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Centrality in the macroeconomic multi-network explains the spatiotemporal distribution of country per-capita income

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Abstract

This paper empirically investigates the role played by cross-country spillovers in shaping spatiotemporal differences in country income. While existing literature focused on effects captured by direct spillovers with partner countries only, here we take a complex network perspective to explore whether the global embeddedness of countries in the macroeconomic multi-network may significantly impact income, net of country local characteristics such as local foreign exposure. We employ data for the period 2000–2020 to build a time sequence of 3-layer multi graphs, with countries as nodes and links weighted by the intensity of bilateral relations in international trade, finance and human migration. Using panel-regression techniques, we then ask if country (eigenvector) centrality in the multi network can account for parts of the observed heterogeneity in country per-capita income, both cross-sectionally and over time. Robustly across a number of alternative specifications of the empirical model, we find that being more central significantly boosts country income. This implies that income-enhancing technological spillovers are not only channeled via local exposure, but also through indirect interactions with more distant nodes.

Keywords: Country per-capita income, Cross-country spillovers, Multi graphs, Centrality, Panel-regressions

Introduction

The investigation of the determinants of the spatiotemporal distribution of country per-capita income has a long tradition in applied and theoretical economics (Solow 1956; Mankiw et al. 1992). Within this vast body of research, a large stream of literature has recently explored the role that cross-country spillovers may play in shaping the observed heterogeneity in the patterns of country income, both cross-sectionally and over time (Keller 2004; Howitt 2000; Alvarez et al. 2013; Barro and Sala-I-Martin 1997).

The main idea is that, everything else being constant, the exposure of a country to foreign markets (e.g., trade of goods and capital) and her openness to cross-border human mobility (both permanent and temporary) may boost domestic income. This may happen, for example, via international technology diffusion, which can be facilitated by foreign influence through the exchange of goods, capital and ideas induced by communication and sharing of tacit knowledge (Frankel and Romer 1999; Andersen and Dalgaard 2011).

Empirical testing of the income-enhancing effect of cross-country spillovers has been traditionally carried out using aggregate measures of country openness, as a proxy of the extent to which a country is exposed to foreign markets and migration flows (Andersen and Dalgaard 2011). For example, country exposure to international trade is typically proxied by a simple measure of country openness, computed as the ratio between country total trade and its gross-domestic product (GDP). Similar openness measures are also employed to quantify spillover effects from migration flows (Ortega and Peri 2014) and finance (Bekaert et al. 2011).[1]

However, openness indicators are essentially "local" measures, insofar as they only consider direct spillovers coming from partner countries, i.e. those directly linked via trade, finance or migration relationships (Fagiolo and Santoni 2015). As we show in more detail in "Section Econometric model", these cannot fully capture indirect spillovers effects originated in countries which are not among their immediate neighbors (Abeysinghe and Forbes 2005).

To address this issue, this paper employs a complex-network approach. We consider world countries as the nodes of a time-sequence of a 3-layer undirected network, where layers represent international trade, finance and migration relationships. Therefore, in each time period, any two countries are linked if they exchange goods via import/export relations (trade layer), hold a bilateral financial relation (finance layer) and share inflow and/or outflow migration corridors (migration layer), see "Section Discussion and conclusions" for a discussion.

Our main working hypothesis is that, net of country-specific factors including traditional (local) openness measures, network-based indicators accounting for the overall (global) position of a country within the complex web of interconnections can better approximate global income-enhancing effects of cross-country spillovers. This relationship can be rationalized in terms of a simple theoretical framework wherein country per-capita income appears to positively depend on eigenvector centrality (Bonacich and Lloyd 2001) in the macroeconomic networks where countries are embedded in (see "Section A simple interpretative framework"). More specifically, we employ data on international trade, finance and migration flows for 180 countries over the period 2000–2020 and compute country (eigenvector-based) centrality indicators—in each layer and in the multi-graph—to proxy country global openness to potential spillover effects. We then employ country centrality indicators as covariates in a large set of panel-regression specifications, documenting a widespread positive and significant impact of country centrality on per-capita income, net of country-specific effects including local openness. Our empirical results appear to be fairly robust to a number of possible estimation biases (e.g., endogeneity and spatial dependence).

This study is closely related to recent works documenting how countries' embedding in macro-economic networks can have an impact on the spatiotemporal evolution of their characteristics. For example, Duernecker et al. (2022) show that country global integration in the international trade network positively affects growth net of

[1] For a complementary approach, accounting for geographical (spatial) externalities and interdependencies in country production processes, see Ho et al. (2018), Ertur and Koch (2007).

openness measures. In a similar vein, Fagiolo and Santoni (2015) find a positive and statistically-significant association between country centrality in the network of temporary migration and country income and productivity. Interestingly, both studies document a substantial absence of correlation between country global importance in the network (e.g., global integration and centrality) and local trade or migration openness measures. In this work, in order to construct the macroeconomic multi-network channeling cross-country spillovers, we build on the large body of literature which documented the importance of international trade, foreign-direct investment, mobility and migration cross-country linkages as drivers of productive knowledge, cf. among others (Bahar et al. 2014; Alvarez et al. 2013; Coe 2009; Keller 2021; Coscia et al. 2020; Hovhannisyan and Keller 2015; Bahar and Rapoport 2018; Piva et al. 2018). Furthermore, a multi-graph description similar to the one explored here has been employed in Pugliese et al. (2019), Patelli et al. (2022), who empirically characterize the innovation systems of countries as a 3-layered network describing scientific, patenting and industrial activities in different sectors.

The rest of the paper is organized as follows. In "Section Empirical framework: data and methods" we describe the data we employ to build the 3-layered network and we introduce a simple theoretical framework motivating our econometric setups. Section 3 contains an exploratory statistical analysis of network structure and presents the main econometric results. The last section discusses and concludes the paper.

Empirical framework: data and methods

Macroeconomic multi-network: definitions and analysis

We employ data on international trade, finance and migration to build a weighted, undirected, 3-layer macroeconomic multi-network (MMN) where nodes are countries and weighted-undirected links represent the intensity of bilateral international ties in trade (T), migration (M) and finance (F). In each layer a link is present if and only if there exists a non-zero observation in the correspondent data.

Trade data come from the COMTRADE (United Nations 2023) database. The raw yearly observation reports total imports of any world country from any other in that year (in nominal US$). As to migration data, we employ Guy Abel repository on "Bilateral International Migration Flow Estimates" (Abel and Cohen 2019), which contains, for any time wave {2000, 2005, 2010, 2015, 2020}, estimates for the number of people born in any given country who permanently moved to another one in the preceding 5-year interval. International finance data are retrieved from the IMF "Coordinated Portfolio Investment Survey" (CPIS) (The International Monetary Fund 2023), which contains yearly information on the total value of portfolio investment securities held by any given country and issued by another one.

We first symmetrize weighted-directed relationships.[2] Therefore, links are weighted by total bilateral trade (imports plus exports) in the T layer, by total permanent-migration flows of people (immigrants plus emigrants) in layer M and total (held and issued) bilateral holdings in the F layer.

[2] This is done to avoid difficulties in interpreting country eigenvector-based centrality indicators in directed networks, where node importance depends on whether centrality scores are obtained through incoming or outgoing links. In "Section Directed networks" we relax this assumption.

Next, to properly match trade and finance data with migration flows over time, we compute averages of trade and finance yearly data over the the preceding years.[3] An alternative way to perform this match would have required to interpolate migration-flow data (within 5-year windows) without averaging out trade and finance bilateral data, resulting in a yearly dataset with a much larger econometric sample size. As mentioned, however, migration data are already estimates coming from stock data observed at a 10-year frequency. Therefore, a further interpolation would have introduced too much exogenous bias, in our opinion, in terms of the variation of bilateral migration flows both over time and across country pairs. This would have possibly led to estimation biases in our regression exercises (see below), especially concerning global and country-specific time trends.

After matching, we end up with a balanced panel of $N = 180$ countries (cf. Table 1) observed over 5 time-snapshots $t \in \{2000, 2005, 2010, 2015, 2020\}$, where the bilateral observation at time t refers to the average or total flow or stock in the preceding years. More formally, we let $\mathbf{H}_t^\ell = \{h_{ijt}^\ell\}$ be the weight matrix at time t for layer $\ell = \{T, M, F\}$, where $i = 1, \ldots, N$ and $j = 1, \ldots, N$. To facilitate comparison across layers and time, link weights were first log-transformed and then re-scaled by the maximum value in $\mathbf{H}_t^\ell$ for each (t, ℓ). Therefore link weights are unit-free and $h_{ijt}^\ell \in [0, 1]$.

Table 2 reports summary statistics for network layers across time waves. Note that trade and migration layers display many more connections than the finance layer, which results in a larger density. However, (rescaled) trade and finance link weights are generally heavier than in migration network, resulting in larger average weight per link. Over time, trade and finance layers have become denser, whilst the migration network shows more stability in its structure.

The network structure of three layers is displayed in the chord diagrams of Fig. 1 for the years 2000 and 2020, where for visualization purposes, we only plot the links associated to top 30 weights in each layer (see "Appendix 2" for choropleth maps showing, for year 2020, the top 1% of the link weight distribution in each layer). Finance and trade top link weights are concentrated around a smaller number of countries, while the migration layer is more dispersed. As one might expect, the three layers are correlated. We explore the evolution of the Pearson correlation coefficient between positive link-weight pairs in Fig. 2. Trade and finance link weights are the most correlated, although not perfectly collinear. This indicates that countries might globally play different roles in different layers. Furthermore, the correlation between migration link weights and the trade/finance ones has increased over the years. Overall, the existent correlation structure suggests that an underlying common gravity-model structure may be at work (more on that below).

Next, we compute country-centrality scores on weight matrices $\mathbf{H}_t^\ell$, for each layer and time wave. Let C_{it}^ℓ be the centrality score of country i at time t in layer ℓ. We focus on Bonacich (eigenvector) centrality (EIC henceforth) (Bonacich and Lloyd 2001) as our measure of global country embeddedness in MMN layers. According to its definition, a country will hold a higher EIC score in the network the more—and more intense—links she holds with countries that are also more central. Therefore, country importance does

[3] More precisely, total bilateral trade in year t is the average of observations in years $\{t-4, \ldots, t\}$. As to finance data, the observation in year t is the average over the 4 preceding years (apart from 2001 when data for antecedent years were not available.

