

# Human-Mobility Networks, Country Income, and Labor Productivity

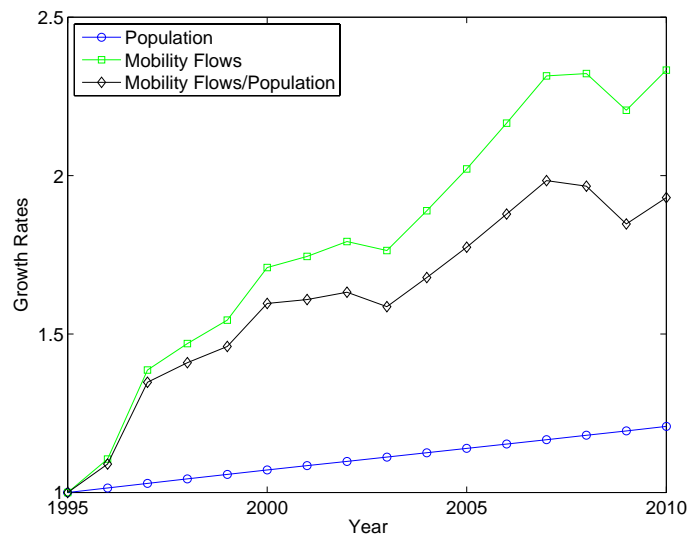
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## *On-Line Appendices*

### A Topological Properties of the International Temporary Human-Mobility Network

#### A.1 Basic Facts about International Temporary Human-Mobility Data

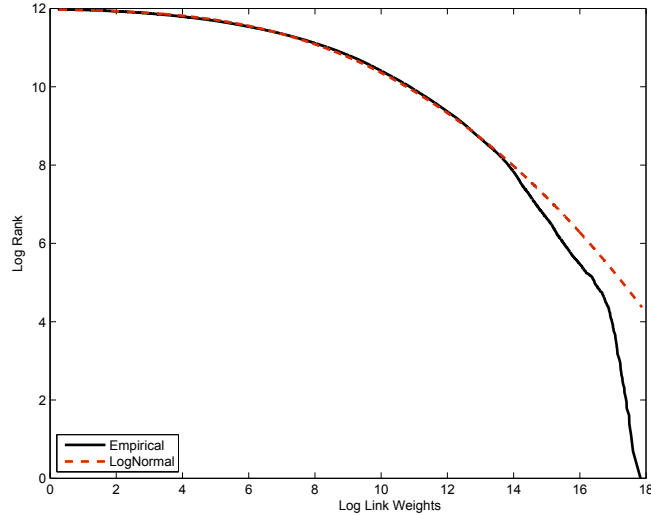
The total flow of travellers has undergone a dramatic increase in the period 1995-2010. As Figure A1 shows for our sample of 213 countries, the total volume of the network has risen by a factor of 2.4. This pattern holds also for the share of total travellers over world population. In 2010 nearly 780 millions of people (11.2% of world population) has temporarily moved worldwide, while in 1995 mobility flows involved only 5.8% of the overall population.



**Figure A1:** Growth rates of total mobility flows, world population and share of travellers over world population. Base year: 1995 = 1.

We now turn to investigate the topological properties of the weighted-directed network of international temporary human-mobility (ITHMN), see Section 3.

Figure A2 plots the pooled link-weight distribution (using a size-rank characterization) and the correspondent log-normal fit. Link weights appear to follow a log-normal distribution (as it happens for the international trade), with only a very small fraction of the data in the right tail that could be approximated by a Pareto density.



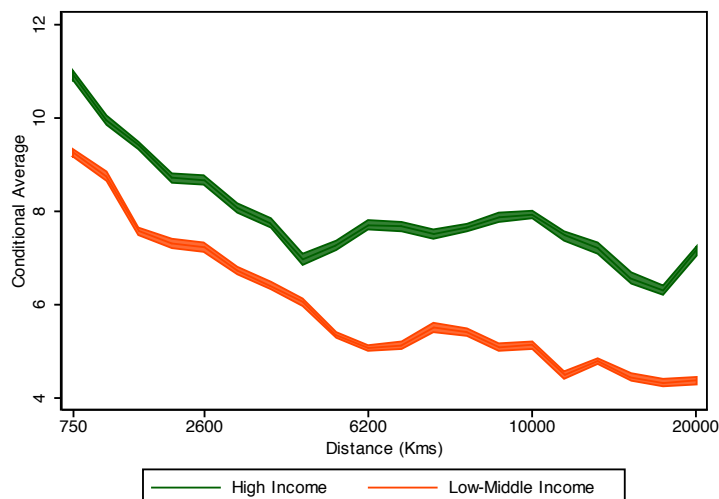
**Figure A2:** Size-rank plot of the pooled mobility-flow distribution.

We now explore the behavior of ITHMN link weights conditional on geographical distance travelled. Note that, in the pooled sample, people have travelled an average bilateral distance of around 6600 kms. As it happens for migration stocks (Fagiolo & Mastrorillo, 2013a), average mobility flows decrease with geographical distance (see Figure A3). Interestingly, the decline is sharper for mobility flows originated from low and middle income countries<sup>1</sup>, suggesting that income also plays a major role in shaping the international temporary human-mobility flow distribution. It is worth noting that in 2010, 70% of the total flows originated from high-income countries and almost half of world international human mobility involves travels between high-income countries (49% of total flows in 2010). A large share of mobility, about one fifth (21%), occurs between low and middle income countries, whereas the remaining 9% is from low/middle-income countries to high-income ones.

