is a propensity for mobility to flow in the direction of increasing F_k (i.e. $F_{j,t,k} > F_{i,t,k}$). Contrariwise, for $\beta < 0$ there is a propensity for mobility to flow in the

direction of decreasing F_k ($F_{j,t,k} < F_{i,t,k}$). The crossover value $\beta \approx 0$ corresponds to mobility that is either impartial or indiscriminate ($F_{j,t,k} \approx F_{i,t,k}$) with respect to F_k.

In order to compare and contrast the estimates for two profession groups, we ran separate estimations using two different mobility data subsets: (i) Medical and (ii) Sci&Eng combined with Technical professions. Figure 7 shows the point estimates for the model parameters, estimated with and without source-country fixed effects. We use source-country fixed-effects, corresponding to an additional term β_i in the model specification, to further control for unobserved variation in country-level time-independent features such as geographic and institutional factors. We report the full set of of parameter estimates in Tables S1-S2.

These model estimates provide three basic insights into "push and pull" factors underlying high-skilled mobility. First, we observe mostly consistent results between both profession groups, except that larger urban population size was important for Sci.&Eng.&Tech. professions, but not for the medical profession, which can be explained by considering the differential role of large cities as attractors of R&D, in addition to the less geographically concentrated demand for medical experts. Second, we ran the regressions using standardized variables to estimate "beta" coefficients that are more suitable for cross-comparison, finding that the two strongest positive factors are government expenditure on education and total labor force size. And third, as anticipated, the model shows that mobility is preferred between neighboring countries and countries with smaller distance between their capitals. These results point to ways in which origin-country policy-makers can make their countries more attractive to high-skilled laborers contemplating the choice to leave or stay. Indeed, a recent study of European researchers indicates that factors affected by national policy relating to professional competitiveness play a significant role in determining scientists' choices to emigrate [29].

Discussion

Brain-circulation by the numbers. The EU has expanded by 13 countries since 2004. In the meantime, roughly 338,000 Europeans have taken their first migration step by receiving official cross-border certification of their professional credentials. Even following the 2007/2008 global financial crisis there was no slowdown, with cross-border mobility averaging around 44,000 professionals per year.

In order to provide new insights into the integration of high-skilled labor markets in Europe, we analyzed the The EU Single Market Regulated professionals database, which tracks applications and outcomes for cross-border certifications across a wide spectrum of 390 high-skilled professions across 32 European countries. We used the brain-drain measure $B_{i,t}$ – defined as the relative difference between the net brain drain and the net brain gain – to identify the countries with the largest relative outflow (LT, EE, RO, and BG) and inflow (UK, CH, LU, NO, and CY).

Indeed, upon closer inspection, the mobility networks point to the complex history of EU integration characterized by the dichotomy between brain drain and integration. For example, 2004 entrant CY experienced a significant brain-grain, mainly from GR, in the Science & Engineering and Business & Legal profession groups. One possible explanation, especially in the context of Business & Legal professions, is Cyprus' history of liberal tax laws which made it an attractive relocation destination.

We also quantified the net high-skilled mobility by geographic region – namely, from the new entrants ("eastern" – E) to the older incumbent EU members ("western" – W) following the 2004 expansion (see Fig. 1). Roughly 29% of the total mobility was from east to west over this period, a percentage which has nevertheless varied over time and by profession. Meanwhile only 6.8% of the mobility was from west to east.

Despite the disparity in $E \rightarrow W$ and $W \rightarrow E$ flows, it is important to consider that both of these mobility channels were nearly non-existent prior to 2004. That is, optimistically speaking, it is important to appreciate these new east-west channels as the initial phase of the integration process towards more uniform levels of brain circulation. To this end, Figure 2 puts the big picture in perspective – that investment in cross-cutting human and social capital is investment towards an integrated Europe, with the links that extend in all directions capturing the diverse options for intra-Europe mobility.

We also categorized the mobility data into 5 broad profession groups: Medical, Education, Technical, Science & Engineering, Business & Legal. Notably, the trend in the $W \rightarrow E$ mobility channel is increasing for the Education, Science & Engineering, and Technical professions. Analysis of the data by profession also indicates which countries are relatively competitive as importers and/or exporters of each type of high-skilled labor. For example, since 2008, many of the EU entrants have shown a relatively high RCA as importers of Science & Engineering professionals, possibly indicating the home-return of prior emigrants.

Convergence towards integration of high-skilled mobility. Two important questions are – by what means and to what extent are Europe's high-skilled labor markets unifying. In order to address these questions, we calculated the 'importance' of each country within the mobility network using the Google PageRank algorithm, which estimates the likelihood that a simulated individual, who randomly traverses the weighted network shown in Fig. 2, might be located at a given country (node) within the network.

Not surprisingly, Germany (DE) and the United Kingdom (UK) are the most central countries. By analyzing the topology of the network using standard community detection algorithms, we find that these two countries plays distinct roles: DE is a hub for its neighboring countries, whereas the UK is largely a gateway hub for 2007 entrants BG and RO in addition to southern countries ES, IT, and PT. Interestingly, DE shows more outgoing mobility than incoming, which is another signal of developing home-migration channels.

With the emergence of $W \rightarrow E$ mobility channels following the 2004 enlargement, the eastern countries are slowly gaining centrality within the network. The extent to

which convergence towards a more unified labor market is being achieved is shown in Figure 5, which compares the centrality measures before and after the 2004 enlargement. Running diagonal is an equivalence line which separates those countries that increased from those that decreased over the sample period. Indeed, the older incumbent EU members are mostly below the diagonal equivalence line (decreasing centrality), whereas the new EU members are above the diagonal equivalence line (increasing centrality). These patterns signal the convergence of EU high-skilled labor markets following the emergence of return-migration pathways that lead away from the high-skilled mobility hubs, pointing back in the direction of the southern and eastern countries which were likely the original source of brain drain.

Investing in brain-circulation. Knowledge economies will be increasingly concentrated within high-skilled innovation hubs [15]. As such, it is important to understand the long-term impact of careers passing through these hubs by fostering opportunities for professionals to leave and return to their home country or region. Indeed, recent evidence indicates that brain drain can nevertheless have positive effects, such as higher propensity for workers in the source country to invest in educational and positive network externalities on trade and technological adoption [14, 23, 26, 38].

Scientists are likely aware of the long-standing tradition of European initiatives aimed at fostering both cross-border mobility (e.g. Marie Curie actions which fund short-term research fellowships) and cross-border activity (e.g. the European Cooperation in Science and Technology (COST) program which provides funding to gather researchers across Europe for short-term conferences, schools, and missions) – both serving as long-term investment in European unity.

Moreover, efforts to lower cross-border mobility barriers extend beyond academia. Additional ongoing efforts to foster cross-border mobility include the europass system, an interoperable system for streamlining and standardizing the intra-EU job-application process, as well as the blue card program aimed at stimulating opportunities on the international labor market outside of Europe.

In order to foster long-term knowledge and social capital investment within and across its borders, towards the ultimate goal of developing an efficient and competitive European innovation system [22, 38], the EU should continue to develop policies that create beneficial conditions for brain circulation, prioritizing home-return [39, 40]. Along these lines, recent research indicates that the high-skilled labor market is particularly responsive to labor policies, as demonstrated by the case of non-compete agreements and inter-organizational mobility [3]. The attractiveness of home-return could be improved by focusing on work environment conditions and short-term economic incentives, such as fixed-term tax waivers and prioritized job placement for returnees, so that the incentives to leave and return home are more symmetric. Furthermore, recent surveys of migrant researchers indicate that issues relevant to national science policy are the main factors considered when deciding to leave home, but that family and quality-of-life factors play the strongest role in deciding to return home

[29].

We also used the longitudinal nature of the mobility data to develop a push-pull migration model to identify country-level economic factors that may influence high-skilled mobility decisions. We operationalized the inclination for migrants to be pushed by lack of opportunities in the origin country or pulled by favorable conditions abroad – the classic "push-pull" framework [36] – by oriented our panel regression model around the relative levels between destination and source country using the ratio $f_{ij,t,k} = F_{j,t,k}/F_{i,t,k}$. Our model includes seven economic dimensions indexed by k – public health expenditures, educational expenditures, unemployment rates, labor force size, R&D labor force size, the concentration of the population in urban centers, and standard of living (GDP per capita) relevant to emigration decisions. We then estimated the elasticity β_k associated with each variable k. One clear result that could be leveraged by policy makers is the propensity for high-skilled mobility to flow from countries with lower to higher expenditure on education ($\beta_E > 0$).