Table 1 List of country names and ISO3 codes used in the analysis

Country	ISO3	Country	ISO3	Country	ISO3
Afghanistan	AFG	Gabon	GAB	Norway	NOR
Albania	ALB	Gambia	GMB	Oman	OMN
Algeria	DZA	Georgia	GEO	Pakistan	PAK
Angola	AGO	Germany	DEU	Panama	PAN
Antigua & Barbuda	ATG	Ghana	GHA	Papua New Guinea	PNG
Argentina	ARG	Greece	GRC	Paraguay	PRY
Armenia	ARM	Grenada	GRD	Peru	PER
Australia	AUS	Guatemala	GTM	Philippines	PHL
Austria	AUT	Guinea	GIN	Poland	POL
Azerbaijan	AZE	Guinea-Bissau	GNB	Portugal	PRT
Bahamas	BHS	Guyana	GUY	Qatar	QAT
Bahrain	BHR	Haiti	HTI	Rep. of Korea	KOR
Bangladesh	BGD	Honduras	HND	Rep. of Moldova	MDA
Barbados	BRB	Hungary	HUN	Russian Federation	RUS
Belarus	BLR	Iceland	ISL	Rwanda	RWA
Belgium	BEL	India	IND	St. Lucia	LCA
Belize	BLZ	Indonesia	IDN	St. Vincent	VCT
Benin	BEN	Iran	IRN	Samoa	WSM
Bhutan	BTN	Iraq	IRQ	Sao Tome & Principe	STP
Bolivia	BOL	Ireland	IRL	Saudi Arabia	SAU
Bosnia Herzegovina	BIH	Israel	ISR	Senegal	SEN
Botswana	BWA	Italy	ITA	Serbia	SRB
Brazil	BRA	Jamaica	JAM	Seychelles	SYC
Brunei Darussalam	BRN	Japan	JPN	Sierra Leone	SLE
Bulgaria	BGR	Jordan	JOR	Singapore	SGP
Burkina Faso	BFA	Kazakhstan	KAZ	Slovakia	SVK
Burundi	BDI	Kenya	KEN	Slovenia	SVN
Cabo Verde	CPV	Kiribati	KIR	Solomon Isds	SLB
Cambodia	KHM	Kuwait	KWT	South Africa	ZAF
Cameroon	CMR	Kyrgyzstan	KGZ	South Sudan	SSD
Canada	CAN	Laos	LAO	Spain	ESP
Central African Rep.	CAF	Latvia	LVA	Sri Lanka	LKA
Chad	TCD	Lebanon	LBN	Sudan	SDN
Chile	CHL	Lesotho	LSO	Suriname	SUR
China	CHN	Liberia	LBR	Sweden	SWE
Hong Kong	HKG	Libya	LBY	Switzerland	CHE
Colombia	COL	Lithuania	LTU	Syria	SYR
Comoros	COM	Luxembourg	LUX	Tajikistan	TJK
Congo	COG	Madagascar	MDG	Thailand	THA
Costa Rica	CRI	Malawi	MWI	Timor-Leste	TLS
Croatia	HRV	Malaysia	MYS	Togo	TGO
Cyprus	CYP	Maldives	MDV	Tonga	TON
Czechia	CZE	Mali	MLI	Trinidad & Tobago	TTO
Cote d'Ivoire	CIV	Malta	MLT	Tunisia	TUN
Congo (DRC)	COD	Mauritania	MRT	Turkey	TUR
Denmark	DNK	Mauritius	MUS	Turkmenistan	TKM
Djibouti	DJI	Mexico	MEX	USA	USA
Dominican Rep.	DOM	Mongolia	MNG	Uganda	UGA
Ecuador	ECU	Montenegro	MNE	Ukraine	UKR

Table 1 (continued)

Country	ISO3	Country	ISO3	Country	ISO3
Egypt	EGY	Morocco	MAR	United Arab Emirates	ARE
El Salvador	SLV	Mozambique	MOZ	United Kingdom	GBR
Equatorial Guinea	GNQ	Myanmar	MMR	Tanzania	TZA
Eritrea	ERI	Namibia	NAM	Uruguay	URY
Estonia	EST	Nepal	NPL	Uzbekistan	UZB
Eswatini	SWZ	Netherlands	NLD	Vanuatu	VUT
Ethiopia	ETH	New Zealand	NZL	Venezuela	VEN
Micronesia	FSM	Nicaragua	NIC	Viet Nam	VNM
Fiji	FJI	Niger	NER	Yemen	YEM
Finland	FIN	Nigeria	NGA	Zambia	ZMB
France	FRA	North Macedonia	MKD	Zimbabwe	ZWE

Table 2 Network layers: Descriptive statistics

Trade	**2000**	**2005**	**2010**	**2015**	**2020**
No. Nodes	180	180	180	180	180
No. Links	12227	13110	13506	13922	14177
Volume/Link	0.874	0.871	0.883	0.894	0.905
Density	0.759	0.814	0.838	0.864	0.88
Diameter	2	3	2	2	2
Size LCC	176	177	179	180	180
Migration	**2000**	**2005**	**2010**	**2015**	**2020**
No. Nodes	180	180	180	180	180
No. Links	8636	8777	9045	8961	8297
Volume/Link	0.329	0.346	0.365	0.344	0.391
Density	0.536	0.545	0.561	0.556	0.515
Diameter	2	2	2	2	3
Size LCC	176	176	178	180	180
Finance	**2000**	**2005**	**2010**	**2015**	**2020**
No. Nodes	180	180	180	180	180
No. Links	1.899	2.798	3.566	4.123	4.250
Volume/Link	0.898	0.872	0.864	0.858	0.868
Density	0.118	0.174	0.221	0.256	0.264
Diameter	4	3	3	3	3
Size LCC	158	172	178	178	178

not only depend on that of immediate partners (i.e., local importance), but also on the importance of the neighbors of neighbors, and so on. This allows one to evaluate global country importance, since computing the EIC score for any given node fully takes into account the information contained in the weight matrix.

In order to check for robustness, we complement EIC indicators computed on weighted-network layers with binary projections thereof, obtained by setting the links equal to 1 the entry of the $N \times N$ binary matrix $\mathbf{A}_t^\ell = \{a_{ijt}^\ell\}$ if the correspondent weight $h_{ijt}^\ell > 0$ and zero otherwise. This allows us to evaluate the role played by intensive (weighted) vs extensive (binary) centrality in affecting country income. An

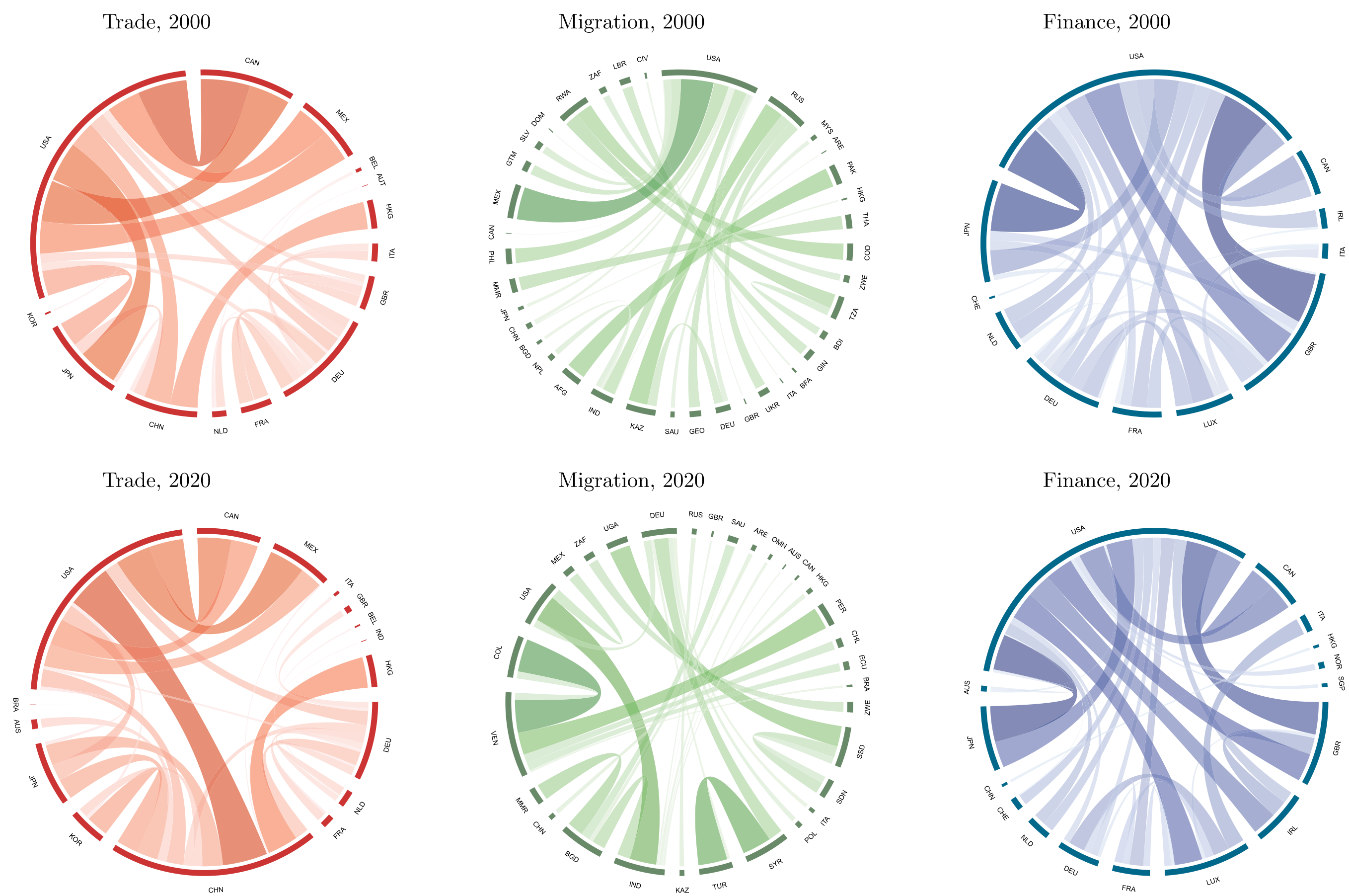

Fig. 1 Chord diagrams for the 3 layers in years 2000 and 2020. Only links associated to the top 30 weights are shown. The width of each of the chords is proportional to the sum of weights of each country in the corresponding layer

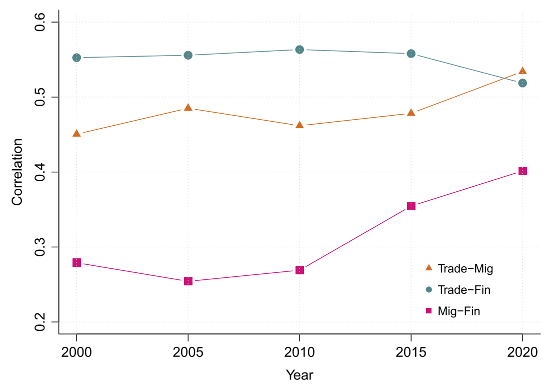

Fig. 2 Evolution over time of Pearson correlation coefficient between link weights of network layers

Table 3 Correlation coefficients between Bonacich Eigenvector Centrality (EIC) and Katz (Alpha) Centrality

Layer	**Weighted Centrality Scores**				
	2000	**2005**	**2010**	**2015**	**2020**
Trade	0.9981	0.9986	0.9988	0.9990	0.9991
Migration	0.9898	0.9928	0.9932	0.9919	0.9908
Finance	0.9973	0.9988	0.9993	0.9996	0.9997
Layer	**Binary Centrality Scores**				
	2000	**2005**	**2010**	**2015**	**2020**
Trade	0.9971	0.9975	0.9973	0.9977	0.9978
Migration	0.9937	0.9940	0.9944	0.9939	0.9926
Finance	0.9935	0.9962	0.9976	0.9987	0.9989

extensive analysis of correlation between EIC scores and ranks is reported in "Section Correlation between country centrality measures".

Alternative eigenvector based measures of node importance can be employed instead of EIC, e.g., Katz (aka, Alpha) centrality (Katz 1953). However, Katz centrality is particularly suited in sparse, directed acyclic networks where Bonacich centrality may not be well defined for some nodes. As our graphs are neither directed nor acyclic, EIC appears to be a good starting point. Nonetheless, we have computed Katz centrality on our data and checked its correlation with EIC, both in weighted and binary representations of the network. As Table 3 suggests, EIC and Katz centrality distribution are almost perfectly and positively correlated across layers and time waves. This is expected as, in undirected and dense networks as those we are considering here, the two centrality indicators provide very similar results. In "Section Discussion and conclusions" we shall briefly comment on alternative centrality indicators that can be possibly employed in the present analysis.