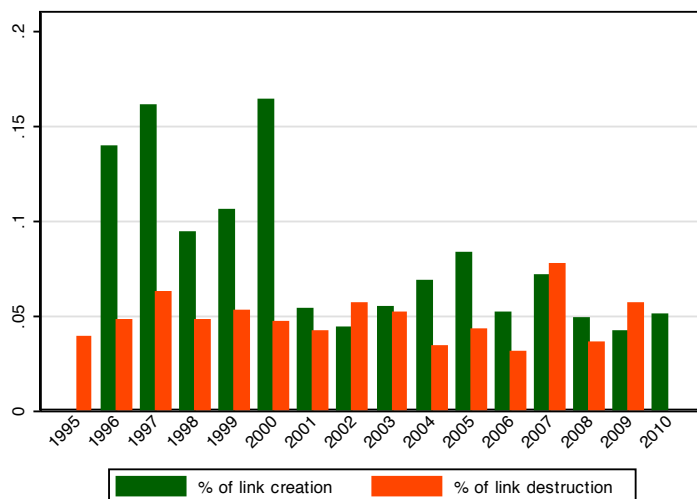
The ITHMN is quite geographically concentrated. For example, over 8.3% of total world mobility flows is accounted by mobility pattern among NAFTA countries (Canada, Mexico and the U.S.). The U.S. are also the largest recipient of incoming flows (7.5%), followed by Spain, France and Italy (together accounting for 17.1%) and China (4.6%). Germany, instead, accounted for 10% of world outgoing flows in 2010, followed by the U.S. (9.4%) and the U.K. (6.7%). It is also worth mentioning the sharp increase in the number of travellers from the BRICs: indeed, about 7.8% of total flows in 2010 originated from those countries, a figure that almost doubled since 1995 (3.8%).

The ITHMN is characterized by a relative large turbulence as far as the emergence and disappearing of mobility corridors. Regarding the emergence of links, the fraction of flows which switch from zero to a positive value is relatively high, on average 6.2% over the whole

<sup>1</sup>Income group is defined according to the World Bank classification (<http://data.worldbank.org/about/country-classifications/world-bank-atlas-method>).



**Figure A3:** Average of mobility flows conditional to geographical distance between countries. X-axis employs 20 geographical-distance bins, i.e. 5-percentiles of the geographical-distance distribution.



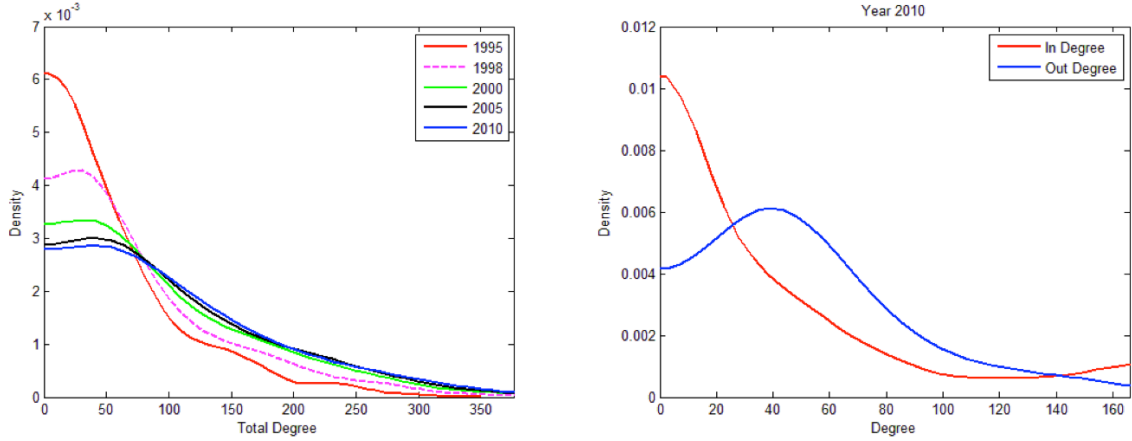
**Figure A4:** Percentage of links in the ITHMN whose weight changes from zero to strictly positive (link creation) and from positive to zero (link destruction).

period (with a sharp decrease after year 2000), see Figure A4. This relatively high number of newly-formed links couples with the relatively low number of disappearing links. Over the whole period, in fact, the fraction of links that switched from a positive flow to zero has remained quite low and stable (around 4%). This explains the large increase in network density.

## A.2 Node Connectivity

We now explore node-degree and strength distributions. As the left panel of Figure A5 shows, node total-degree distributions have shifted to the right and their tails have become fatter.

This is explained by the increase in the overall connectivity of the network. The average number of link (both incoming and outgoing ones), has grown from 73 to about 112, while the median number of mobility corridors increased by 40% (from 57 to 93), thus entailing a rise in the overall density of the network. Statistical tests show that the pooled, total node-degree distribution follows a log-normal density, except for the highest 22% of the observation for which the decay is Pareto.



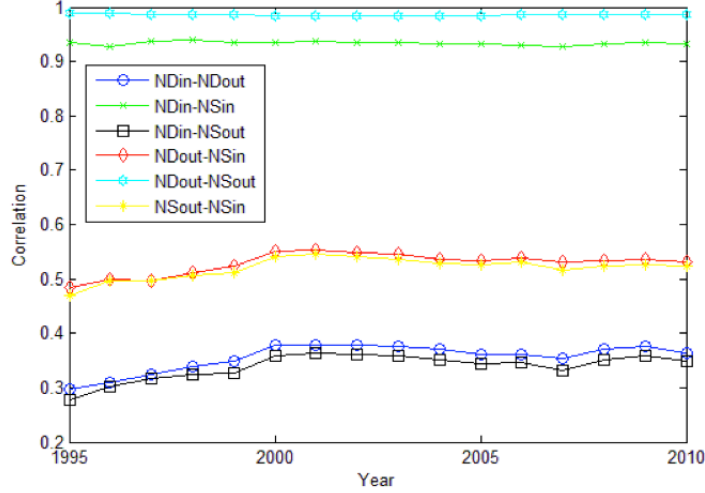
**Figure A5:** Total degree (left) and year-2010 in/out degree (right) distributions.