'Brexit' and mobility redistribution in Europe. Finally, high-skilled mobility deserves serious consideration in the wake of the 06/23/2016 'Brexit' referendum. While economists and policy makers have warned about the negative impact that 'Brexit' may have on trade between the UK and the EU, largely stemming from the time-consuming, costs and uncertainty associated with the renegotiation process, there has been less dialogue concerning the impact of 'Brexit' on the "Free Movement" of high-skilled workers to and from the UK.

Similar to the implications of Brexit on international trade, here we addressed a particularly important facet – the impact of 'Brexit' on the structure of high-skilled mobility networks in Europe. Our results show why it is particularly important for European stakeholders to strongly consider the privileges associated with being part of a unified labor market, in particular access to large stocks of high-skilled laborers who together make considerable contributions to local economies.

Against this backdrop, we developed a heuristic redistribution model to estimate the long-term impact of Brexit on the European high-skilled mobility network. We operationalized the degree to which the UK reduces 'Freedom of Movement' agreements with the EU, i.e. the 'hardness' of Brexit within the context of high-skilled mobility, using a parameter q which controls the amount of incoming mobility that is redirected from the UK to other European countries. We use the PageRank centrality to quantify the role of each country in the mobility network, finding that for both soft Brexit (small q) and hard Brexit (large q), that the parity within the EU increases. Remarkably, by varying q, we also find that the relative change in parity is nearly independent of q.

The 2014 Swiss referendum, which limited the freedom of movement across its borders, first demonstrated the unintended consequences of national policy shifts on high-skilled professions, in particular academics. As a result, the Erasmus program in Switzerland was interrupted, and Swiss academics

temporarily lost access to the European Research Council funding program, with the Swiss National Science Foundation (SNF) having to make unanticipated efforts to fill the science funding gap for its researchers. As such, the potential impact of 'Brexit' on science in the UK could be enormous, especially when considering that UK is the leading host country of 2015 ERC Consolidator grants, with more than half of its 67 grantees being foreign nationals [41]. Supporting this boon are Germany and Italy, the two largest exporters of ERC grantees over the period 2007-2013 (see Figure 6.17 in ref. [42] for incoming and outgoing ERC grantee nationals by country).

Nevertheless, despite the negative impact of 'Brexit' on UK science, our findings indicate that the substitution of destination country, away from the UK, may increase the integration of Europe by facilitating the convergence of high-skilled labor markets in Europe. As such, our analysis highlights how mobile professionals are a fundamental type of cross-border link, which are crucial conduits for cross-border knowledge and skill transfer as well as fostering European unity.