A simple interpretative framework

Our main working hypothesis can be rationalized in terms of a simple interpretative framework.[4] Note that, from a theoretical perspective, the link between (technological) spillovers and growth have been explored to understand convergence across countries (Barro and Martin 1997; Howitt 2000) or as a possible vehicle of the positive relationship between trade and economic growth (Grossman and Helpman 1991). Although most of this literature is rooted in the endogenous growth tradition, our interpretative framework, for simplicity, is based on a standard neoclassical Solow growth model (Solow 1956; Mankiw et al. 1992), to which we add interdependence between country (exogenous) production efficiencies. This is more in the spirit of the model in Ertur and Koch (2007), who study country growth in presence of technological interdependencies and spillovers.

Consider N world countries $(i = 1, \ldots, N)$ embedded in an undirected weighted network—with symmetric $N \times N$ weight matrix $W = \{w_{ij}\}$—that channels spillovers between countries with intensity proxied by link weights. Countries hold constant returns-to-scale production functions:

$$y_i = f_i(k_i; \phi_i, a_i) = \phi_i k_i^{a_i}, \tag{1}$$

where y_i and k_i are per-worker output and capital, $a_i \in (0,1)$, ϕ_i is a technical-progress coefficient (i.e., production efficiency), here assumed to be Hicks-neutral for simplicity, and k_i is set at its steady-state level:

$$k_i^* = \left(\frac{\phi_i s_i}{n_i + d_i}\right)^{\eta_i}, \tag{2}$$

where n_i (the rate of growth of the labor force), d_i (the depreciation rate of capital), s_i (the saving rate) and $\eta_i = (1 - a_i)^{-1}$ are constant, country-specific parameters. This implies that:

$$y_i^* = \phi_i^{\eta_i} H_i, \tag{3}$$

where $H_i = s_i^{\eta_i}(n_i + d_i)^{-\eta_i}$ only depends on country-specific factors.

Suppose that country efficiency ϕ_i depends on the efficiency of countries she interacts with. More formally, if country i is linked to country j with link weight w_{ij}, we assume she may enjoy a share ζw_{ij} of her efficiency ϕ_j, where $\zeta \in [0,1]$ is a global parameter. Thus, we have that:

$$\phi_i = \sum_{j=1}^{N} \zeta w_{ij} \phi_j, \tag{4}$$

whose solution ϕ_i^* is country Bonacich centrality in W. Therefore, country per-worker output reads

[4] Our framework should not be considered as a fully-fledged economic model delivering clearcut testable implications. Rather, we view it as a toy-model whose skeleton can be employed to motivate our empirical analysis, by providing a way to interpret a possible association between network centrality in the network channeling spillovers and country income.

$$y_i^* = (\phi_i^*)^{\eta_i} H_i, \tag{5}$$

implying that country income should positively depend on country Bonacich centrality in W.[5]

Econometric model

We test whether country centrality in the MMN explains country per-capita GDP (pcGDP) using fixed-effects panel regression models, as rationalized in our simple theoretical framework. We employ data on pcGDP from the "World Development Indicators" database maintained by the World Bank (The World Bank 2023) and refer to country gross-domestic product per capita based on purchasing power parity (PPP), i.e. converted to (constant 2017) international dollars using purchasing power parity rates.

The most natural panel-regression specification to test our hypothesis reads:

$$y_{it} = \alpha_i + \beta_t + \eta \mathbf{C}_{it} + \gamma \mathbf{X}_{it} + \epsilon_{it}, \tag{6}$$

where $i = 1, \ldots, N$ are country labels, t is time, y_{it} is the log of pcGDP, α_i are country-level fixed effects (FEs), β_t are time dummies, $\mathbf{C}_{it}$ is a vector of country network indicators (e.g., EIC scores), $\mathbf{X}_{it}$ are additional country specific, time-varying covariates (e.g., demographic, socio-economic, and institutional factors) Fagiolo and Santoni (2015) and ϵ_{it} are i.i.d. errors.

Among $\mathbf{X}_{it}$ regressors, it is customary to control for country openness. As mentioned, this variable should capture the extent to which a country is open to foreign influence and it is usually defined as the ratio between total country activity in a certain dimension (i.e., trade, migration, and finance, in our context) and country economic or demographic size (country GDP is typically employed for trade and finance, while population is used for migration). Openness indicators, therefore, only capture "local" exposure, as they only account for the number and intensity of direct linkages with partner countries.[6] EIC scores, on the contrary, take into account both direct and indirect connections, being able to better grasp "global" country exposure or importance in the network. The fact that local measures (e.g., openness) and global indicators (e.g., centrality) may not necessarily be strongly and positively correlated has already been documented in the literature, see e.g. Duernecker et al. (2022). This appears to be the case also in our data. Table 4 reports Pearson correlation coefficients between EIC country scores (computed both in weighted and binary network layer) and openness statistics, where openness to trade is calculated as total country trade (imports plus exports) over GDP, openness to migration is total country migration (immigration plus emigration) over population, and openness to finance is total country portfolio investment securities (held and issued) over GDP. In order to match the data employed for link weights in network layers, all openness measures at year t are computed using averages over the preceding 5-year

[5] This testable implication is expressed in terms of per-worker and not per-capita output. However, all our main results are confirmed replacing pcGDP with productivity. Notice also that Eq. (5) holds also in the case the network is unweighted (i.e. W is a binary adjacency matrix A).

[6] Indeed, from our weighted-undirected network perspective, total country trade, migration and finance can be recovered by the row (or equivalently column) sum of the correspondent-layer weight matrix. That is, the numerator of country openness equals total country (node) strength.

Table 4 Correlation coefficients between Bonacich Eigenvector Centrality (EIC) and Country Openness. Openness to trade is total country trade over country GDP. Openness to migration is total country migration over country population. Openness to finance is total country assets over country GDP. All openness measures at year t are computed using averages over the preceding 5-year window

Layer	Weighted Centrality Scores				
	2000	**2005**	**2010**	**2015**	**2020**
Trade	− 0.4172	− 0.3834	− 0.4509	− 0.4596	− 0.5220
Migration	− 0.2815	− 0.2854	− 0.2961	− 0.2695	− 0.1363
Finance	0.0350	− 0.0585	− 0.1112	− 0.1003	− 0.1290
Layer	**Binary Centrality Scores**				
	2000	**2005**	**2010**	**2015**	**2020**
Trade	− 0.3441	− 0.3324	− 0.4068	− 0.5134	− 0.5946
Migration	− 0.1963	− 0.2199	− 0.2257	− 0.2055	− 0.0729
Finance	0.0847	− 0.0318	− 0.0814	− 0.0529	− 0.0795

window. The figures in Table 4 clearly show that, overall, openness and centrality are weakly and negatively correlated, suggesting that local and global measures may portrait very different pictures.[7]

Going back to the specification in Eq. (6), concerns have been raised that it may involve over-controlling (or over-fitting) biases (Dell et al. 2014). In our specific case this is crucial as country covariates $\mathbf{X}_{it}$ may indeed depend on centrality $\mathbf{C}_{it}$. Therefore, estimation of Eq. (6), which assumes a functional relationships $y = f(\mathbf{C}_{it}, \mathbf{X}_{it})$, may not capture the sheer net effect of $\mathbf{C}_{it}$ on y_{it}, as the true functional relationships is instead $y_{it} = f(\mathbf{C_{it}}, \mathbf{X_{it}}(\mathbf{C_{it}}))$. Furthermore, the choice of covariates may induce an omitted-variable bias (Wilms et al. 2021). Furthermore, adding a sufficiently large number of macroeconomic controls $\mathbf{X}_{it}$ may decrease country sample size, due to missing values.[8] To address those issues, we follow the influential work by Burke et al. (2015) and employ here the specification:

$$y_{it} = \alpha_{i0} + \alpha_{i1}t + \alpha_{i2}t^2 + \beta_t + \eta\mathbf{C}_{it} + \epsilon_{it}, \tag{7}$$

where country-specific covariates are removed and the 2-degree, country-specific time polynomial is meant to control for all country-specific (time invariant and variant) factors. This may substantially alleviate omitted-variable and over-controlling biases. The idea is to replace regressors $\mathbf{X}_{it}$, which may depend on $\mathbf{C}_{it}$ and might not be able to fully control for country-specific, time-varying heterogeneity, with a flexible battery of country-specific non-linear trends. Since $2N - 2$ additional dummies now inflate the

[7] Cf. Duernecker et al. (2022) for an interpretation. An intuitive proxy for local exposure may also be defined in terms of the number and total intensity of direct links, i.e., using node degree and node strength as measures of local centrality. We discuss this issue in more detail in "Section Panel regressions".

[8] This was actually the case in the present study. By adding macroeconomic covariates typically employed in the literature, we ended up with less than 100 countries available for estimation. Notice that this implies that centrality scores inserted in the regressions should now be recomputed on the resulting smaller-size networks. This may further bias the analysis, as the networks themselves, and their properties, now depend on the selection process that is used to choose the macroeconomic covariates.

regression, one may be sufficiently sure to limit overfitting and reduce omitted-variable biases.[9]

The vector $\mathbf{C}_{it}$ contains Bonacich country (eigenvector) centrality indicators. We experiment with four setups, according to whether EIC scores are computed on weighted vs binary network layers; and whether all three layer EIC scores enter jointly in a single regression (i.e., $\mathbf{C}_{it} = \{C_{it}^T, C_{it}^M, C_{it}^F\}$) or separately in three different regressions (i.e., $\mathbf{C}_{it} = \{C_{it}^T\}$ or $\mathbf{C}_{it} = \{C_{it}^M\}$ or $\mathbf{C}_{it} = \{C_{it}^F\}$).

Another well-known issue that may confound the estimate of η is the potential presence of endogeneity, which may result from reverse causation (i.e., pcGDP affecting country centrality) and/or any remaining omitted-variable bias. We address possible endogeneity issues in the relation between EIC and pcGDP by using a strategy typically employed in the relevant literature (cf., e.g. Ref. Fagiolo and Santoni (2015) and papers cited therein), consisting, first, in instrumenting the observed network via a structural gravity model featuring origin and destination country-time fixed effects and bilateral exogenous variables (e.g., geographical distance). Second, EIC scores are computed on the predicted networks and inserted in the regression in place of those computed on the observed networks. More formally, for any layer and time wave, we fit to positive link weights the model:

$$h_{ijt}^{\ell} = a_{it}^{\ell} + b_{jt}^{\ell} + c^{\ell}\Delta_{ij} + \eta_{jt}^{\ell}, \tag{8}$$

where a_{it}^{ℓ} and b_{jt}^{ℓ} are country-time origin and destination FEs, Δ_{ij} is the log of population-weighted geographical distance between country i and j (Mayer and Zignago 2011) and η_{jt}^{ℓ} are i.i.d. errors. We employ an OLS estimator to obtain gravity predictions $\hat{h}_{ijt}^{\ell}$ for link weights and, consequently, instrumented weight matrices $\hat{\mathbf{H}}_t^{\ell}$, which we employ to compute an instrumented version of country EIC scores and ranks. Notice that OLS estimates automatically exclude observations equal to zero (i.e., only links that are present enter the sample). This implies that predicted binary matrices $\hat{\mathbf{A}}_t^{\ell}$ coincide with non-instrumented ones $\mathbf{A}_t^{\ell}$. In other words, using this procedure, instrumented and non-instrumented binary centrality would be the same. To allow for a properly-defined instrumented binary EIC, we fit a_{ijt}^{ℓ} with a logit gravity model as in Eq. (8). This allows one to obtain predicted probabilities of link existence and, keeping only the links whose predicted probability is strictly larger than observed network density, to eventually get a single instance for the instrumented binary network (Duenas and Fagiolo 2013).[10] It has been argued elsewhere (Fagiolo and Santoni 2015) that binary network statistics should not strongly suffer from endogeneity issues induced by reverse causation. Indeed, changes in the dependent variable may feed back more naturally to intensive margins rather than to extensive ones, i.e., changes in country pcGDP should impact on link weights without destroying or creating links. If one buys this argument, instrumenting binary EIC may be redundant. However, we are concerned here with endogeneity

[9] Linear, cubic or higher-order country-specific time polynomials may be also employed. The choice should be made so as to solve the trade-off between explanatory power and degrees of freedom left for estimation. In our exercises, a 2-degree polynomial turned out to be the best option.