The right panel of Figure A5 depicts the distribution of in and out degree for year 2010. Interestingly, the two distributions exhibit a different behavior. In particular, out degree is characterized by a well-defined modal value (around 38 links), whereas the in-degree distribution is much more skewed to the left, with a fat right tail. This is mainly due to the fact that in the ITHMN there exists a much more uniform number of sending countries than of destination countries. This is reflected in a coefficient of variation of the number of incoming mobility path 40% higher than for outgoing corridors (which remain very stable over time).

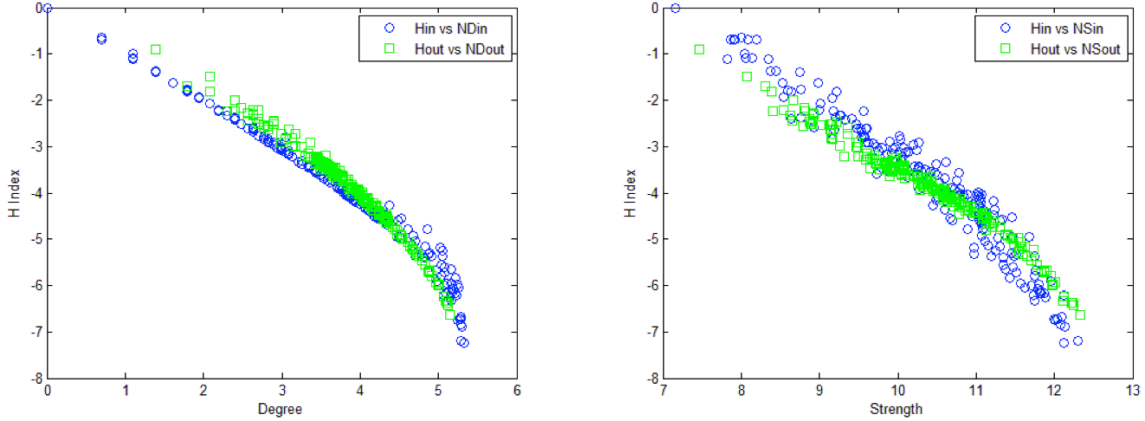
This is not true for in- and out-strength distributions, which are both well-approximated by log-normal densities. This skewed behavior, as it happens for migration networks (Fagiolo & Mastrorillo, 2013a), is robust to rescaling for country population, indicating that the presence of hubs in the weighted network does not depend on country size.

Figure A6 plots Pearson correlation coefficients between node in/out degree and strength over time. Note that countries with more inward or outward traveling corridors also hold the largest in and out mobility flows. On the contrary, countries that are chosen as preferred destinations (both from a binary and weighted perspective), are not necessarily holding many outward corridors or send many travellers abroad.

In order to evaluate the level of diversification of in and out mobility flows at a country level, we compute the Herfindahl concentration index of in and out link weight portfolios. Results are reported in Figure A7, where the H-index is plotted against node degree and strength for year 2010 in a log-log scale. A power-law relation emerges, implying that countries with a larger share of mobility routes and total in and out flows are associated with less concentrated portfolios of origin/ destinations. This parallels what has been already found for migration networks (Fagiolo & Mastrorillo, 2013a).