Acknowledgements

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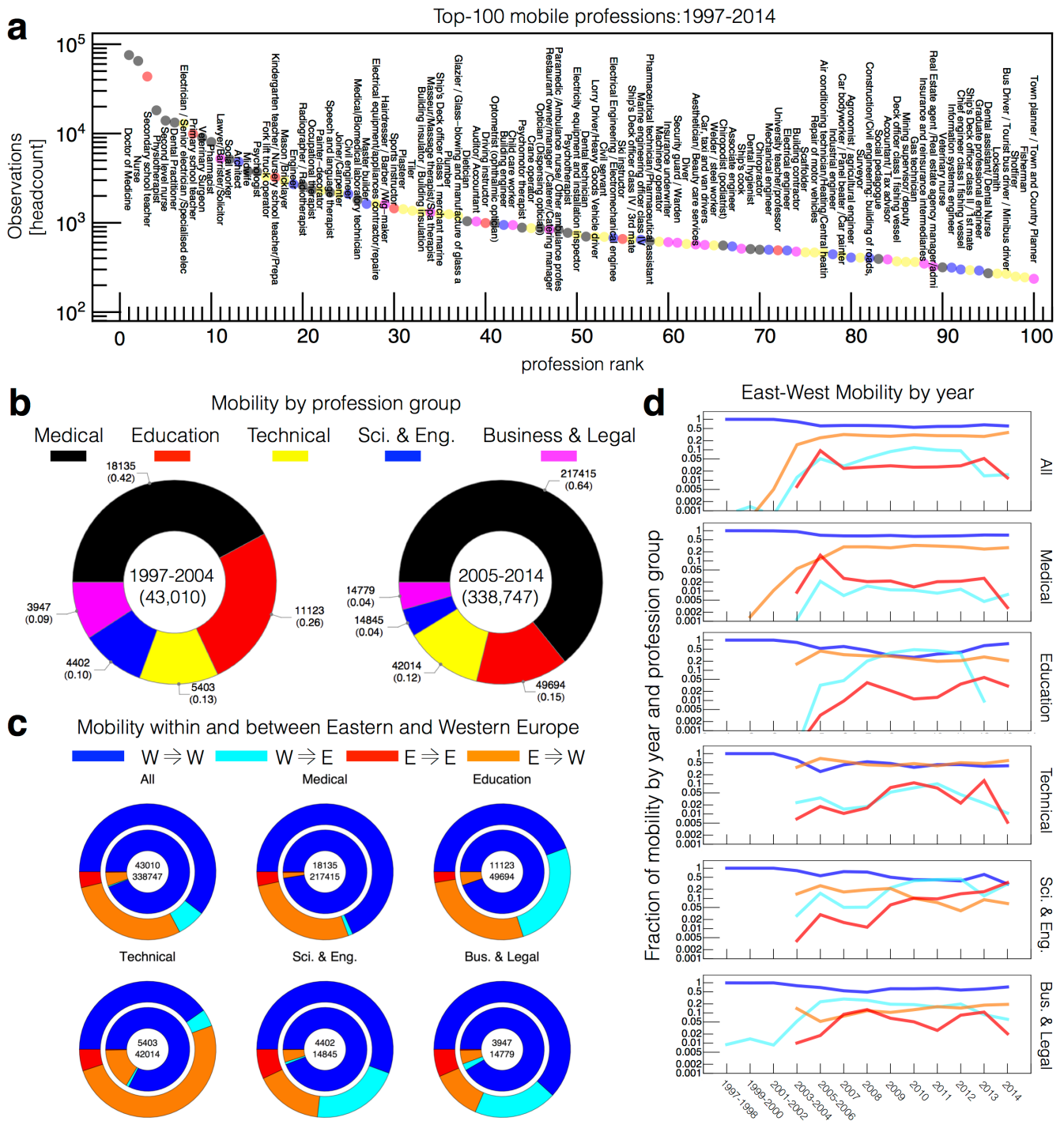
FIG. 1: **High-skilled mobility – by profession and geographic region – before and after the 2004 EU expansion.** (a) Rank-distribution of the top-100 high-skilled professions over the entire period of analysis, 1997–2014. The color of each datapoint corresponds to its classification within the 5 broad profession groups. Dividing any given value by the total number of observations (381,757) gives the frequency, i.e. the top two professions are "Doctor of Medicine" and "Nurse," accounting for 20% and 17% of the total observations, respectively. The top-100 professions shown account for 97% of the total observations. (b) Distribution of the observations by profession group – before and after the 2004 EU expansion. Totals within each profession group and within each period are shown. (c) Comparison of the mobility within and between Eastern and Western Europe before (inner ring) and after (outer ring) the 2004 EU expansion. Listed in the center of each ring chart are the total mobility before (top) and after (bottom) 2004. (d). Disaggregation of the East-West mobility flow by year and profession group. Note that the y-axis is shown on logarithmic scale.
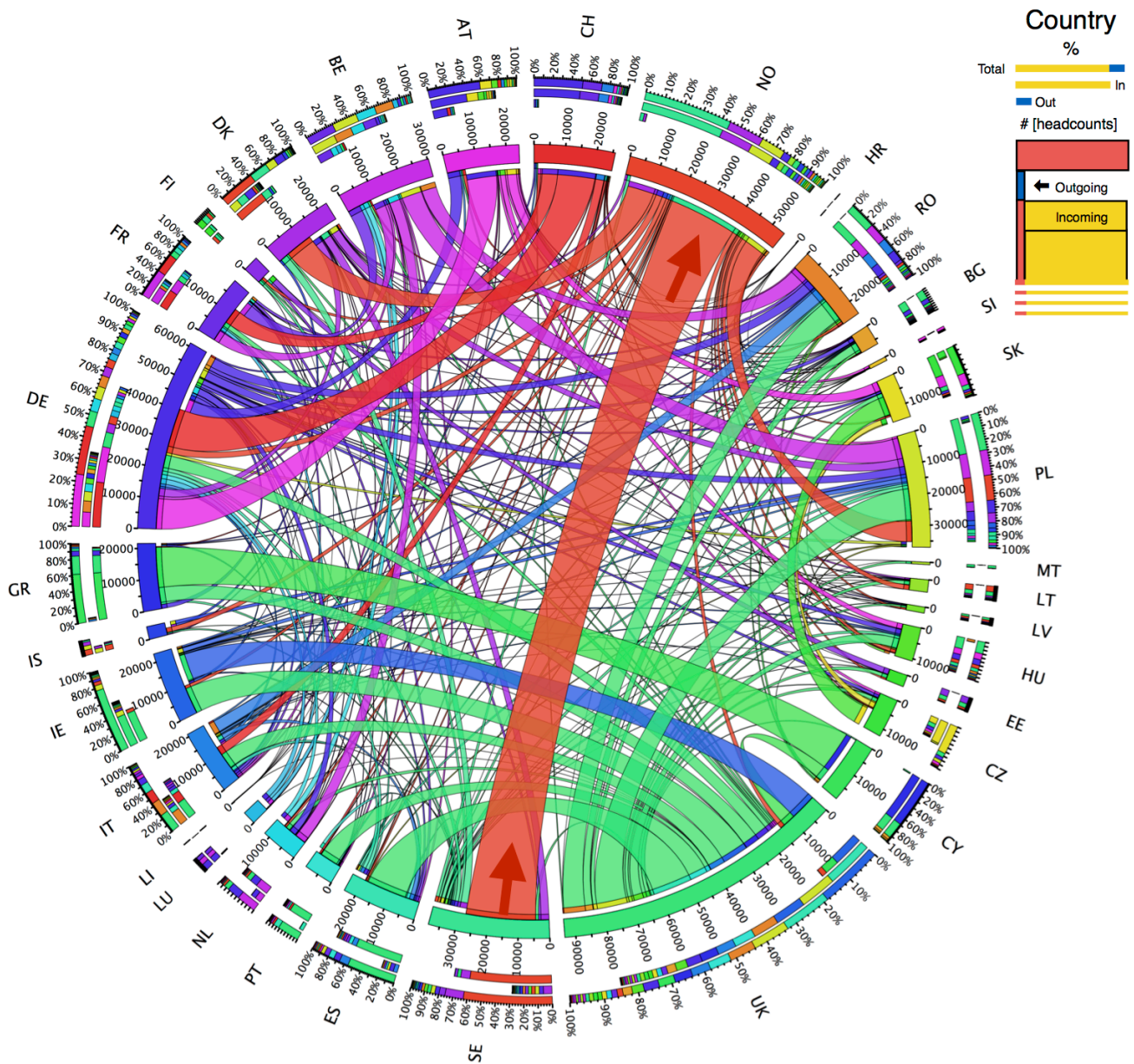
FIG. 2: **High-skilled mobility network: 2005–2014.** Each country is represented on the circumference with an arc-length that is proportional to the total incoming and outgoing mobility of each country after the 2004 EU enlargement. The ribbons between each country are proportional to the mobility $M_{ij,t}$. The mobility direction is encoded in the color of the ribbon, which is the same as the destination country, as well as the endpoint characteristics of the ribbon, denoted by the gap between the ribbon and the termination arc. The legend provides a schematic example of a country which receives incoming mobility from just a single (yellow) country, and provides outgoing mobility to just a single (blue) country. As such, the mobility of each country can be summarized by 3 histograms shown: the outer-most arc represents the total distribution of mobility by all partner countries, the middle arc represents the distribution of incoming mobility by source country, and the inner arc represents the distribution of outgoing mobility by destination country. For example, roughly 80% of mobility for UK is incoming; of the remaining 20% of outgoing mobility, almost 10% is going to IE. Shown are only the links representing more than 1% of the total flow into or out of a given country; the links shown account for 93% of the total mobility.