[10] An alternative strategy consists in using the logit-predicted matrix of probabilities to simulate, using i.i.d. Bernoulli distributions, a sufficiently-large sample of predicted binary networks and, eventually, a distribution of binary EIC statistics, whose mean/median can be used in regression exercises. A preliminary analysis showed that results using this second strategy were very similar to the ones obtained employing observed network density as a threshold to keep binary links.

induced by omitted-variable biases, which might still be present and possibly bias our results. Therefore, we stay on the safe side and instrument binary EIC as well.

As a further check, we also control for autocorrelation in pcGDP data, introducing a lag in the right-hand side of Eq. (7) as follows:

$$y_{it} = \theta y_{it-1} + \alpha_{i0} + \alpha_{i1}t + \alpha_{i2}t^2 + \beta_t + \eta \mathbf{C}_{it} + \epsilon_{it}, \tag{9}$$

Therefore, in either the weighted or binary network case, our first set of econometric exercises cover six different setups, according to whether: (i) centrality scores enter jointly or separately; (ii) the regression specification is the baseline one (i.e., no instrumented network, no lag for pcGDP); the specification features instrumented-network statistics using Eq. (8); or a lag in pcGDP is inserted as in Eq. (9). In addition, "Section Panel regressions" presents some robustness checks aimed at exploring what happens when a multi-graph definition of country centrality is employed instead of treating layers as separate and when spatial (geographical) correlation in pcGDP is dealt with.

Results

Correlation between country centrality measures

Before presenting the main results from panel-regression exercises—aimed at documenting the net impact on pcGDP of the overall importance of countries in the MMN—it is instructive to explore the correlation structure of centrality indicators, both within and across network layers, and over time.

Panels (a) and (b) in Fig. 3 show correlation plots of EIC scores and ranks. In each plot, upper-diagonal elements refer to correlation coefficients between EIC computed in weighted-network layers, while lower-diagonal display correlation coefficients between EIC computed in binary-network layers, for all layers and time waves. Note first that centrality indicators exhibit a strong within-layer persistence over time (cf. circles within squares), especially in the finance network. Between-layer correlation is lower and suggests that countries play different roles in the three layers. Furthermore, correlation between EIC computed on binary networks (cf. lower-diagonal entries) is generally smaller than that computed on weighted networks (cf. upper-diagonal entries), both in terms of scores and ranks. This indicates that intensity of links matter. In other words, differences in the intensity of interactions between any two countries (given the existence of a link) contribute to a stronger correlation between EIC scores.

To get a better feel on this point, Fig. 3 provides a scatter plot—for the year 2020—of weighted and binary centrality ranks (cf. panel (c) and (d), respectively). In the two scatter plots, country percentage ranks in the trade and migration layers are in the x- and y-axis, while country rank in the finance layer is represented using a color scale (from light green to dark grey). The plots show that, first, most central countries are so in all the three layers, while less central countries display more variability. Second, the clouds of rank dots coming from binary EIC is much more dispersed than that coming from weighted EIC, as the correlation coefficients in panels (a) and (b) suggested.

Panel regressions

We now discuss our main results from the regression exercises. We begin with estimation of Eq. (7). As mentioned, we consider two alternative setups as far as centrality

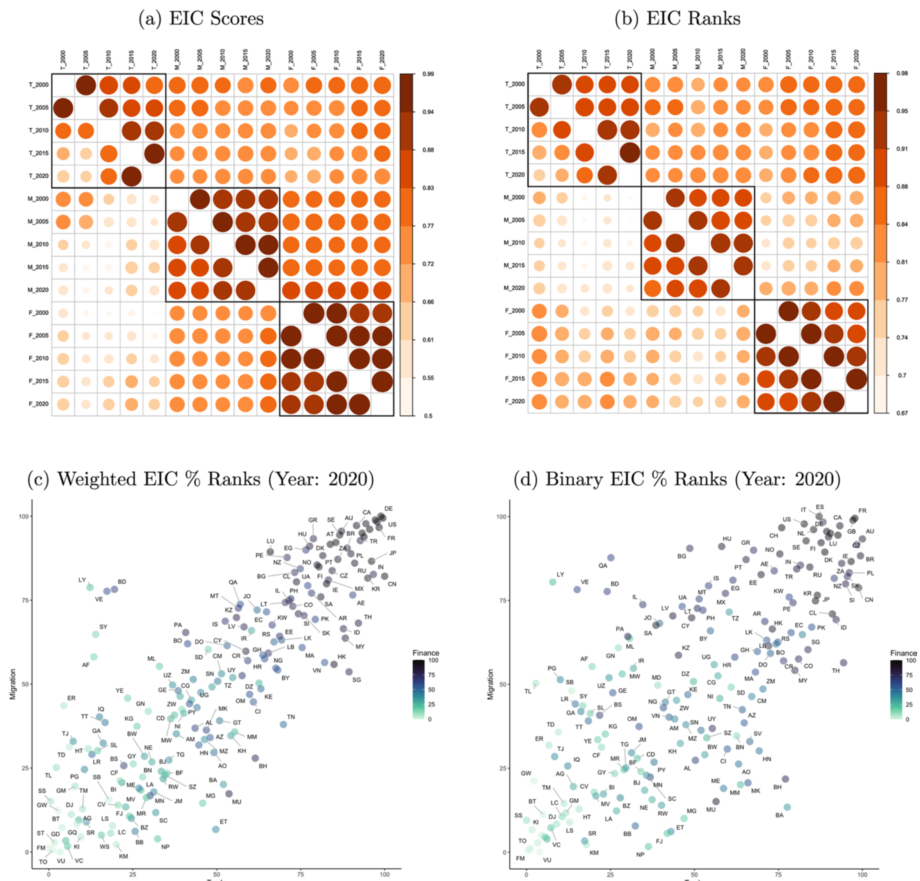

Fig. 3 Correlation between centrality indicators. **a** Pearson correlation plot of weighted EIC scores (upper diagonal elements) and binary EIC scores (lower diagonal elements). **b** Correlation plot of weighted EIC ranks (upper diagonal elements) and binary EIC ranks (lower diagonal elements). Axes: {T_year,M_year,F_year} identify the layer-year pair, where {T,M,F} stand for trade, migration and finance layer and 'year' ranges in 2000, 2005, 2010, 2015, 2020. **c** Scatter plot in year 2020 of weighted EIC percentage country ranks. **d** Scatter plot in year 2020 of binary EIC percentage country ranks. X-axis: Country rank in the trade layer. Y-axis: Country rank in the migration layer. Color scale: Country rank in the finance layer. Labels: Country 2-digit ISO codes

scores are concerned. In the first one (labeled as "Jointly"), we run a single regression where the vector $\mathbf{C}_{it}$ contains all country EIC scores in the three layers. In the second one (labeled as "Sep"), we run three separate regressions, where the vector $\mathbf{C}_{it}$ features only country EIC score in a single layer. For each setup, we consider three different specifications. In the first one ("Base"), centrality scores are computed on the original weight or adjacency matrices (i.e. either $\mathbf{H}_t^\ell$ or $\mathbf{A}_t^\ell$). The second one ("Instr") features instrumented EIC scores, using the gravity-based procedure described in "Section Econometric model". Finally, in the third one ("Lag"), we augment the "Base" specification with a pcGDP lag, as in Eq. (9).

We present regression results using forest plots (Lewis and Clarke 2001), where the x-axis shows estimated coefficients $\hat{\eta}$ and bars around the estimates are 95% confidence intervals (see "Appendix 2" for traditional regression tables).

As Figs. 4 and 5 show, country centrality in the MMN generally appears to significantly boosts pcGDP, net of all other determinants. Note that $\hat{\eta}$ estimates are generally positive and

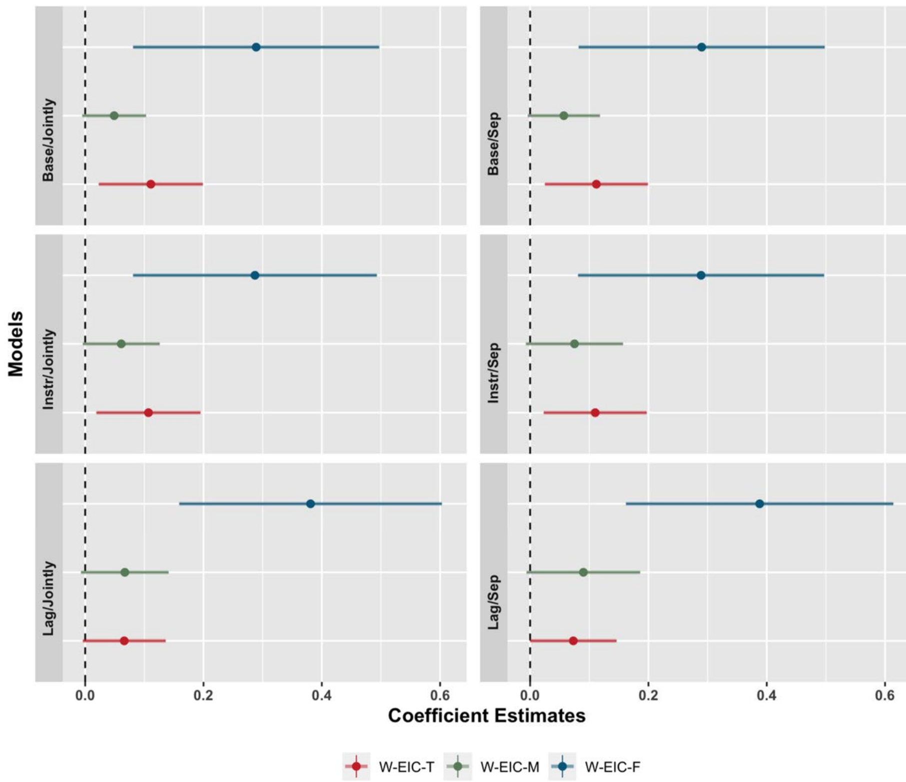

Fig. 4 Regression Results. Forest plots for the estimated coefficients of **weighted** centrality scores (W-EIC). Trade layer (T) in red. Migration layer (M) in green. Finance layer (F) in blue. Models: Base=Baseline specification; Instr=Gravity-instrumented networks; Lag=Lag of dependent variable included; Jointly=All three EIC scores within the covariates; Sep=Three separate regressions each including only one of the three EIC scores. Bars represent 95% confidence intervals for the estimated coefficient

significant not only in the baseline specification (top panels), but also when potential endogeneity endogeneity (mid panels) and when possible autocorrelation in pcGDP is accounted for (lower panels). The positive impact of EIC mostly occurs in capital (finance) and goods (trade) markets, whereas in the permanent-migration network is weaker—or sometimes statistically different from 0 in certain specifications—and is stronger when centrality is computed in weighted networks than in their binary counterparts.