**Figure A6:** Pearson correlation coefficients between node in/out degree and strength over time.

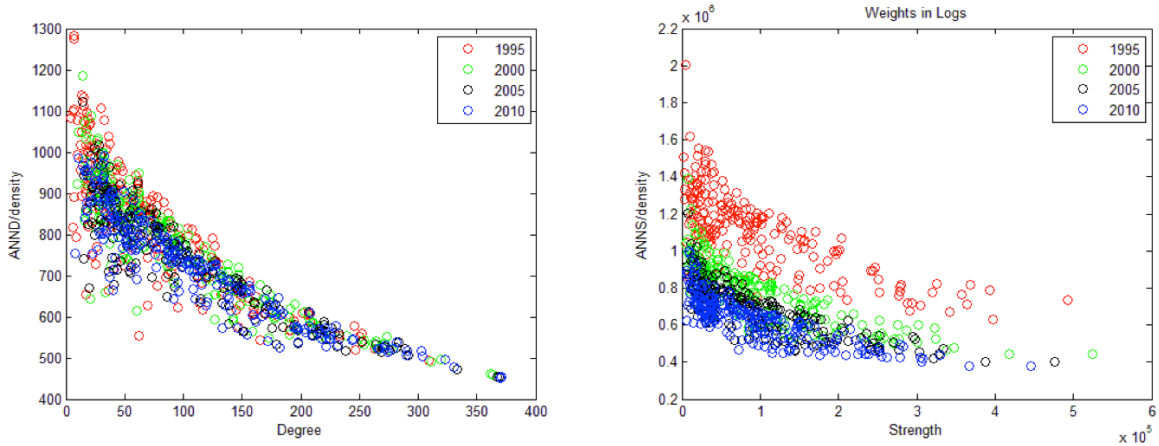


**Figure A7:** Herfindahl (H) concentration index vs node degree (left) and strength (right). Year 2010. Log-log scale.

### A.3 Assortativity, Clustering, and Rich-Club Behavior

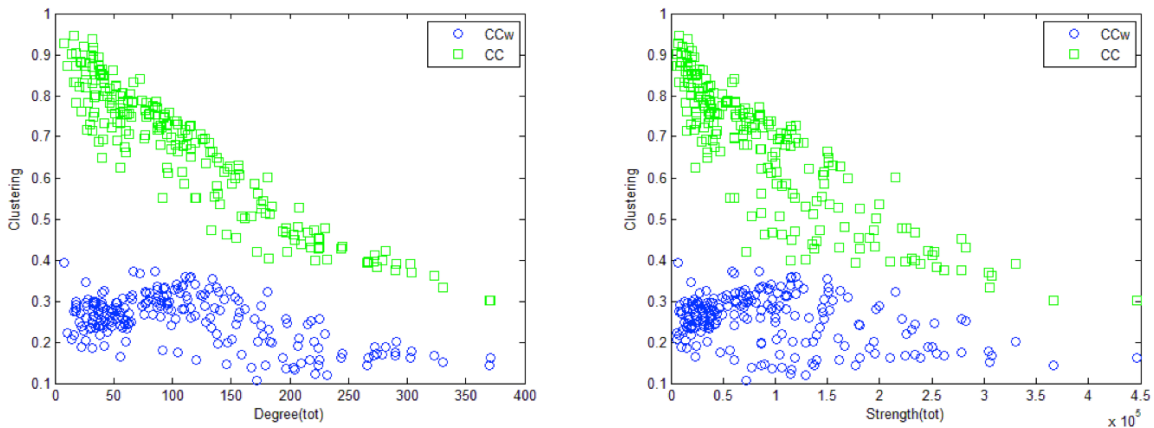
We evaluate the assortativity (disassortativity) of the ITHMN by computing Pearson correlation coefficients between total node degree (strength) and average nearest-neighbor degree (strength) for each given country across time. Results are reported in Figure A8. As it happens for international migration, the ITHMN appears to be weakly disassortative: more connected players are usually connected to countries with a relatively small number of mobility routes and mobility-flow intensity.

Moving to network clustering, we observe that the HIMN is characterized a relatively high binary clustering coefficient (CC), with average CC that grows over time: from 0.60 in 1995 to 0.67 in 2010. In weighted terms, the average weighted clustering coefficient (CCw) grows from 0.23 to 0.25 in the same period. Coupled with the evidence about a decreasing APL over time (see Table 1), this suggests that the HIMN shows some small-world behavior. To further



**Figure A8:** Disassortative behavior in the ITHMN. Total node degree (left) and strength (right) vs. average nearest-neighbor degree (ANND) and strength (ANNS). In the weighted case, logged link weights have been employed.

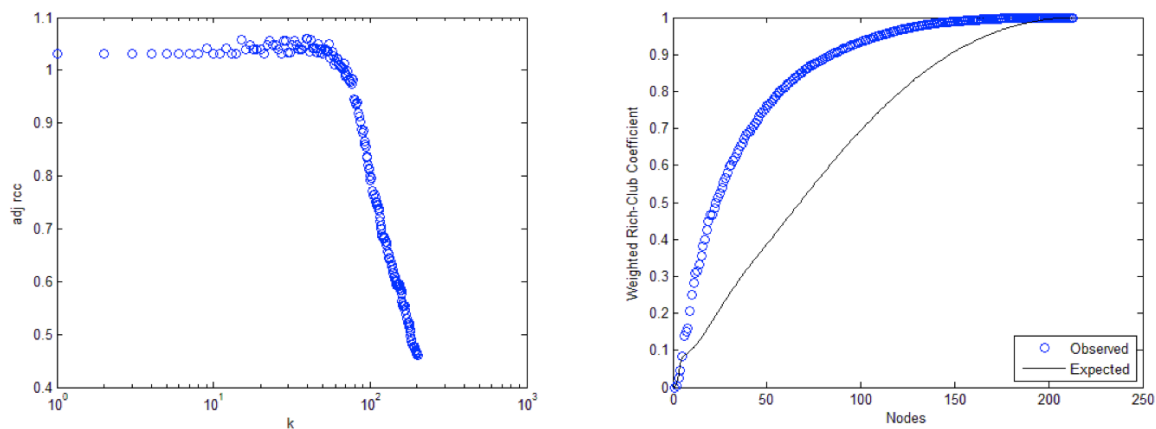
analyze this issue, we have computed average CC and APL values, along with their expected counterparts in Erdos-Renyi (ER) random graphs that keep fixed the observed density of the network. The observed APL is indeed higher than the expected one, while the CC is substantially higher (about three times) than its ER counterpart (about three times). This implies that over time, new mobility channels progressively close open triplets, shrinking the overall geodesic distance and increasing the clustering coefficient of the network.



**Figure A9:** Binary clustering coefficient (CC) and weighted clustering coefficient (CCw) vs node degree and strength in year 2010.

Figure A9 reports the correlation between binary (CC) and weighted (CCw) clustering coefficient vs total degree and total strength in year 2010. The binary coefficient appears to be negatively correlated with both degree and strength, suggesting a hierarchical structure in the network where most connected nodes tend to form few triangles with their neighbors (as it happens in the international migration network, see [Fagiolo & Mastrorillo, 2013a](#)). Conversely, nodes with a small number of mobility routes, or with marginal ones in term of intensity, are

usually connected with countries that are more likely connected with each other. The absence of a clear positive correlation among  $CC_w$  and  $NS$  implies that the weight of such triangles is relatively weak.



**Figure A10:** Binary (adjusted) rich-club coefficient (left, adj rcc) and weighted rich-club coefficient (right) in year 2010.