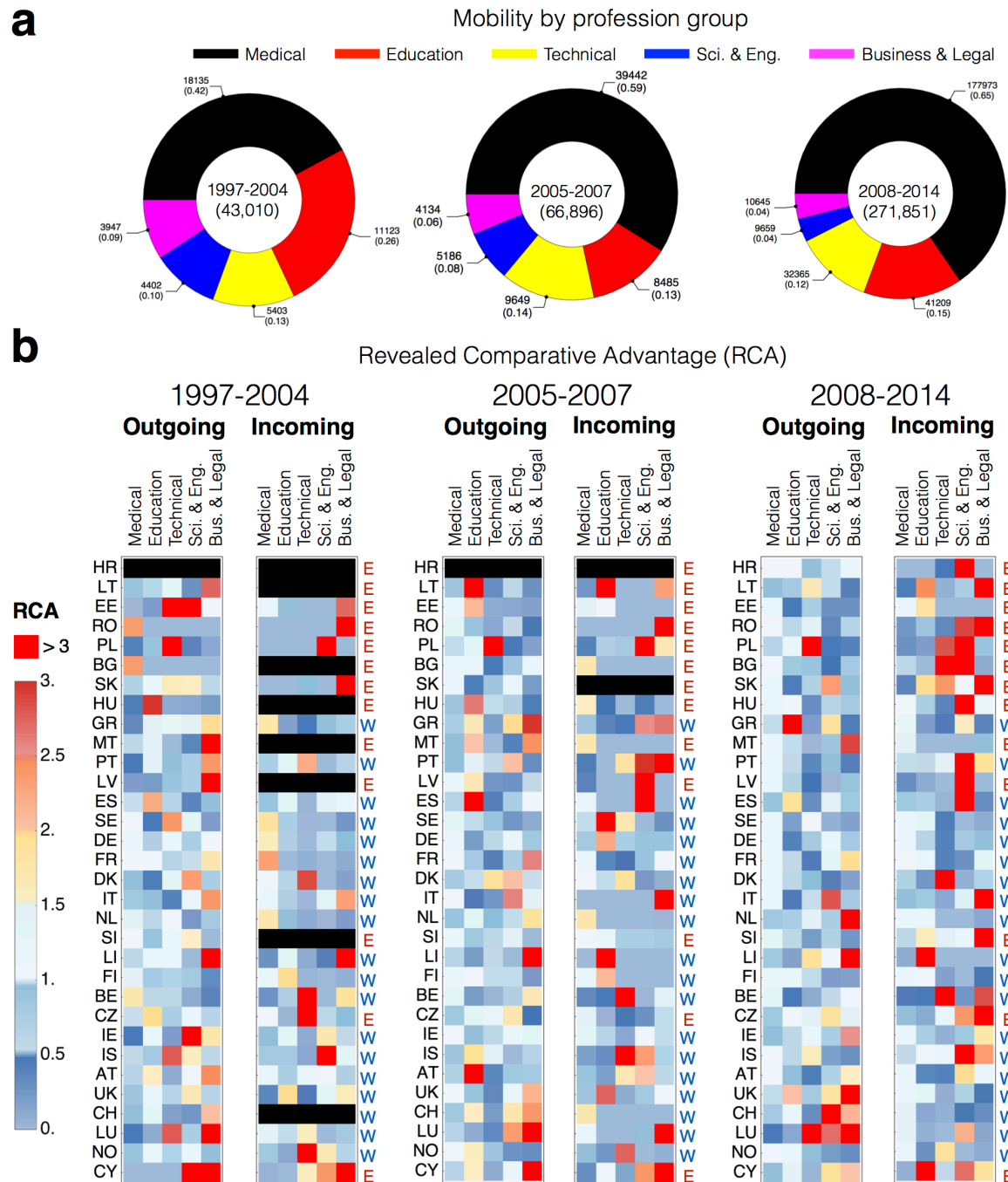
FIG. 3: **Comparative importers and exporters of high-skilled labor.** (a) High-skilled mobility: before 2004, and in the periods before and after the 2007 global financial crisis – by profession group. (b) Revealed comparative advantage (RCA) by country and profession. Countries are ordered according to the overall level of high-skilled emigration over the entire period 1997-2014, and are assigned to the subgroup "E" if they are among the 2004/2007/2013 EU entrants and "W" otherwise. Within the RCA matrices, black squares indicate countries with no observed counts for the specified time period. The color scale splits the range of values into 7 groups: six groups of width 0.5 and one group for those extreme values for which $RCA_{i,p} > 3$. Thus, blue shade values can be considered as significantly below or around the baseline $RCA_{i,p} = 1$ value, whereas yellow/red values are significantly above $RCA_{i,p} = 1$.
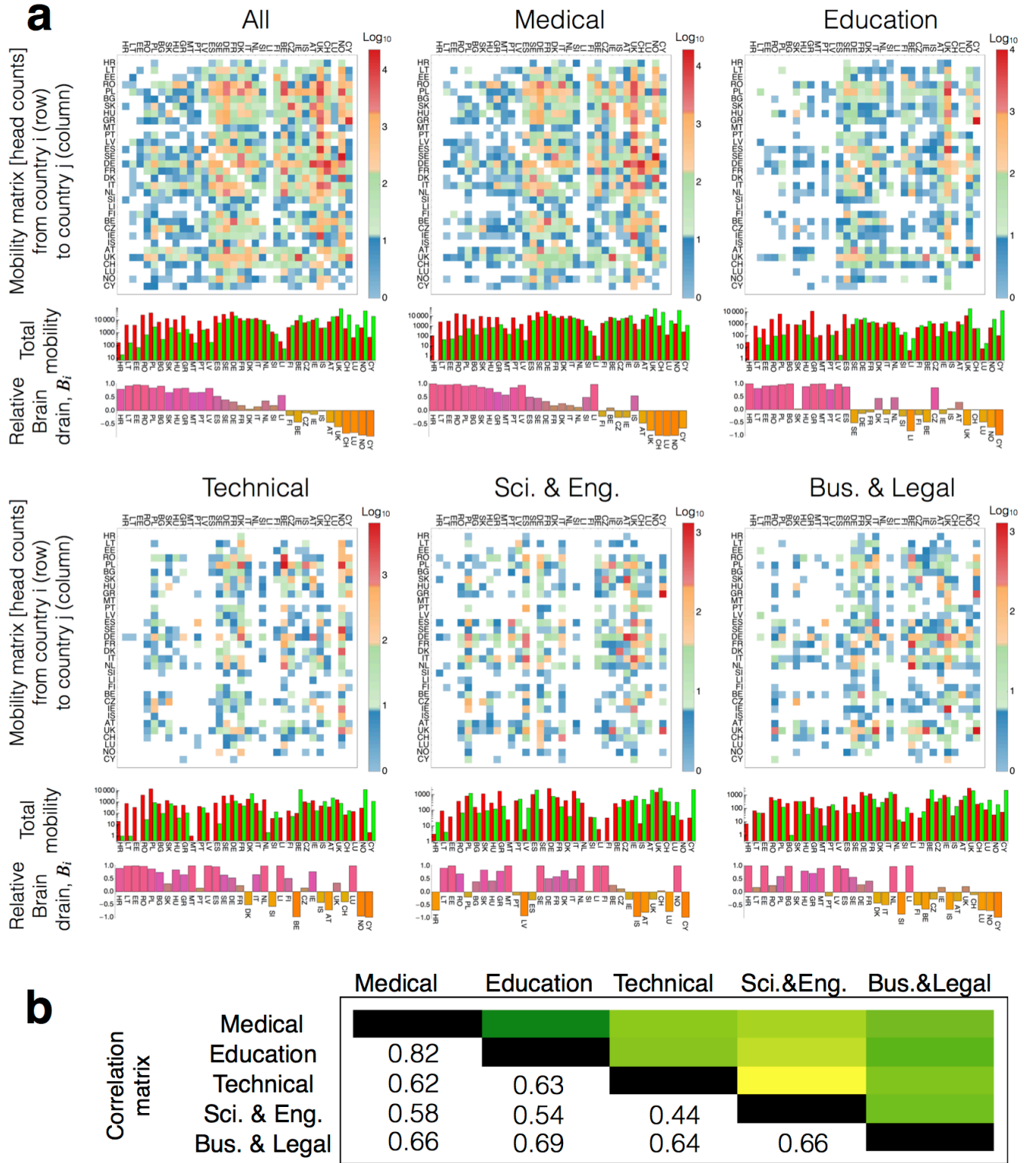
FIG. 4: **High-skilled mobility matrices separated by profession group.** (a) Shown are the mobility matrices representing net headcount from row country i to column country j over the period 2005-2014. The aggregated matrix ("All") is the total across all 5 profession classes. The color scale for each matrix visualization represents a partitioning of the $\log_{10} M_{ij}$ matrix entries into quartiles to facilitate visual inspection and for identifying the strongest dyadic flows. Below each matrix we also show for each country the total outgoing mobility O_i (red bars), total incoming mobility I_i (green bars), and relative brain drain $B_i = (O_i - I_i)/(O_i + I_i)$. (b) Matrix showing the Pearson correlation between each of the profession-specific mobility matrices shown in (a); correlation calculated between logarithmically scaled matrices, $\log_{10}(1 + M_{ij,t})$; correlation values are shown in the corresponding lower triangular cells.
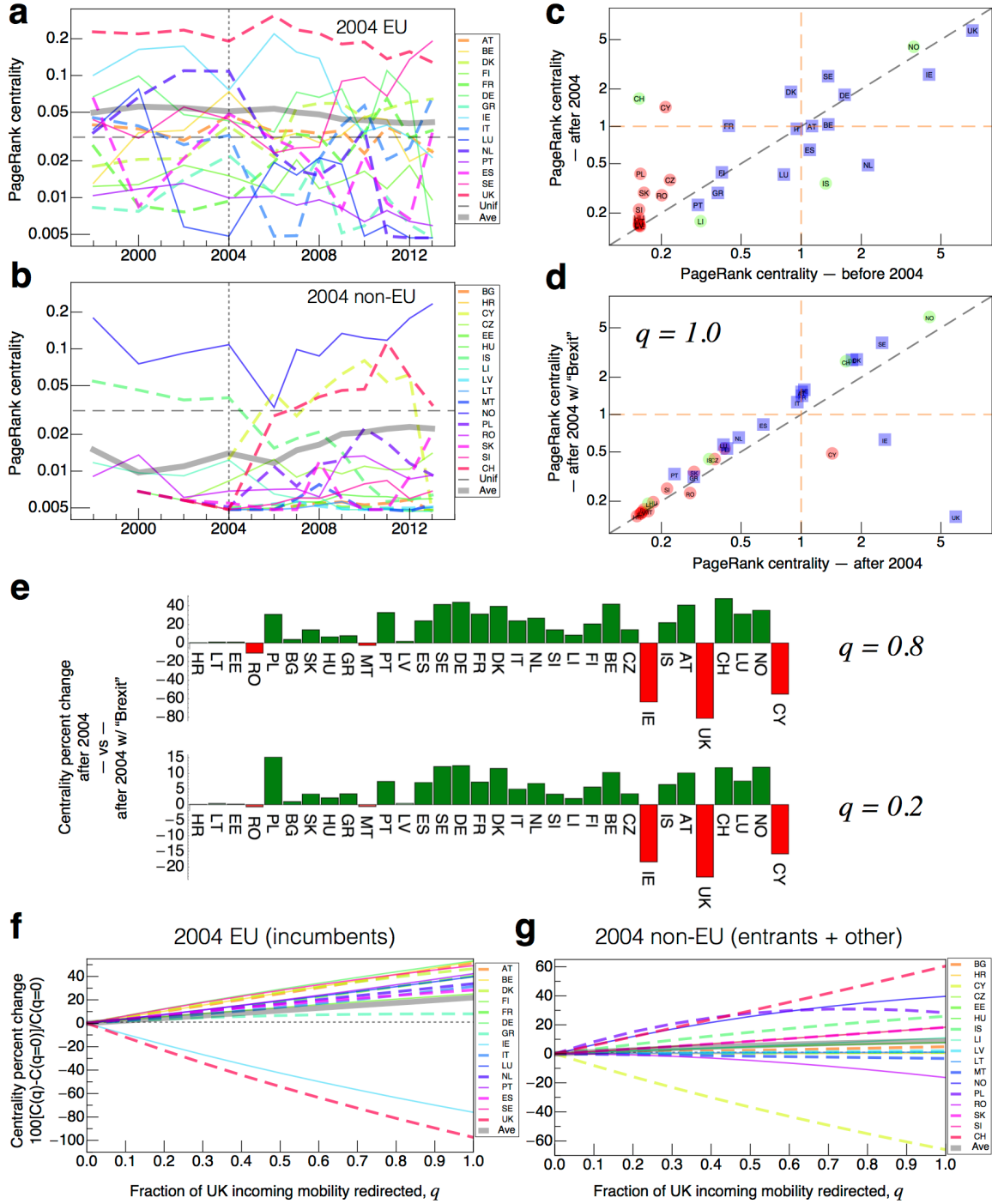