We shall go back to discuss differences in estimation results in "Section Discussion and conclusions". Now, we turn to three sets of robustness checks.

To begin with, we replace country centrality scores, which were separately computed on the trade, migration and finance layers and then inserted in the regression either separately or jointly, with a single eigenvector country-centrality score computed on the MMN. We do so in three different ways. In the first case, we compute EIC centrality scores and ranks on an aggregated network obtained by averaging out individual-layer link weights to get:

$$\tilde{h}_{ijt} = \frac{1}{3}(h^T_{ijt} + h^M_{ijt} + h^F_{ijt}). \tag{10}$$

This procedure combines the MMN into a single-layer network and may end up in adding links with respect to the original layers if, for example, any two countries are not

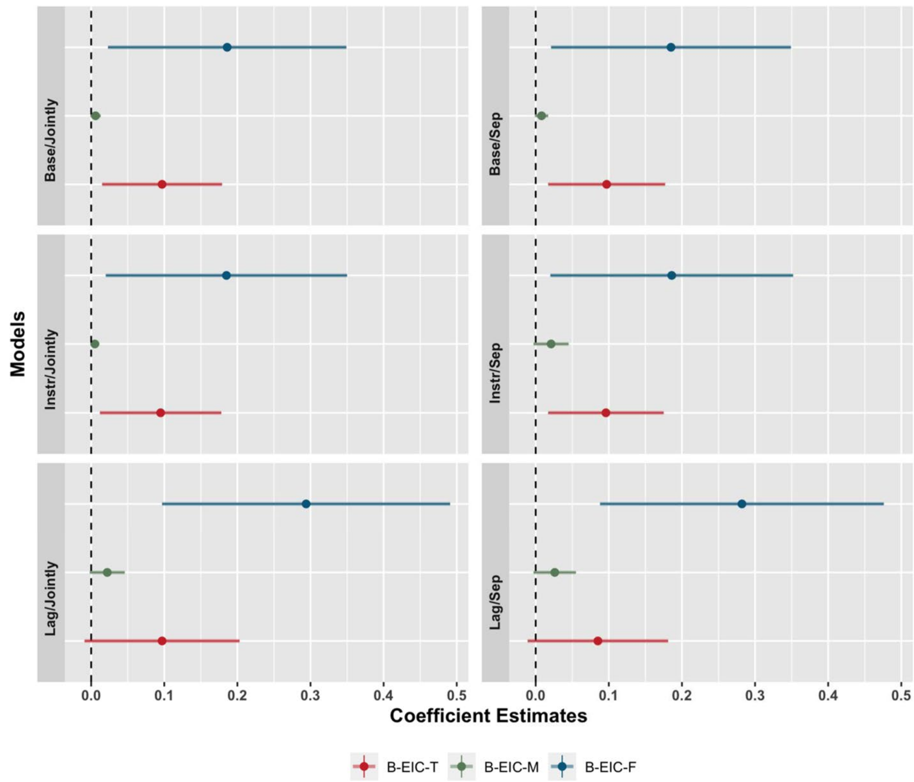

Fig. 5 Regression Results. Forest plots for the estimated coefficients of **binary** centrality scores (B-EIC). Trade layer (T) in red. Migration layer (M) in green. Finance layer (F) in blue. Models: Base=Baseline specification; Instr=Gravity-instrumented networks; Lag=Lag of dependent variable included; Jointly=All three EIC scores within the covariates; Sep=Three separate regressions each including only one of the three EIC scores. Bars represent 95% confidence intervals for the estimated coefficient

linked in at least one layer but they are in the remaining ones. Therefore, the correspondent binary projection, where links are defined as $\tilde{a}_{ijt} = 1$ if $\tilde{h}_{ijt} > 0$ (and zero otherwise) may therefore also differ from multi-layer slices. In the second case, we consider, both in the weighted and binary case, the three EIC country scores and perform a principal-component analysis, taking the first component and consider that as the EIC score vector to insert in panel regressions. In the third case, we simply take the arithmetic average of the three EIC country scores. In all three cases, the vector $\mathbf{C}_{it}$ in Eq. 7 will feature a single variable, i.e. the aggregate country EIC score. Results are summarized in the forest plot of Fig. 6. Our main findings seem to be preserved. Again, both in the binary and weighted case, country centrality appears to significantly and positively affect pcGDP.

The second set of robustness exercises addresses the potential spatial dependence in pcGDP data (Fawaz and Rahnama-Moghadamm 2019). Indeed, being our observation world countries, it may be the case that their cross-section income distributions display some spatial correlation, which may bias our estimates. To check if this is the case, we fit Eq. (7) with a spatial-error model (SEM) by imposing that the errors read:

$$\epsilon_{it} = \lambda \sum_{k=1}^{N} m_{ik}\epsilon_{it} + \nu_{it}, \tag{11}$$

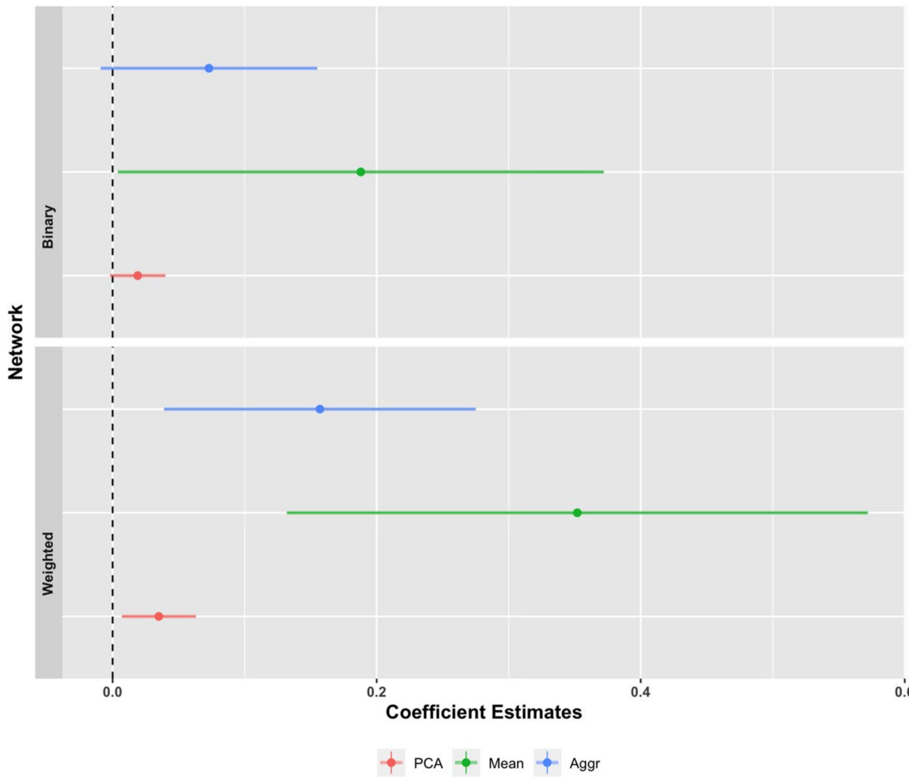

Fig. 6 Regression Results for multi-network EIC. Forest plots for the estimated coefficients of **binary** and **weighted** multi-network centrality scores. PCA: Country centrality scores computed using a principal-component analysis over the three layers. Mean: Country centrality scores computed by averaging out EIC scores of the three layers. Aggr: Country centrality scores computed on the aggregated network obtained by summing up layer-level link weights. Trade layer (T) in red. Migration layer (M) in green. Finance layer (F) in blue. Bars represent 95% confidence intervals for the estimated coefficient

where $\mathbf{M} = \{m_{ik}\}$ is the spatial-weight matrix, which is assumed to be time invariant, and ν_{it} are i.i.d. disturbances. The choice for a SEM is justified as both dependent and independent variables can be spatially autocorrelated, which may jointly induce spatial dependence in the residuals. As to spatial weights, we experiment with two alternatives: (i) $\mathbf{M}$ is defined as in terms of a binary contiguity matrix (i.e. entries are equal to 1 if any two countries share a border); (ii) entries in $\mathbf{M}$ are equal to the inverse of the log of population-weighted geographical distance. Notice that population-weighted geographical distance was used above, when addressing potential endogeneity with a gravity-model approach, as an exogenous regressor that may be useful in improving predictions of link weights and existence. Instead, in this case, contiguity and distance are employed to build spatial-weight matrices, and hence modeling errors, with the aim of exploring possible estimation biases related to spatial dependence. Both country contiguity and geographical distance are retrieved from data discussed in Mayer and Zignago (2011). Before estimating Eq. (11), we compute Moran's I statistic on the residuals of our baseline regressions, observing throughout a statistically-significant, strong rejection of the null hypothesis of spatial independence, with p values way smaller that 0.001 in all setups and specifications. Forest plots in Figs. 7 and 8 summarize our estimation results. Notice first that the positive and statistically-significant impact of centrality on pcGDP

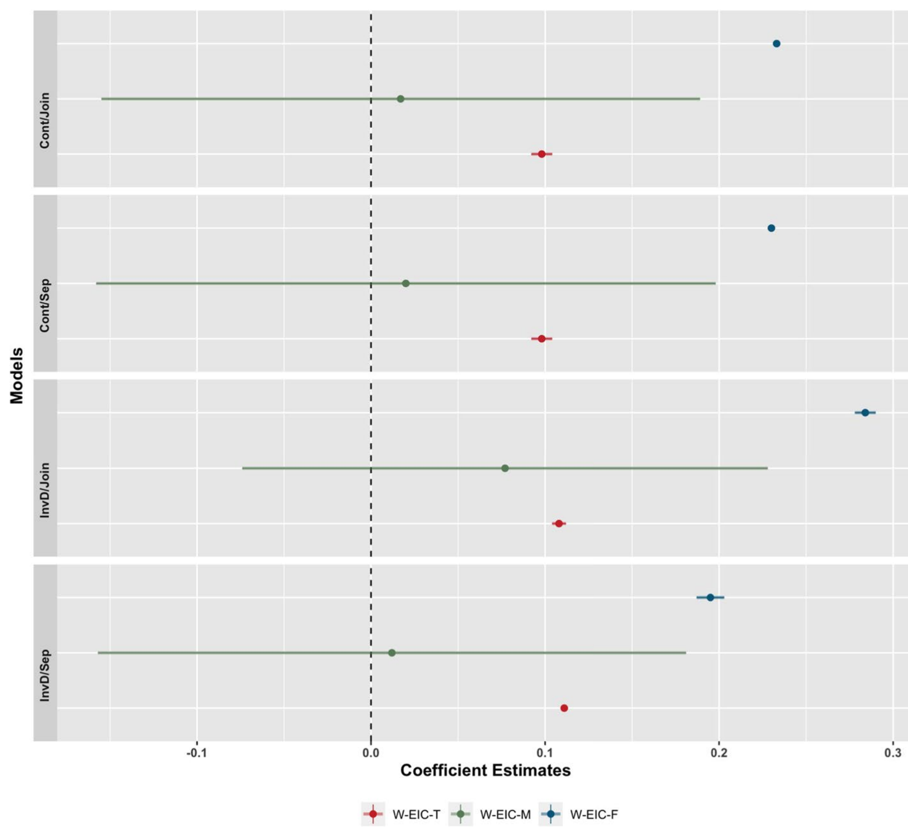

Fig. 7 Regression Results. Forest plots for the estimated coefficients of **weighted** centrality scores with spatial-error models. Cont: Spatial weights modeled using country contiguity. InvD: Spatial weights modeled using inverse of logged geographical distance. Join: All three EIC scores enter jointly in the regression. Sep: Each EIC score enters separately in the regression. Trade layer (T) in red. Migration layer (M) in green. Finance layer (F) in blue. Bars represent 95% confidence intervals for the estimated coefficient

is preserved, especially in the trade and finance layers, both in the case of weighted and binary EIC scores. The point estimate of centrality in the migration layer is still positive but confidence bands enlarge and cross the zero axis, indicating a statistically weak impact. On the contrary, accounting for spatial correlation makes much more precise estimates in the trade and finance layers, in particular as far as the weighted centrality scores are concerned. Finally, as regression tables in "Appendix 2" show, the estimate for the spatial coefficient λ in Eq. (11) turns out to be always statistically significant, confirming the importance of spatial effects in our data.