Finally, we explore whether the ITHMN exhibits any rich-club behavior. Following [Colizza \*et al.\* \(2006\)](#), [Opsahl \*et al.\* \(2008\)](#), we compute both binary (adjusted) and weighted coefficients, see Figure A10. It is easy to see that whereas the binary version of the network does not exhibit any rich-club ordering (the coefficient stays very close to one), the weighted counterpart displays a lot of concentration of mobility flows within the rich club made of the first 25 nodes (around 50%). To attain 90% of the volume of the network is sufficient to consider the “richest” 90 countries in the world, where richness is in terms of total strength (where link weights are computed in levels).

## B Variable Definitions and List of Countries used in the Analysis

Name	Definition	Source
Real GDP per capita	Real GDP, PPP (constant 2005 US\$) divided by mid-year population	WDI
Real GDP per worker	Real GDP, PPP (constant 2005 US\$) divided by workforce (from employment over population ratio)	WDI
POP	Resident population	WDI
OPMOB	Openness to mobility: arrivals plus departures over country workforce	WDI
OPTRA	Openness to trade: imports plus exports over country real GDP (PPP)	Penn World Table 7.1 and CEPII-BACI
$w_{ij}^t$	Bilateral mobility flows: People moving from $i$ to $j$ in year $t$ (and staying there for less than one year)	UNWTO
$\omega_{ij}^t$	Bilateral mobility flows / country $j$ workforce	UNWTO and WDI
ND	Node degree: Number of (inward- and outward-) country links in the ITHMN	UNWTO*
NS	Node strength: sum of (inward- and outward-) country link weights in the ITHMN	UNWTO*
BON	Bonacich Centrality ( <a href="#">Bonacich, 1987</a> )	UNWTO*
KATZ	Katz Centrality ( <a href="#">Katz, 1953</a> )	UNWTO*
TROPICS	Proportion of land in tropics and subtropics	<a href="#">Gallup et al. (1999)</a>
LATITUDE	Distance from equator (absolute latitude / 90)	CEPII*
LANDLOCKED	Dummy if the country is landlocked	CEPII
RENT	Rent from natural resources percentage of GDP	WDI
INST	Quality of institutions (Polity-2)	<a href="#">Marshall &amp; Jagers (1999)</a>
AREA	Country area in Km <sup>2</sup>	CEPII
BORDER	Dummy equal to one if two countries share common borders	CEPII
DIST	Distance from most populated cities	CEPII
COLONY	Dummy equal to one for country pairs ever in colonial relationship	CEPII
LANGUAGE	Dummy equal to one if country pairs have common official primary language	CEPII
Regional Dummies	Sub-Saharan Africa, E Asia & Pacific, Latin America & Caribbean, S Asia, Europe & C Asia, M East & N Africa	WDI

**Table B1:** Variables Definition and Data Sources.

WDI: World-Development Indicators (<http://data.worldbank.org/data-catalog/world-development-indicators>), January 2014; CEPII-BACI ([http://cepii.fr/CEPII/fr/bdd\\_modele/presentation.asp?id=1](http://cepii.fr/CEPII/fr/bdd_modele/presentation.asp?id=1)); UNWTO: World Tourism Organization (<http://www2.unwto.org>); Penn World Table 7.1 ([https://pwt.sas.upenn.edu/php\\_site/pwt71/pwt71\\_form.php](https://pwt.sas.upenn.edu/php_site/pwt71/pwt71_form.php)).  
 (\*): Our own calculations.