FIG. 5: **Convergence within the European high-skilled mobility network.** (a) Centrality time series ($c_{i,t}$) for each of the incumbent EU members in 2004. (b) $c_{i,t}$ for each of the European countries that were not EU members in 2004. For visual comparison, each panel includes a horizontal dashed line corresponding to the uniform baseline $c^* = 1/32$. Panels (a) and (b) include the average $\bar{c}_t$ (thick grey curve) calculated across the countries in each panel, respectively; the y-axes is plotted on logarithmic scale. (c) Scatter plot of the PageRank centrality of each country representing each country's relative importance within the network, calculated using a standard algorithm for weighted networks applied to the pre- and post-2004 mobility networks. Points above (below) the diagonal dashed line indicate that the country's centrality increased (decreased) between the two periods. (d) Scatter plot of the PageRank centrality of each country using the post-2004 (2005-2014) mobility networks, with the vertical value representing the centrality in a hypothetical 'extremely hard Brexit' scenario with $q = 1$ corresponding to 100% of incoming UK mobility redirected elsewhere. The c_i data points in panels (c) and (d) are normalized by c^*, and thus we show the baseline (mean) centrality value equal to 1, indicated by the dashed orange horizontal/vertical lines; data plotted using logarithmic axes. (e) Percent change $\%(q \equiv 1)$ in the PageRank centrality under the $q = 0.8$ and $q = 0.2$ 'Brexit' scenarios. (f) Percent change $\%(q)$ in the PageRank centrality of 2004 incumbent EU members as a function of q, the fraction of redirected incoming UK mobility; (g) Percent change $\%(q)$ in the PageRank centrality of 2004 entrant and non-EU members as a function of q. Thus, as shown in (e), the $q = 1$ values in (f,g) represent the maximum percent change values for most countries. Within (e,f), the average $\%(q)$ value is indicated by the opaque grey curve.
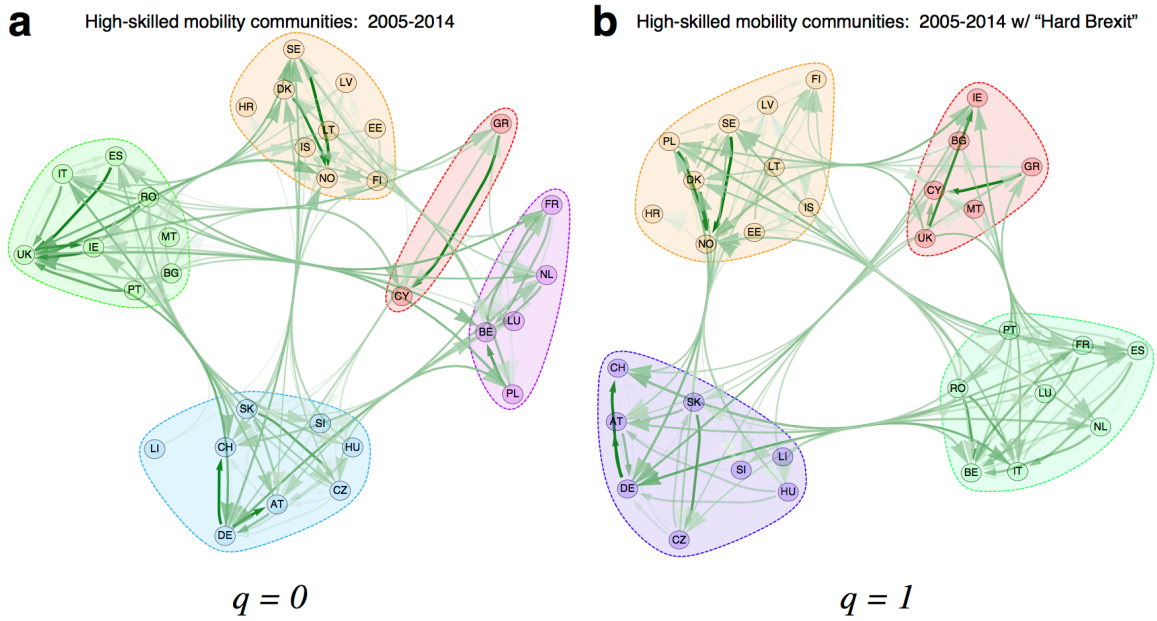
FIG. 6: **Comparison of the mobility network community structure: empirical versus hypothetical "hard brexit" scenario.** (a) Community structure for the empirical mobility network ($q = 0$) characterized by 5 communities. (b) Community structure for the hypothetical 'extremely hard Brexit' scenario ($q = 1$) characterized by 4 communities. Larger arrow size and link darkness indicate higher mobility.
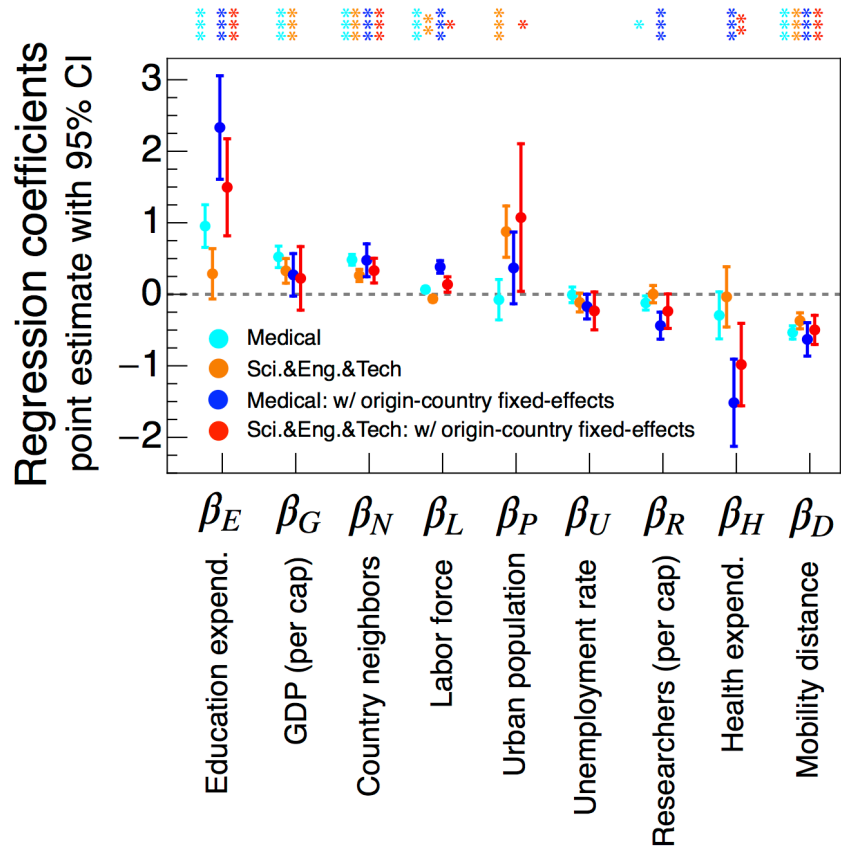