In the third set of robustness checks, we investigate whether, net of local measures of country centrality, global country exposure still exerts a positive and statistically-significant impact on country pcGDP. The rationale of these additional exercises stems from the observation that node degree (ND) and node strength (NS) (Barrat et al. 2004) may be interpreted as proxies of local country exposure, in line with our discussion on country openness indicators in "Section Econometric model". However, unlike openness—which is computed as a share of country GDP or population and thus discounts size effects—degrees and strengths may simply capture, extensively and intensively, the extent to which a country is open to direct neighbors in terms of the number of channels through which spillovers may be locally transmitted, and

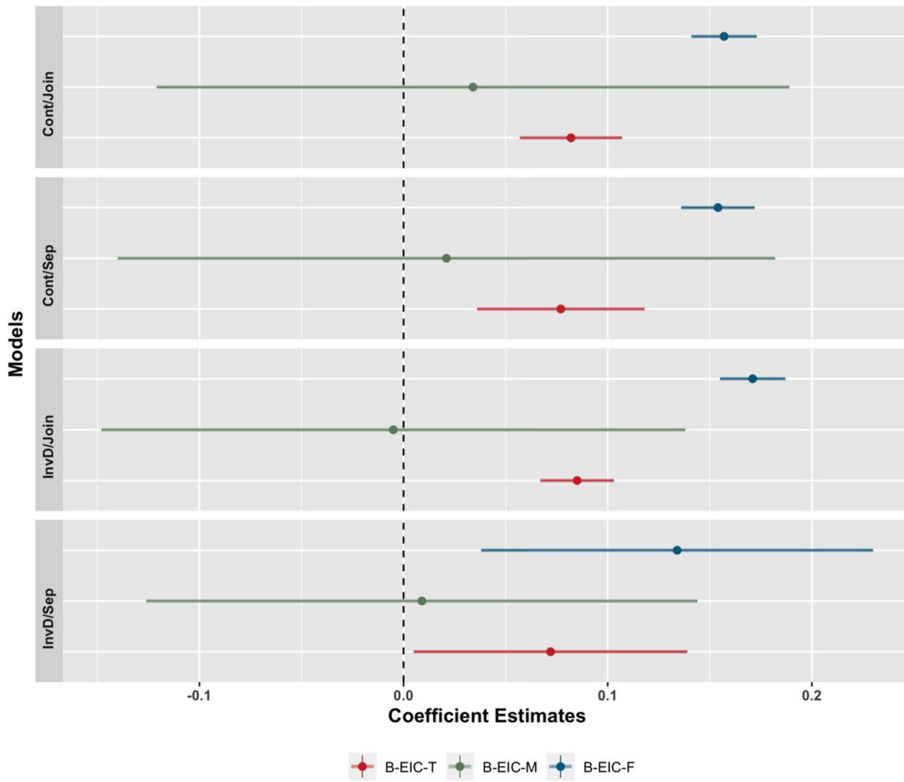

Fig. 8 Regression Results. Forest plots for the estimated coefficients of **binary** centrality scores with spatial-error models. Cont: Spatial weights modeled using country contiguity. InvD: Spatial weights modeled using inverse of logged geographical distance. Join: All three EIC scores enter jointly in the regression. Sep: Each EIC score enters separately in the regression. Trade layer (T) in red. Migration layer (M) in green. Finance layer (F) in blue. Bars represent 95% confidence intervals for the estimated coefficient

their total intensity, as ND and NS are not rescaled by country economic or demographic size. Furthermore, contrary to country openness, in our networks ND and NS are positively, although not strongly, correlated with the correspondent binary and weighted EIC statistics.[11] This is expected, as all our layers are relatively dense networks, wherein the number and intensity of first-order connection already controls for a share of node centrality. However, since the international networks of trade, migration and finance (as defined in this paper) are characterized by a marked binary and weighted disassortativity[12] and right-skewed ND/NS distributions, higher-order linkages may convey global importance to countries holding a small number of first-order interactions. In other words, there may be countries with small ND or NS that are able to acquire some global importance in terms of their EIC scores due to indirect linkages (and the other way around), as suggested by the high but not very large Pearson correlation coefficients between ND/NS and binary/weighted EIC scores.

Therefore, despite some potential multicollinearity issues may arise, we run two sets of regressions. Using the baseline specification with layer-specific network covariates

[11] Pearson correlation coefficients range in [0.44,0.63] for the trade layer, [0.37,0.49] for the migration layer, and [0.51,0.74] for the finance layer.

[12] A network is said to be disassortative if, on average, nodes with a large degree or strength tend to be linked with nodes with a low degree or strength. For an analysis of disassortativity of the three layers employed here see Fagiolo et al. (2009), Fagiolo and Mastrorillo (2013), Schiavo et al. (2010).

entering separately, we first replace binary and weighted EIC with ND and NS, respectively. This allows for a preliminary check of whether local exposure alone affects pcGDP. Second, we insert in the same regression both ND or NS, together with either binary or weighted EIC, in order to investigate if, net of local network exposure, centrality still explains pcGDP. Estimated OLS coefficients for ND, NS, binary and weighted EIC are summarized in Table 5, where rows (1)-(4) refer to the trade layer, rows (5)-(8) to the migration layer, and rows (9)-(12) to the finance layer; and single lines within each 4-row block represent different regressions. Results show that local country-network exposure are almost always not significant and, when they are, their coefficient is very small. Once both local and global exposure jointly appear in the covariates, country global centrality still exerts a positive and statistically-significant impact, much higher in magnitude as compared to that coming from local network openness. Finally, notice that this occurs net of controlling for country-specific quadratic time trends, which, on the one hand, seem to offset local centrality effects modeled using ND or NS, while on the other hand still preserve the income-enhancing impact of global centrality indicators. Overall, these findings suggest that most of the positive effect of country importance on per-capita GDP comes from indirect channels in the diffusion of spillovers across countries.

Directed networks

An important assumption of the present study is the use of undirected networks. Symmetrizing link weights provides indeed a benchmark case that is particularly meaningful whenever, as it happens in our data, the frequency of bidirectional links in the original directed network is relatively large.[13] In fact, reciprocity ratios, computed as the share of all binary directed links $i \to j$ that are reciprocated (i.e., for which also the directed link $j \to i$ does exist), oscillate across the years around 0.65 for the trade layer, 0.33 for the migration layer, and 0.40 for the finance layer. Similarly, the correlation coefficient between upper diagonal and lower diagonal entries of weight matrices fluctuates around 0.61 for the trade layer, 0.30 for the migration layer (see also the discussion in the last paragraph), and 0.60 for the finance layer. This indicates that we are not losing a lot of information by symmetrizing the network.

However, by symmetrizing weights, we are underscoring all those instances wherein links exist in both directions, but are characterized by a very uneven magnitude, e.g., whenever a very big country interacts with a very small one. In terms of undirected centrality measures, small countries may end up enjoying a higher centrality just because the sum of the inward and outward weight is large, but this may not be reflected in an even distribution of the inward and outward flow of ideas and/or spillovers.

In this section, we provide therefore some evidence about the impact of country centrality when the underlying networks are modeled as directed graphs. Notice that centrality statistics in directed (weighted) networks must account for the extent to which a country is central because it is pointed by (or it point towards) other central countries. In other words, in directed networks, node centrality cannot be characterized anymore by a single coefficient, as it is the case for undirected networks. A possible solution is to employ Kleinberg (hub-authority) centrality (Kleinberg 1998), which attaches two centrality scores to each node, discriminating between nodes that are authorities because

[13] At least as compared to many other real-world graphs such as the interbank network and several biological networks, see e.g. Squartini et al. (2013).

Table 5 Impact of local country network exposure

Layer		ND	NS	B-EIC	W-EIC	N	adj R^2
Trade	(1)	0.001	–	–	–	870	0.965
	(2)	–	0.000*	–	–	870	0.964
	(3)	0.000	–	0.172**	–	870	0.964
	(4)	–	− 0.001*	–	0.245**	870	0.964
Migration	(5)	0.000	–	–	–	870	0.965
	(6)	–	0.001	–	–	870	0.965
	(7)	− 0.002	–	0.277*	–	870	0.965
	(8)	–	0.003	-	0.302*	870	0.964
Finance	(9)	0.002*	–	–	–	870	0.964
	(10)	–	0.002*	–	–	870	0.964
	(11)	0.001*	–	0.068**	–	870	0.965
	(12)	–	0.001*	–	0.424***	870	0.965

Estimated coefficients from regression exercises. ND, Node degree; NS, Node strength. Baseline specification with OLS estimator and network statistics of different layers separately entering as covariates. Each row in the table in a distinct regression where ND/NS enter either alone or together with EIC variables. B-EIC, Binary EIC; W-EIC, Weighted EIC. Significance: *0.10, **0.05, ***0.01

they receive links by hubs, and nodes that are hubs because they point to authorities.[14] As Table 6 shows, both hubs and authorities scores still boost per-capita income. In particular, estimated coefficients appear to be rather symmetric, confirming our observation about the detected large percentage of bidirectional links. If any, being relevant authorities (i.e., receiving spillovers from relevant hubs) affects more per-capita GDP than being relevant hubs (i.e., sending spillovers to relevant authorities) in both trade and migration layers. This result seems to robustly hold in all fitted specifications, where hubs and authority scores are inserted as covariates either layer-by-layer or jointly.

Discussion and conclusions

Cross-country spillovers are one of the main drivers of economic growth, and ultimately shapes the spatiotemporal distribution of country income. In this paper, we employ data about merchandise trade, permanent human migration and international-finance linkages, to construct a multi-layer network representing three of the main interaction channels through which technological spillovers can be transmitted across world countries. We are interested in investigating whether country global importance in the multi-networks of bilateral international relations wherein they are entrenched can explain their pcGDP, net of country-specific, time-varying characteristics and common trends. Our econometric findings suggest that, robustly across alternative modeling setups and specifications, country eigenvector centrality in the MMN significantly boosts country income, especially in the trade and finance layers.