**Table B2:** Country List for Cross-Section (cs) and Panel (pnl) Estimation

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AGO (cs,pnl)	DNK (cs,pnl)	KWT (cs,pnl)	ROM (cs,pnl)
ALB (cs,pnl)	DOM (cs,pnl)	LAO (cs,pnl)	RUS (cs,pnl)
ARE (cs,pnl)	DZA (cs,pnl)	LBN (pnl)	RWA (cs,pnl)
ARG (cs,pnl)	ECU (cs,pnl)	LBY (pnl)	SAU (cs,pnl)
ARM (cs,pnl)	EGY (cs,pnl)	LCA (pnl)	SDN (cs,pnl)
AUS (cs,pnl)	ERI (cs,pnl)	LKA (cs,pnl)	SEN (pnl)
AUT (cs,pnl)	ESP (cs,pnl)	LTU (cs,pnl)	SGP (pnl)
AZE (cs,pnl)	EST (cs,pnl)	LUX (cs)	SLB (pnl)
BDI (cs,pnl)	ETH (cs,pnl)	LVA (cs,pnl)	SLE (cs,pnl)
BEL (cs,pnl)	FIN (cs,pnl)	MAR (cs,pnl)	SLV (cs,pnl)
BEN (cs,pnl)	FJI (pnl)	MDA (cs,pnl)	STP (pnl)
BFA (cs,pnl)	FRA (cs,pnl)	MDG (cs,pnl)	SUR (cs,pnl)
BGD (cs,pnl)	GAB (cs,pnl)	MDV (pnl)	SVK (cs,pnl)
BGR (cs,pnl)	GBR (cs,pnl)	MEX (cs,pnl)	SVN (cs,pnl)
BHR (pnl)	GEO (cs,pnl)	MKD (cs,pnl)	SWE (cs,pnl)
BHS (pnl)	GHA (cs,pnl)	MLI (cs,pnl)	SWZ (cs,)
BIH (cs,pnl)	GIN (cs,pnl)	MLT (pnl)	SYR (cs,pnl)
BLR (cs,pnl)	GMB (cs,pnl)	MNG (cs,pnl)	TCD (cs,pnl)
BLZ (pnl)	GNB (pnl)	MOZ (pnl)	TGO (cs,pnl)
BOL (cs,pnl)	GRC (cs,pnl)	MRT (cs,pnl)	THA (cs,pnl)
BRA (cs,pnl)	GTM (cs,pnl)	MUS (pnl)	TJK (cs,pnl)
BRB (pnl)	GUY (cs,pnl)	MWI (cs,pnl)	TKM (pnl)
BRN (pnl)	HND (cs,pnl)	MYS (cs,pnl)	TON (pnl)
BTN (cs,pnl)	HRV (cs,pnl)	NAM (cs)	TTO (cs,pnl)
BWA (cs)	HTI (cs,pnl)	NER (cs,pnl)	TUN (cs,pnl)
CAF (cs,pnl)	HUN (cs,pnl)	NGA (cs,pnl)	TUR (cs,pnl)
CAN (cs,pnl)	IDN (cs,pnl)	NIC (cs,pnl)	TZA (cs,pnl)
CHE (cs,pnl)	IND (cs,pnl)	NLD (cs,pnl)	UGA (cs,pnl)
CHL (cs,pnl)	IRL (cs,pnl)	NOR (cs,pnl)	UKR (cs,pnl)
CHN (cs,pnl)	IRN (cs,pnl)	NPL (cs,pnl)	URY (cs,pnl)
CIV (pnl)	IRQ (cs,pnl)	NZL (cs,pnl)	USA (cs,pnl)
CMR (pnl)	ISL (pnl)	OMN (cs,pnl)	UZB (cs,pnl)
COG (cs,pnl)	ISR (cs,pnl)	PAK (cs,pnl)	VCT (pnl)
COL (cs,pnl)	ITA (cs,pnl)	PAN (cs,pnl)	VEN (cs,pnl)
COM (pnl)	JOR (cs,pnl)	PER (cs,pnl)	VNM (cs,pnl)
CPV (pnl)	JPN (cs,pnl)	PHL (cs,pnl)	VUT (pnl)
CRI (cs,pnl)	KAZ (cs,pnl)	PNG (cs,pnl)	WSM (pnl)
CYP (cs,pnl)	KEN (cs,pnl)	POL (cs,pnl)	YEM (cs,pnl)
CZE (pnl)	KGZ (cs,pnl)	PRT (cs,pnl)	ZAF (cs,pnl)
DEU (cs,pnl)	KHM (cs,pnl)	PRY (cs,pnl)	ZAR (cs,pnl)
DJI (cs,pnl)	KOR (cs,pnl)	QAT (cs,pnl)	ZMB (cs,pnl)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
log(OPMOB)	0.482*** (0.035)	-0.043 (0.219)	0.213 (0.226)	0.043 (0.330)	0.482*** (0.036)	-0.054 (0.225)	0.231 (0.218)	0.036 (0.344)	0.480*** (0.036)	-0.063 (0.225)	0.226 (0.218)	0.023 (0.354)
log(OPTRA)		1.217** (0.600)	0.519 (0.424)	0.701 (0.568)		1.212** (0.606)	0.477 (0.401)	0.691 (0.581)		1.210** (0.601)	0.476 (0.392)	0.703 (0.587)
log(ND)					0.582*** (0.134)	0.954*** (0.255)	0.700*** (0.267)	0.666** (0.281)				
log(BON)	0.747*** (0.171)	1.273*** (0.335)	0.981** (0.392)	0.944** (0.401)					1.603*** (0.357)	2.497*** (0.657)	1.827*** (0.662)	1.776** (0.714)
log(KATZ)												
Africa		-0.978*** (0.329)	-0.778*** (0.287)	-0.540 (0.352)		-0.869*** (0.313)	-0.736** (0.291)	-0.478 (0.370)		-0.802*** (0.304)	-0.718** (0.301)	-0.446 (0.379)
America		-0.077 (0.276)	0.036 (0.337)	0.172 (0.376)		0.064 (0.268)	0.083 (0.350)	0.219 (0.399)		0.195 (0.266)	0.142 (0.369)	0.275 (0.415)
Asia		-0.278 (0.333)	-0.328 (0.289)	-0.140 (0.384)		-0.122 (0.318)	-0.259 (0.292)	-0.069 (0.401)		-0.006 (0.310)	-0.214 (0.301)	-0.023 (0.406)
Europe		0.002 (0.270)	0.085 (0.306)	0.185 (0.384)		0.213 (0.252)	0.178 (0.322)	0.296 (0.410)		0.353 (0.242)	0.231 (0.336)	0.362 (0.422)
TROPICS			-0.751*** (0.256)	-0.630* (0.323)			-0.746*** (0.249)	-0.635* (0.325)			-0.756*** (0.246)	-0.645** (0.326)
LATITUDE			-0.773 (0.562)	-0.210 (0.801)			-0.811 (0.561)	-0.268 (0.790)			-0.807 (0.564)	-0.293 (0.781)
LANDLOCKED			-0.126 (0.122)	-0.035 (0.144)			-0.136 (0.120)	-0.053 (0.144)			-0.142 (0.119)	-0.050 (0.141)
log(RENT)			0.171*** (0.056)	0.172** (0.067)			0.170*** (0.056)	0.170** (0.067)			0.168*** (0.056)	0.170** (0.068)
British Colony				0.074 (0.183)				0.087 (0.185)				0.094 (0.183)
French Colony				0.175 (0.272)				0.165 (0.270)				0.172 (0.267)
European Settlers <sup>1900</sup>				0.004 (0.004)				0.004 (0.004)				0.004 (0.004)
Humidity (avg)				-0.002 (0.009)				-0.002 (0.009)				-0.001 (0.009)
Temperature (avg)				0.020 (0.015)				0.020 (0.015)				0.019 (0.015)
Malaria 1994				-0.643 (0.596)				-0.735 (0.654)				-0.784 (0.680)
Observations	154	150	134	123	154	150	134	123	154	150	134	123
R-squared	0.764	0.622	0.808	0.783	0.763	0.613	0.812	0.782	0.763	0.614	0.815	0.782
First Stage F	55.12	2.451	3.407	2.123	60.59	2.416	3.560	2.040	73.57	2.432	3.663	2.016