FIG. 7: **Mobility regression model estimates.** See Eq. (7) for the model specification and Tables S1-S2 for the full set of model parameter estimates for each profession and specification. Significance levels: * ($p<0.05$), ** ($p<0.01$), *** ($p<0.001$).

Supplementary Material:

High-skilled labour mobility in Europe before and after the 2004 enlargement

Figures S1-S4 and Tables S1-S2

Alexander M. Petersen[1], Michelangelo Puliga[2]

[1] Ernest and Julio Gallo Management Program
School of Engineering, University of California, Merced, CA 95343

[2] labouratory for the Analysis of Complex Economic Systems,
IMT School for Advanced Studies Lucca, Lucca 55100, Italy

[a] Please send correspondence to: Alexander M. Petersen
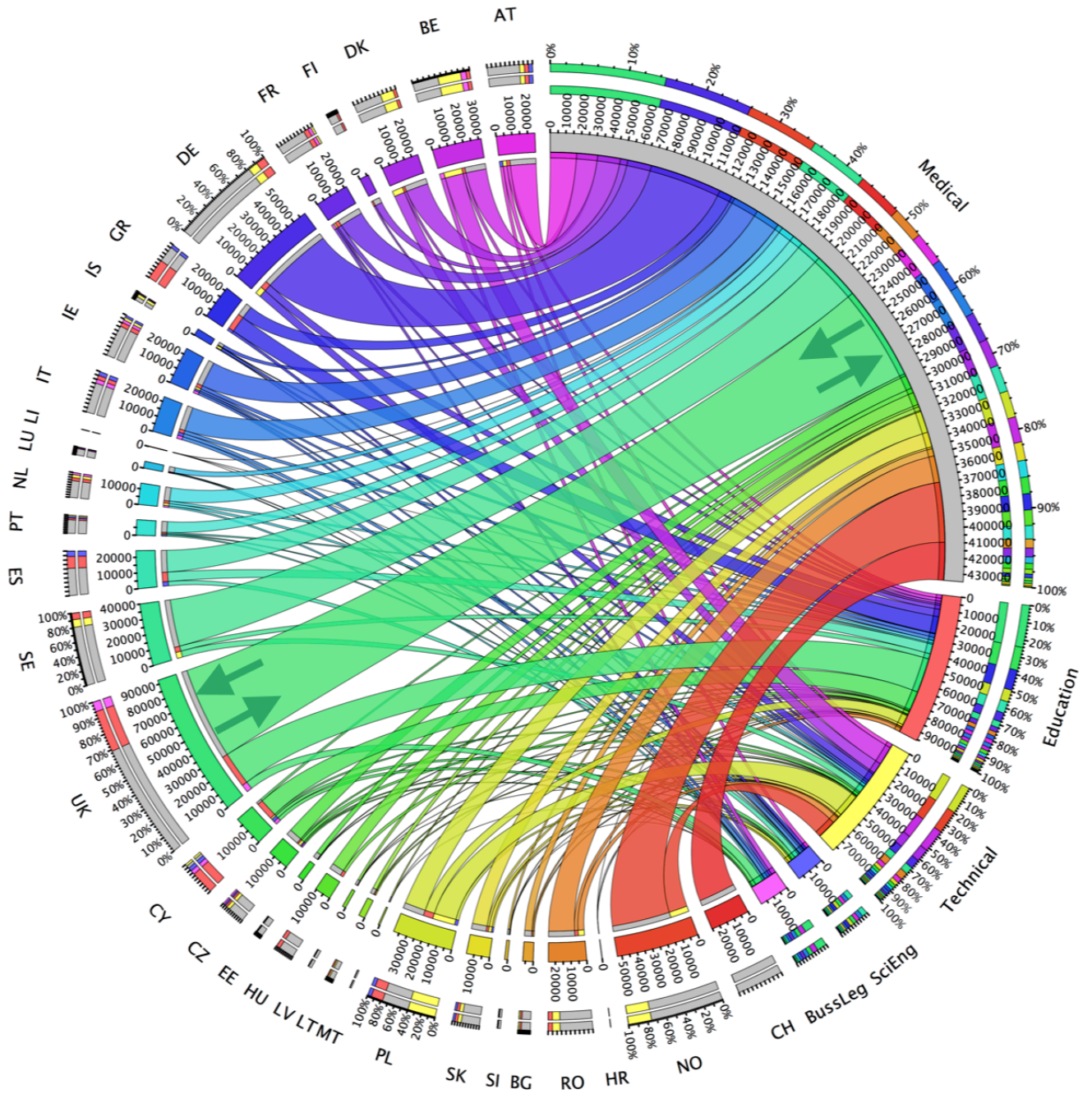*E-mail*: apetersen3@ucmerced.edu

FIG. S1: **High-skilled mobility by country and profession.** Bi-partite projection of the network between country mobility and profession type following the 2004 EU enlargement (2005-2014). Each link shows the total amount of mobility by country i in profession p. Outer rings show the distribution of the total mobility, either by country or by profession; because this is a bipartite projection both outer rings are redundant. Countries are ordered according to 2004 EU membership status.