Overall, our analysis indicates that "local" country importance—as measured, e.g, by country openness indicators—is not necessarily collinear, or strongly and positively correlated, with "global" measures of network centrality. Therefore, in our interpretation, being intensively and extensively locally connected in the trade, migration and finance networks

[14] Our interpretative framework (see "Section A simple interpretative framework") can be extended to weighted directed networks in a straightforward way, for example by letting the technical-progress coefficient ϕ_i be equal to the product of two parameters, separately controlling for inward and outward centrality. If country inward (respectively, outward) centrality depends on a linear combination of country outward (respectively, inward) centrality—with weights being the entries of the matrix W—per-capita output shall positively depend on Kleinberg authority and hubness scores.

Table 6 Estimated coefficients from regression exercises where country centrality is computed with hubs and authority scores (Kleinberg 1998) and layers are modeled as weighted directed networks

Specs	Trade		Migration		Finance	
	Authorities	Hubs	Authorities	Hubs	Authorities	Hubs
(1)	0.231**	–	–	–	–	–
(2)	–	0.134*	–	–	–	–
(3)	0.190**	0.126*	–	–	–	–
(4)	–	–	0.079*	–	–	–
(5)	–	–		0.028*	–	–
(6)	–	–	0.067*	0.032*	–	–
(7)	–	–	–	–	0.125**	
(8)	–	–	–	–		0.125**
(9)	–	–	–	–	0.127**	0.128*
(10)	0.228**		0.052**	–	0.119**	
(11)	–	0.133*	–	0.026	–	0.124**
(12)	0.179**	0.128**	0.032*	0.021*	0.125**	0.121**

OLS estimates for the model in Eq. (7). Each row in the table in a distinct regression specification. Significance: *0.10, **0.05, ***0.01

does not automatically imply absorbing more technological spillovers. What our analysis shows is that countries become more exposed to foreign influence, and therefore increase their income, if they are connected with partners that are in turn globally important in the MMN because they hold the "right" linkages. As a consequence, network centrality indicators, such as EIC, can better proxy global country exposure to technological spillovers and better predict the spatiotemporal distribution of country income.

From a policy perspective, the income-enhancing effect of country centrality suggests that planners should steer for the country to improve her position in the global networks where she is embedded in, by strategically favoring the creation of links with important nodes in the network. In particular, countries should push for a strategic selection of their extensive margins and for a careful, rather than a blind, expansion of their intensive margins. Indeed, our empirical evidence suggests that country per-capita GDP increases as global country centrality improves. This can be achieved by favoring, extensively and intensively, those linkages that are more conducive in terms of possible spillovers, i.e. connections with other globally central countries. In that respect, an interesting extension of the present work would be to investigate if country centrality in the MMN affects also country GDP growth, in addition to country income levels.

As mentioned, one possible channel through which global exposure can affect per-capita GDP is technological diffusion. However, our results may be interpreted in alternative ways, since a deeper integration in trade, migration and portfolio investment networks may affect, e.g. the credibility of the exchange rate regime, the financing capacity of companies, or the institutional pressure exerted by migrants to improve public and private governance. Therefore, more work is needed to dig into different channels at work in the detected empirical relationships.

As to the choice of the eigenvector-based Bonacich centrality indicator, the utterly simple theoretical framework presented in "Section A simple interpretative framework" provides some support to use it as our primary measure of global country importance. Furthermore, in (weighted) undirected networks, there is no real gain in using other eigenvector-based indicators, as Table 3 clearly shows for Katz centrality. Of course, other global centrality measures that are not eigenvector based can be considered. For example, node betweenness (Freeman 1977) can in principle be a good candidate to capture global spillovers effects, as it counts the number of shortest paths going through each country. However, it is well-known that node betweenness is unambiguously defined only for binary networks (Opsahl et al. 2010). Studying the impact of country betweenness on pcGDP only in binary layers would have limited the scope of our analysis, also in view of the important difference between intensive and extensive margins that we have detected throughout. Computing node betweenness on weighted links, requires one to choose both the functional form used to transform weights in costs, and the function that aggregates link weights along a shortest path. Since results are often heavily dependent on those choices, we have preferred to postpone the exercise of playing with additional degrees of freedom in the formulation of a weighted betweenness indicator to a future analysis.

A critical choice made in the paper was about the data employed to empirically describe the three main channels through which technological spillovers may be transmitted across countries. To begin with, we believe that focusing on trade, migration, and finance is a good starting point, as those three dimensions represent the most important economic channels as far as international relations are concerned. However, alternative network data may be considered to better proxy the extent to which those channels are able to facilitate spillover diffusion. For example, employing data about international trade in services (U.S. International Trade Commission 2023) could complement the analysis that so far has considered commodity trade only. Similarly, data on temporary migration for business purposes (Fagiolo and Santoni 2015), migration of scholars (Sanliturk et al. 2023), cross-border patents (Burnel and Zylkin 2022), or air-fight traffic (ICAO 2023), may better proxy both intensive and extensive margins of linkages vehiculating (technological) spillover effects through the exchange of ideas.

The choice of using total-portfolio investment (TPI) to proxy the effects from the financial layer is perhaps the most questionable one. Indeed, it is well-known that TPI volumes are typically smaller, more volatile and shorter in horizon than those for other types of country investment such as foreign-direct investment (FDI), which would have been a more natural proxy to capture technological transfers or other spillover channels. The reason why we chose TPI in this study is twofold. On the one hand, TPI data have been widely employed in the complex-network literature in the past and the topological properties of TPI networks (aka the International Financial Network, IFN) are well understood [cf., e.g., Refs. Schiavo et al. (2010), Chinazzi et al. (2013), Korniyenko et al. (2018)], among others), as it happens for the two other layers used in this analysis. Conversely, the topological properties of the international FDI network and their evolution have been much less explored[15], and a substantial amount of work is still required to make existing databases (United Nations Conference on Trade and Development 2023; The International Monetary Fund 2023; Dueñas et al. 2017) comparable and study their topological properties. Therefore, using TPI as a first approximation allows us to focus on our main working hypothesis while disregarding a necessary and preliminary network analysis.

Of course, one of the first points in our agenda is to properly incorporate data about country centrality in additional country financial-interaction layers, such as cross-border FDI, and also bank lending (Bank for International Settlements 2023; Cerutti and

[15] An example focusing on the international merger and acquisition network is in Ref. Dueñas et al. (2017).

Zhou 2017). Combining all those data sources in a higher-dimensional MMN, where the number of layers increases in all the three original dimensions (trade, people, finance), may allow one to better characterize—and assess the relative importance of—the different channels through which spillovers can flow among countries (Bonaccorsi et al. 2019).

This might be particularly important as far as the flow of ideas via geographical relocation of people is concerned. Indeed, our econometric exercises indicate that country centrality in the migration layer impacts income more weakly, and sometimes in a statistically not significant way. Whether this is a robust results or not is an open question, as it may be the case that data on permanent migration employed here are not able to fully capture the contribution of human resettling in the process of ideas diffusion. Besides, permanent-migration data, unlike, e.g., those for temporary migration and cross-border patents, are available only at five-year intervals and are more persistent over time, which may in principle constrain the analysis and result in a weaker explanatory power.

Finally, several additional exercises may help in obtaining more robust results and extending our analyses. For example, one might further explore issues related to reverse-causation endogeneity issues in our econometric specifications by fitting models with GMM estimators (Arellano and Bond 1991). Besides, with new data allowing for a longer time span and more waves (e.g., yearly observations), one may better investigate persistency issues in the relation between centrality and income. Indeed, if diffusion in the macroeconomic network is a gradual process, it can take time for spillovers to percolate across the system. Therefore, country global exposure may be better proxied by adding among covariates lagged EIC terms. In addition, one might exploit the well-known decomposition of some eigenvector-based centrality measures—such as Katz (Alpha) centrality—into the sum of powers of the weight or adjacency matrix to dig further into the contribution to country income coming from nodes that are connected through walks of increasing length.

Appendix 1: Choropleth maps (year 2020)

See Figs. 9, 10 and 11.

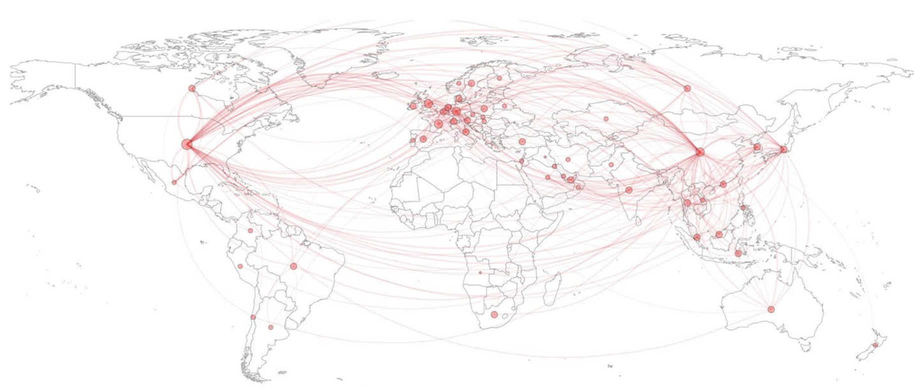

Fig. 9 Choropleth map for the trade layer in year 2020. Only top 1% link weights are shown. Link thickness is proportional to link weights and node size is proportional to country weighted eigenvector centrality in the full layer network

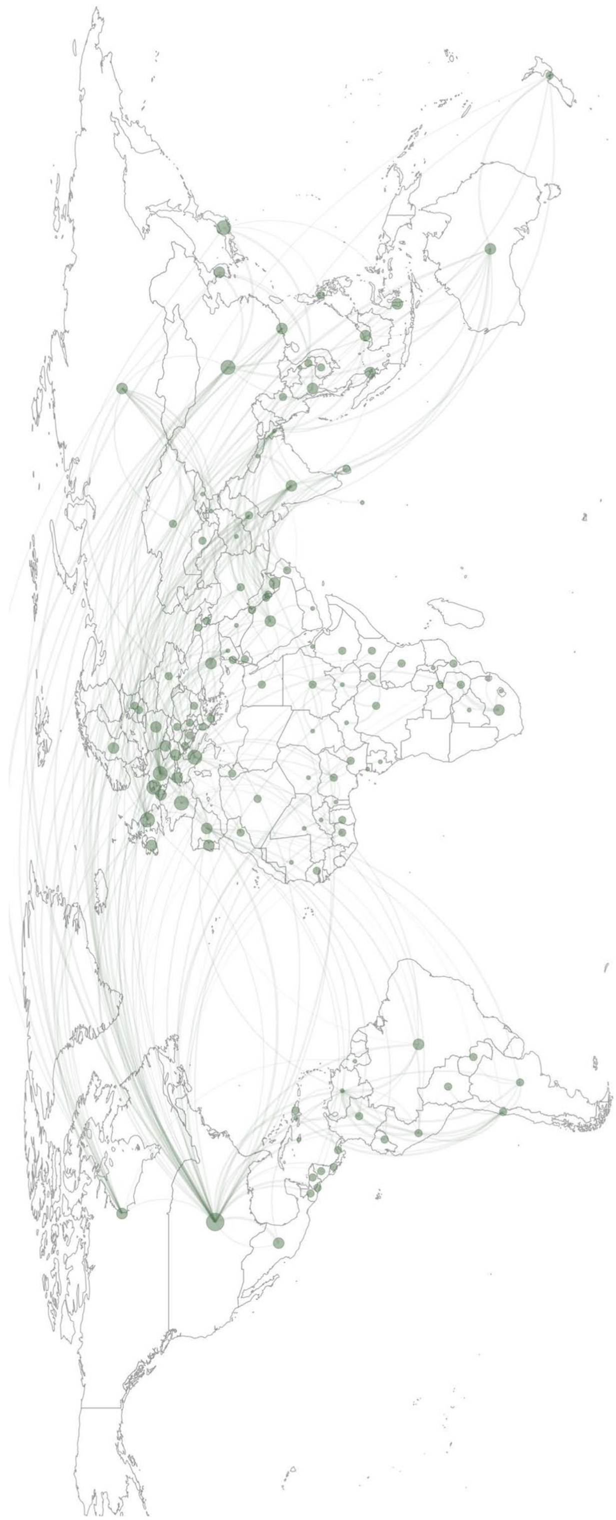

Fig. 10 Choropleth map for the migration layer in year 2020. Only top 1% link weights are shown. Link thickness is proportional to link weights and node size is proportional to country weighted eigenvector centrality in the full layer network