**Table B3:** Robustness of results to alternative controls. The Effect of Country Centrality on Income Robustness. Cross-Section 2SLS estimation, second stage. Year 2000. OPTRA and OPMOB are instrumented using gravity predictions. Robust Standard Errors in parenthesis. \*, \*\*, \*\*\* significance at the 10, 5 and 1 percent level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
log(OPMOB)	0.464*** (0.042)	-0.228 (0.334)	0.181 (0.206)	-0.049 (0.322)	0.469*** (0.041)	-0.226 (0.334)	0.201 (0.197)	-0.057 (0.332)	0.470*** (0.041)	-0.231 (0.332)	0.199 (0.194)	-0.072 (0.338)
log(OPTRA)		1.603* (0.834)	0.602 (0.396)	0.917* (0.557)	1.591* (0.833)	1.591* (0.833)	0.555 (0.374)	0.906 (0.565)	1.598* (0.824)	1.598* (0.824)	0.545 (0.364)	0.915 (0.567)
log(ND)					0.496*** (0.160)	1.127*** (0.408)	0.696*** (0.254)	0.633** (0.289)				
log(BON)	0.657*** (0.215)	1.573*** (0.566)	1.001*** (0.373)	0.932*** (0.409)					1.312*** (0.409)	2.851*** (1.026)	1.730*** (0.624)	1.610** (0.726)
Africa		-0.638* (0.344)	-0.485* (0.292)	-0.291 (0.409)	-0.539 (0.357)	-0.443 (0.300)	-0.443 (0.300)	-0.226 (0.436)	-0.508 (0.376)	-0.431 (0.315)	-0.431 (0.315)	-0.193 (0.453)
America		0.311 (0.413)	0.324 (0.322)	0.440 (0.410)	0.451 (0.448)	0.368 (0.336)	0.368 (0.336)	0.487 (0.441)	0.554 (0.479)	0.420 (0.357)	0.420 (0.357)	0.538 (0.464)
Asia		0.066 (0.392)	-0.108 (0.274)	-0.010 (0.426)	0.223 (0.415)	-0.037 (0.282)	-0.037 (0.282)	0.067 (0.453)	0.313 (0.439)	0.002 (0.298)	0.002 (0.298)	0.116 (0.467)
Europe		0.357 (0.392)	0.232 (0.301)	0.511 (0.414)	0.561 (0.437)	0.319 (0.318)	0.319 (0.318)	0.615 (0.448)	0.668 (0.466)	0.357 (0.335)	0.357 (0.335)	0.669 (0.467)
TROPICS			-1.030*** (0.257)	-0.812** (0.345)		-1.033*** (0.251)	-1.033*** (0.251)	-0.829** (0.348)		-1.052*** (0.247)	-1.052*** (0.247)	-0.851** (0.350)
LATITUDE			-1.117** (0.552)	-0.475 (0.863)		-1.154** (0.548)	-1.154** (0.548)	-0.535 (0.853)		-1.133** (0.542)	-1.133** (0.542)	-0.560 (0.847)
LANDLOCKED			-0.182 (0.137)	-0.113 (0.166)		-0.203 (0.136)	-0.203 (0.136)	-0.144 (0.168)		-0.224* (0.133)	-0.224* (0.133)	-0.156 (0.161)
log(RENT)		0.199** (0.055)	0.199** (0.055)	0.208*** (0.066)	0.194*** (0.055)	0.194*** (0.055)	0.194*** (0.055)	0.203*** (0.066)	0.189*** (0.055)	0.189*** (0.055)	0.189*** (0.055)	0.199*** (0.066)
British Colony				0.121 (0.186)				0.135 (0.188)				0.145 (0.187)
French Colony				0.262 (0.294)				0.251 (0.293)				0.258 (0.291)
European Settlers <sup>1900</sup>				0.003 (0.004)				0.002 (0.004)				0.002 (0.004)
Humidity (avg)				-0.011 (0.009)				-0.010 (0.009)				-0.010 (0.009)
Temperature (avg)				0.021 (0.016)				0.020 (0.016)				0.020 (0.015)
Malaria 1994				-0.934 (0.616)				-1.036 (0.663)				-1.095 (0.678)
Observations	148	144	133	122	148	144	133	122	148	144	133	122
R-squared	0.735	0.387	0.791	0.744	0.734	0.375	0.795	0.741	0.734	0.375	0.799	0.740
First Stage F	47.30	1.809	3.413	2.130	49.66	1.806	3.606	2.074	58.87	1.839	3.739	2.067

**Table B4:** Robustness of results to alternative controls. The Effect of Country Centrality on Productivity Robustness. Cross-Section 2SLS estimation, second stage. Year 2000. OPTRA and OPMOB are instrumented using gravity predictions. Robust Standard Errors in parenthesis. \*, \*\*, \*\*\* significance at the 10, 5 and 1 percent level.