FIG. S2: **Brain drain and brain gain by country and profession.** Bi-partite projection of the brain-drain network illustrating the net incoming or outgoing mobility by country for each profession following the 2004 EU enlargement (2005-2014). Outer ring show the distribution across the total net flow, either by country or by profession; because this is a bipartite projection both outer rings are redundant. Countries are ordered according to 2004 EU membership status.
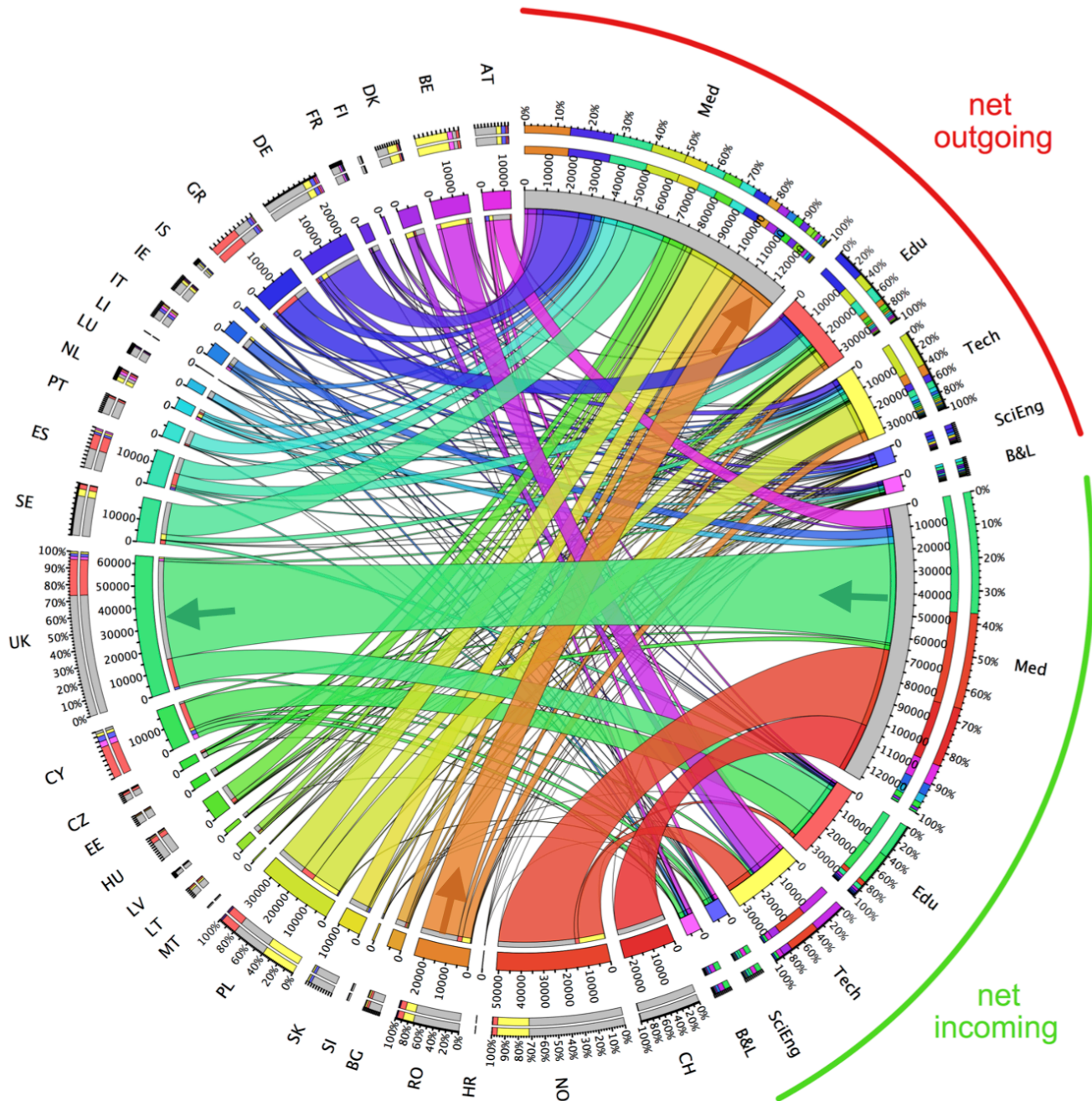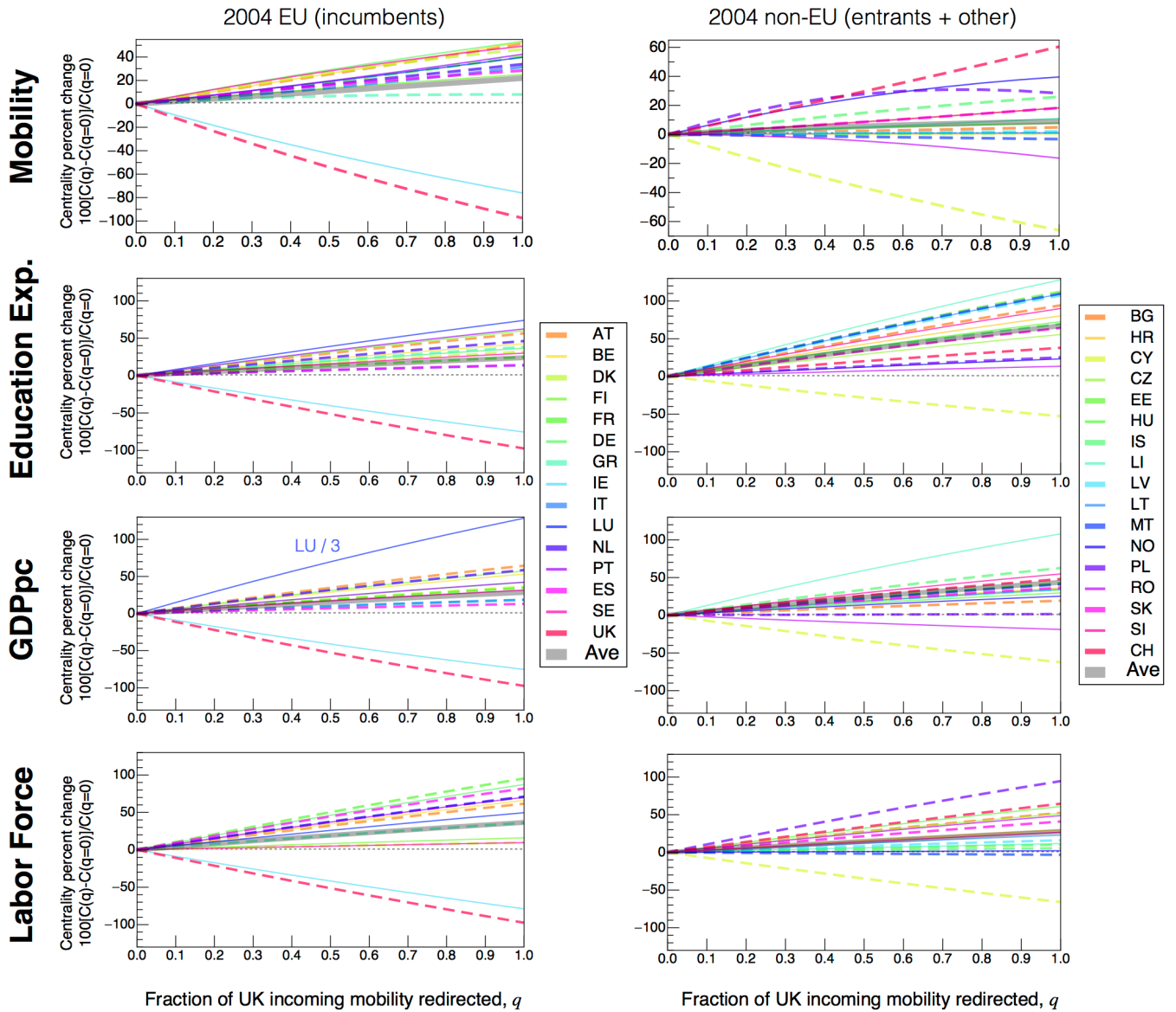
FIG. S3: **Robustness check of redirection model using additional World Bank country variables to estimate redirection weights.** Comparison of the percent change in network centrality estimated in our redirection model as a function of q – the fraction of redirected incoming UK mobility – using 3 different economic variables to define the redirection weight $F_{j,t,k}$. In the main manuscript Fig. 5(f,g) we use $F_{j,t,k} \equiv M_{ij,t}$; we reproduce these results in the first row to facilitate cross-comparison. In the remaining three rows we show additional estimates from the redirection model using the three most-positive push-pull factors in our panel regression model to define $F_{j,t,k}$: (i) the total expenditure on education as a percentage of government expenditure on all sectors, (ii) GDP per capita, and (iii) the total labour force size, reported as the economically active population size including individuals 15 years or older. It is worth mentioning that this generic redirection scheme still conserves the total observed mobility, i.e. $M_t = \sum_{i,j} M_{ij,t} = 338,747$ for all q over the period 2005–2014. (Left column) Percent change $\%(q)$ in the PageRank centrality of 2004 incumbent EU members as a function of q; (Right column) Percent change $\%(q)$ in the PageRank centrality of 2004 entrant and non-EU members as a function of q. The $q = 1$ values in each panel represent the percent change corresponding to the most extreme 'hard Brexit'. Within each panel, the average $\%(q)$ value is indicated by the opaque grey curve. The panel in the first column and third row shows the time series for LU divided by a factor of 3 so that it fits on the common scale.
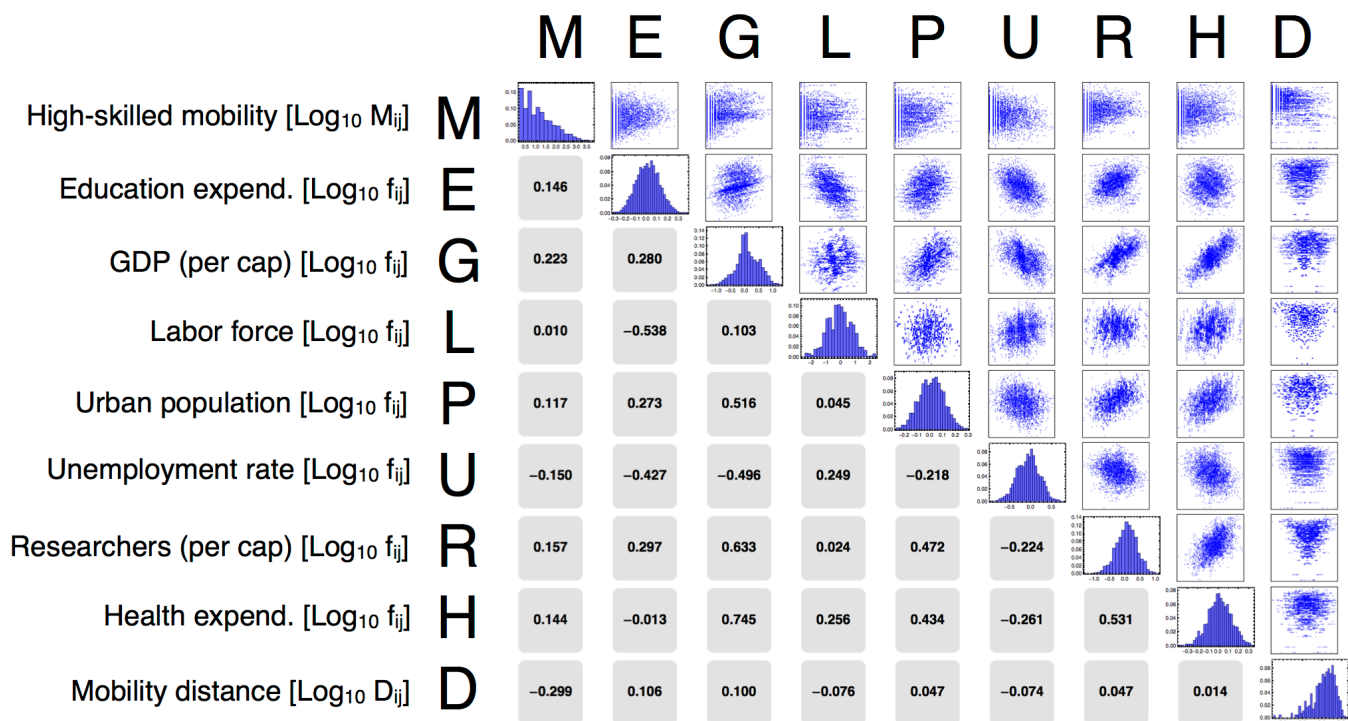
FIG. S4: **Model parameter probability distributions and cross-correlations.** The cells in the upper quadrant show the scatter plot of pairwise combinations of model covariates; the corresponding lower-quadrant cells contain the corresponding Pearson correlation coefficient. The cells along the diagonal show the probability distribution of the individual economic variables. For the scatter plots, the row variable is plotted on the x-axis while the column variable is plotted on the y-axis. To be concise, we only show the matrix using the mobility data for all professions pooled together, as the analogous cross-correlation results calculated using mobility data for just Medical or Sci.&Eng.+Tech. professions are consistent in sign and magnitude with the pooled data.