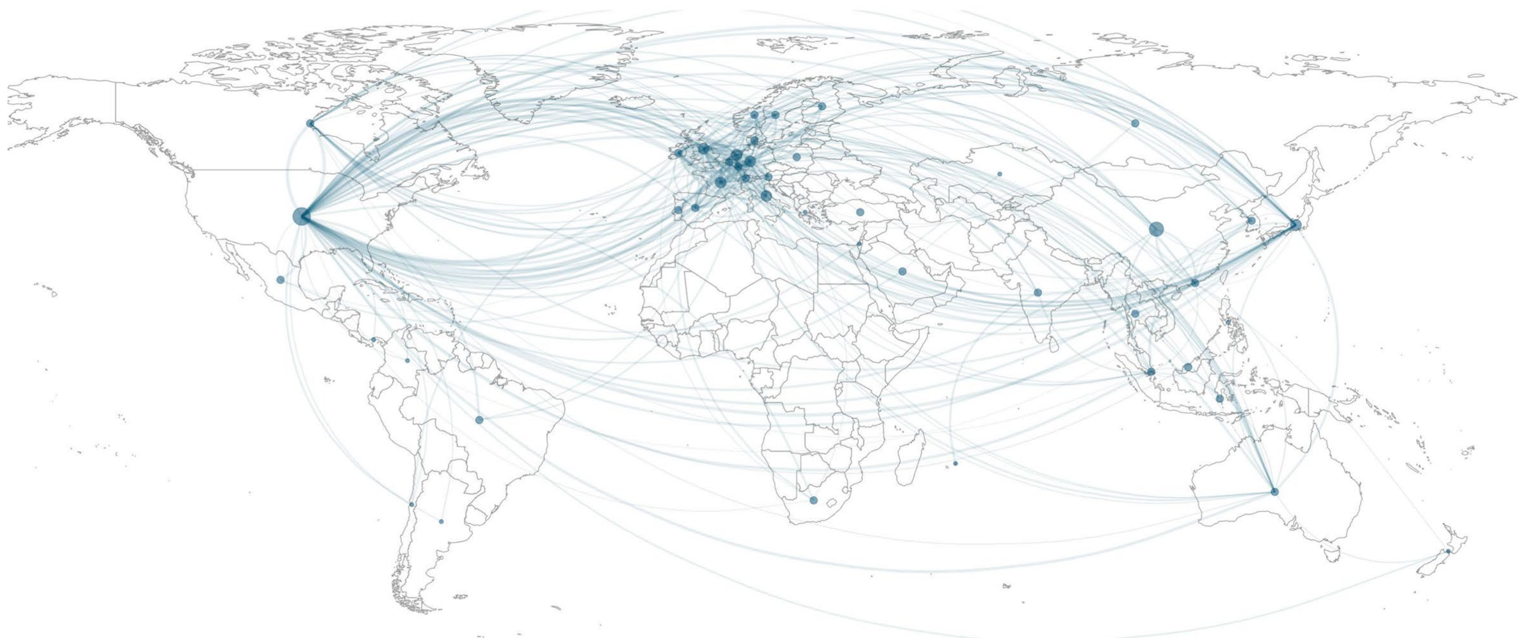

Fig. 11 Choropleth map for the finance layer in year 2020. Only top 1% link weights are shown. Link thickness is proportional to link weights and node size is proportional to country weighted eigenvector centrality in the full layer network

Appendix 2: Regression tables

See Tables 7, 8, 9, 10 and 11.

Table 7 Panel regression exercises

Dependent Variable: pcGDP. Weighted EIC							
Setup	**Network**	**Coeff**	**Std Err**	***p* value**	**Stars**	**N**	**adj R^2**
Separately	Trade	0.112	0.045	0.013	**	870	0.965
	Migration	0.057	0.031	0.067	*	870	0.964
	Finance	0.29	0.106	0.007	***	870	0.965
Jointly	Trade	0.111	0.045	0.014	**	870	0.966
	Migration	0.049	0.028	0.079	*	870	0.966
	Finance	0.289	0.106	0.007	***	870	0.966
Dependent Variable: pcGDP. Binary EIC							
Setup	**Network**	**Coeff**	**Std Err**	***p* value**	**Stars**	**N**	**adj R^2**
Separately	Trade	0.097	0.041	0.018	**	870	0.964
	Migration	0.008	0.004	0.074	*	870	0.964
	Finance	0.185	0.083	0.028	**	870	0.965
Jointly	Trade	0.097	0.042	0.021	**	870	0.965
	Migration	0.006	0.004	0.092	*	870	0.965
	Finance	0.186	0.083	0.027	**	870	0.965

Baseline Specification. Estimation results. Significance: *0.10, **0.05, ***0.01

Table 8 Panel regression exercises

Dependent Variable: pcGDP. Weighted EIC, Gravity-Instrumented Networks							
Setup	**Network**	**Coeff**	**Std Err**	***p* value**	**Stars**	**N**	**adj R^2**
Separately	Trade	0.11	0.044	0.014	**	870	0.965
	Migration	0.075	0.042	0.076	*	870	0.964
	Finance	0.289	0.106	0.007	***	870	0.965
Jointly	Trade	0.107	0.045	0.018	**	870	0.966
	Migration	0.061	0.033	0.069	*	870	0.966
	Finance	0.287	0.105	0.007	***	870	0.966
Dependent Variable: pcGDP. Binary EIC, Gravity-Instrumented Networks							
Setup	**Network**	**Coeff**	**Std Err**	***p* value**	**Stars**	**N**	**adj R^2**
Separately	Trade	0.096	0.040	0.018	**	870	0.964
	Migration	0.021	0.012	0.082	*	870	0.964
	Finance	0.186	0.084	0.029	**	870	0.965
Jointly	Trade	0.095	0.042	0.026	**	870	0.965
	Migration	0.005	0.003	0.079	*	870	0.965
	Finance	0.185	0.084	0.029	**	870	0.965

Gravity-Instrumented Networks. Estimation results. Significance: *0.10, **0.05, ***0.01

Table 9 Panel regression exercises

Dependent Variable: pcGDP. Weighted EIC, Lag of pcGDP included							
Setup	**Network**	**Coeff**	**Std Err**	***p* value**	**Stars**	**N**	**adj R^2**
Separately	Trade	0.073	0.037	0.052	*	695	0.973
	Migration	0.09	0.049	0.068	*	695	0.973
	Finance	0.388	0.115	0.001	***	695	0.975
Jointly	Trade	0.066	0.036	0.067	*	695	0.975
	Migration	0.067	0.038	0.079	*	695	0.975
	Finance	0.381	0.113	0.001	***	695	0.975
Dependent Variable: pcGDP. Binary EIC, Lag of pcGDP included							
Setup	**Network**	**Coeff**	**Std Err**	***p* value**	**Stars**	**N**	**adj R^2**
Separately	Trade	0.085	0.049	0.086	*	695	0.973
	Migration	0.026	0.015	0.077	*	695	0.972
	Finance	0.282	0.099	0.005	***	695	0.974
Jointly	Trade	0.097	0.054	0.076	*	695	0.975
	Migration	0.022	0.012	0.079	*	695	0.975
	Finance	0.294	0.100	0.004	***	695	0.975

Lag of pcGDP included. Estimation results. Significance: *0.10, **0.05, ***0.01

Table 10 Panel regression exercises

Dependent Variable: pcGDP. Multi-Graph Weighted EIC						
EIC	**Coeff**	**Std Err**	***p* value**	**Stars**	**N**	**adj R^2**
PCA	0.035	0.015	0.017	**	870	0.965
Mean	0.352	0.112	0.002	***	870	0.965
Aggr	0.157	0.060	0.01	**	870	0.965
Dependent Variable: pcGDP. Multi-Graph Binary EIC						
EIC	**Coeff**	**Std Err**	***p* value**	**Stars**	**N**	**adj R^2**
PCA	0.019	0.011	0.085	*	870	0.964
Mean	0.188	0.094	0.047	**	870	0.965
Aggr	0.073	0.042	0.082	*	870	0.964

Multi-Graph Centrality. Estimation results. Significance: * 0.10, ** 0.05, *** 0.01

Table 11 Panel regression exercises. Spatial Error Models. Estimation results. Significance: * 0.10, ** 0.05, *** 0.01

Dependent Variable: pcGDP. Contiguity spatial weights, Weighted EIC						
Setup	**Network**	**Coeff**	***p* value**	**Stars**	**Lambda**	**Std Err**
Separately	Trade	0.098	0.003	***	0.339***	0.033
	Migration	0.02	0.091	*	0.341***	0.012
	Finance	0.23	0.001	***	0.334***	0.069
Jointly	Trade	0.098	0.003	***	0.325***	0.033
	Migration	0.017	0.088	*	0.325***	0.010
	Finance	0.233	0.001	***	0.325***	0.070

Table 11 (continued)

Dependent Variable: pcGDP. Contiguity spatial weights, Binary EIC

Setup	Network	Coeff	*p* value	Stars	Lambda	Std Err
Separately	Trade	0.077	0.021	**	0.342***	0.033
	Migration	0.021	0.082	*	0.348***	0.012
	Finance	0.154	0.009	***	0.344***	0.058
Jointly	Trade	0.082	0.013	**	0.350***	0.033
	Migration	0.034	0.079	*	0.350***	0.019
	Finance	0.157	0.008	***	0.350***	0.059

Dependent Variable: pcGDP. Inverse-distance spatial weights, Weighted EIC

Setup	Network	Coeff	*p* value	Stars	Lambda	Std Err
Separately	Trade	0.111	0.001	***	0.065*	0.033
	Migration	0.012	0.086	*	0.084***	0.007
	Finance	0.195	0.004	***	0.085***	0.067
Jointly	Trade	0.108	0.002	***	− 0.100*	0.034
	Migration	0.077	0.077	*	− 0.100*	0.043
	Finance	0.284	0.003	***	− 0.100*	0.094

Dependent Variable: pcGDP. Inverse-distance spatial weights, Binary EIC

Setup	Network	Coeff	*p* value	Stars	Lambda	Std Err
Separately	Trade	0.072	0.034	**	0.047***	0.034
	Migration	0.009	0.069	*	0.071*	0.005
	Finance	0.134	0.049	**	0.673***	0.068
Jointly	Trade	0.085	0.009	***	0.046*	0.032
	Migration	− 0.005	0.073	*	0.046*	− 0.003
	Finance	0.171	0.008	***	0.046*	0.064

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Author contributions
GF and DSL equally contributed to both empirical analyses and theoretical framework. Both authors read and approved the final manuscript.

Availability of data and materials
The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

Competing interests
The authors declare that they have no competing interests.

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