TABLE S1: **Mobility data for Medical professions.** Results of a basic (1) and fixed-effects (2) model, for which the dependent variable is the logarithm of the mobility from country i to country j, $\log_{10} M_{ij}$. Model-2 parameters estimated using year and source-country (i) fixed-effects. Only observations with $M_{ij} > 0$ are analyzed; see Eq. (7) for the full model specification. Estimates calculated using robust standard errors. Since World Bank data for 2013 and 2014 is not yet available for several of the variables, only observations thru 2012 are used.

	Basic model (1) Mobility, $\log_{10} M_{ij}$		Fixed-effects model (2) Mobility, $\log_{10} M_{ij}$	
Education expenditure (% of gvt. exp.), β_E	0.954***	(0.000)	2.332***	(0.000)
GDP (per cap.), β_G	0.523***	(0.000)	0.272	(0.071)
Country neighbors, β_N	0.482***	(0.000)	0.476***	(0.000)
labour force (total), β_L	0.0666***	(0.000)	0.383***	(0.000)
Urban population (% of total), β_P	-0.0759	(0.598)	0.369	(0.143)
Unemployment rate (% of labour force), β_U	-0.00779	(0.889)	-0.172	(0.052)
Researchers in R&D (per cap.), β_R	-0.121*	(0.016)	-0.438***	(0.000)
Health expenditure (% GDP), β_H	-0.294	(0.079)	-1.516***	(0.000)
Distance between capitals, β_D	-0.534***	(0.000)	-0.630***	(0.000)
$D_{1997/1998}$	-0.0811	(0.316)	-0.136*	(0.027)
$D_{1999/2000}$	(omitted)	(.)	(omitted)	(.)
$D_{2001/2002}$	-0.0554	(0.431)	-0.0119	(0.794)
$D_{2003/2004}$	0.192**	(0.004)	0.260***	(0.000)
$D_{2005/2006}$	0.187**	(0.004)	0.213**	(0.001)
D_{2007}	0.276***	(0.000)	0.309***	(0.000)
D_{2008}	0.285***	(0.000)	0.340***	(0.000)
D_{2009}	0.313***	(0.000)	0.315***	(0.000)
D_{2010}	0.389***	(0.000)	0.391***	(0.000)
D_{2011}	0.308***	(0.000)	0.326***	(0.000)
$D_{W \to W}$	0.233***	(0.000)	0.727***	(0.000)
$D_{W \to E}$	-0.229*	(0.013)	(omitted)	(.)
$D_{E \to E}$	-0.567***	(0.000)	-0.797***	(0.000)
$D_{E \to W}$	(omitted)	(.)	(omitted)	(.)
Constant	2.225***	(0.000)	2.273***	(0.000)
N	2737		2737	
adj. R^2	0.300		0.408	
F	56.71		154.3	
Prob. > F	0.0000		0.0000	
df_m	21		19	
df_r	2715		29	

p-values in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

TABLE S2: **Mobility data for Science & Engineering + Technical professions.** Results of a basic (1) and fixed-effects (2) model, for which the dependent variable is the logarithm of the mobility from country i to country j, $\log_{10} M_{ij}$. Model-2 parameters estimated using year and source-country (i) fixed-effects. Only observations with $M_{ij} > 0$ are analyzed; see Eq. (7) for the full model specification. Estimates calculated using robust standard errors. Since World Bank data for 2013 and 2014 is not yet available for several of the variables, only observations thru 2012 are used.

	Basic model (1)		Fixed-effects model (2)	
	Mobility, $\log_{10} M_{ij}$		Mobility, $\log_{10} M_{ij}$	
Education expenditure (% of gvt. exp.), β_E	0.286	(0.110)	1.496***	(0.000)
GDP (per cap.), β_G	0.328***	(0.000)	0.223	(0.313)
Country neighbors, β_N	0.263***	(0.000)	0.331***	(0.001)
labour force (total), β_L	-0.0634**	(0.002)	0.137*	(0.014)
Urban population (% of total), β_P	0.876***	(0.000)	1.073*	(0.042)
Unemployment rate (% of labour force), β_U	-0.115	(0.086)	-0.232	(0.083)
Researchers in R&D (per cap.), β_R	0.00201	(0.974)	-0.236	(0.054)
Health expenditure (% GDP), β_H	-0.0359	(0.867)	-0.983**	(0.002)
Distance between capitals, β_D	-0.371***	(0.000)	-0.498***	(0.000)
$D_{1997/1998}$	-0.108	(0.289)	(omitted)	(.)
$D_{1999/2000}$	(omitted)	(.)	0.150	(0.081)
$D_{2001/2002}$	-0.0374	(0.679)	0.161	(0.057)
$D_{2003/2004}$	0.0779	(0.378)	0.291**	(0.002)
$D_{2005/2006}$	0.0616	(0.478)	0.237**	(0.007)
D_{2007}	-0.0237	(0.782)	0.151	(0.089)
D_{2008}	-0.00522	(0.951)	0.181*	(0.022)
D_{2009}	0.0597	(0.488)	0.216*	(0.023)
D_{2010}	0.0163	(0.850)	0.184*	(0.028)
D_{2011}	0.0595	(0.496)	0.213**	(0.010)
$D_{W \to W}$	0.0424	(0.478)	0.187	(0.114)
$D_{W \to E}$	(omitted)	(.)	(omitted)	(.)
$D_{E \to E}$	-0.252**	(0.001)	-0.225	(0.089)
$D_{E \to W}$	-0.210*	(0.048)	(omitted)	(.)
Constant	1.915***	(0.000)	1.988***	(0.000)
N	1692		1692	
adj. R^2	0.184		0.238	
F	19.19		29.06	
Prob. > F	0.0000		0.0000	
df_m	21		19	
df_r	1670		28	

p-values in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$