## C Weighted Centrality Indicators and Country Productivity

Dep. Var.	log(real GDP per-worker)					
	(1)	(2)	(3)	(4)	(5)	(6)
log(OPMOB)	0.290*** (0.093)	0.123 (0.155)	0.271*** (0.097)	0.034 (0.181)	0.313*** (0.090)	0.151 (0.147)
log( <i>NS</i> )			0.076** (0.037)	0.097** (0.042)		
log( <i>BON</i> )	0.194** (0.093)	0.274** (0.110)				
log( <i>KATZ</i> )					0.555** (0.239)	0.726** (0.286)
log(OPTRA) <sub>1990–2000</sub>	0.201 (0.136)		0.238* (0.139)		0.208 (0.143)	
log(OPTRA)		0.365 (0.323)		0.524 (0.374)		0.373 (0.328)
INST	0.015 (0.011)	0.012 (0.010)	0.017 (0.011)	0.015 (0.011)	0.013 (0.010)	0.010 (0.011)
TROPICS	-0.646*** (0.161)	-0.653*** (0.179)	-0.642*** (0.156)	-0.735*** (0.185)	-0.651*** (0.158)	-0.681*** (0.174)
LATITUDE	-0.576 (0.469)	-0.599 (0.454)	-0.687 (0.472)	-0.694 (0.493)	-0.670 (0.456)	-0.706 (0.436)
LANDLOCKED	-0.233* (0.123)	-0.304** (0.124)	-0.266** (0.122)	-0.376*** (0.130)	-0.212* (0.118)	-0.286** (0.116)
log(RENT)	0.186*** (0.043)	0.209*** (0.039)	0.188*** (0.042)	0.208*** (0.042)	0.188*** (0.044)	0.209*** (0.041)
Constant	10.417*** (0.634)	11.904*** (0.586)	8.668*** (0.984)	9.994*** (0.628)	9.544*** (0.757)	10.752*** (0.394)
No. of Observations	134	130	134	130	134	130
Kleibergen-Paap F stat	7.104	3.260	5.786	3.019	7.700	3.571
Stock-Yogo critical values <sup>†</sup>	7.03/4.58		7.03/4.58		7.03/4.58	

**Table C1:** The Effect of Country *Weighted* Centrality on Productivity. Cross-Section 2SLS estimation, second stage. Year 2000. Weighted network centrality measures are instrumented using centrality computed on the predicted ITHMN. All regressions contain regional dummies: Sub-Saharan Africa, East Asia & Pacific, Latin America & Caribbean, South Asia, Europe & Central Asia, Middle East & North Africa; not reported. log(OPTRA)<sub>1990–2000</sub> refers to the log of trade openness averaged over the period 1990-2000 (data are from Penn World Tables 7.1), INST is the average Polity-2 score in the same period. OPTRA and OPMOB are instrumented using gravity predictions. Robust Standard Errors in parenthesis. \*, \*\*, \*\*\* significance at the 10, 5 and 1 percent level. *Note.* (†): Critical values for 10% and 15% max IV size.

Dep. Var.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\log(y_j^{t-1})$	0.977*** (0.007)	0.980*** (0.008)	0.979*** (0.009)	0.986*** (0.007)	0.988*** (0.008)	0.989*** (0.009)	0.977*** (0.007)	0.979*** (0.008)	0.981*** (0.008)
$\log(NS_j^t)$	0.037*** (0.010)			0.039*** (0.010)			0.045*** (0.010)		
$\log(BON_j^t)$		0.018*** (0.004)			0.018*** (0.004)			0.020*** (0.005)	
$\log(KATZ_j^t)$			0.108*** (0.031)			0.100*** (0.035)			0.116*** (0.034)
$\log(OPMOB_j^t)$	0.002 (0.006)	-0.001 (0.005)	0.006 (0.006)	-0.002 (0.005)	-0.005 (0.005)	0.001 (0.006)	0.000 (0.005)	-0.003 (0.006)	0.003 (0.006)
$\log(OPTRA_j^t)$	0.007 (0.015)	0.004 (0.014)	0.005 (0.019)	0.003 (0.012)	0.002 (0.013)	-0.001 (0.012)	0.014 (0.009)	0.009 (0.012)	0.009 (0.011)
No. of Observations	2,130	2,130	2,130	2,130	2,130	2,130	2,130	2,130	2,130
No. of ID	153	153	153	153	153	153	153	153	153
AR(1) p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
AR(2) p-value	0.939	0.920	0.946	0.944	0.919	0.950	0.937	0.910	0.943
Hansen p-value	0.049	0.039	0.042	0.097	0.041	0.050	0.248	0.207	0.196
No. of Instruments	101	101	101	127	127	127	152	152	152

**Table C2:** The Effect of Country *Weighted* Centrality on Productivity. Dynamic Panel: 1995-2010. System GMM Estimates. All regressions contain country and time dummies. Endogenous variables: lagged dependent variable, centrality indicator, openness to mobility and trade. In all regressions we use two-year lags as instrument for endogenous regressors; Columns 1-3 instruments for lagged dependent variable have been collapsed. In Columns 7-9 we employ  $t - 4$  lag for the lagged dependent variable. Significance levels: \* $p < 0.1$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ .

## D The System-GMM Estimator: Robustness Checks

In this Appendix, we report on some robustness checks we have performed to ensure that the choice for a System-GMM estimator was the right one, given the structure of our data.

First of all, we note that the number of elements in the matrix of instruments grows quadratically in the time dimension. Therefore, we want to check if the sample we are using contains adequate information for estimation. In order to exclude a “small-sample bias” issue, we exploit the fact that estimating a dynamic model with OLS will produce an upward bias for the autoregressive coefficient, while if using an FE estimator will generate a downward bias.

We use the coefficients estimated via OLS vs. a fixed-effect (FE) model as upper and lower bounds for our preferred estimator, i.e. the System-GMM. As reported in Table D1 (income) and D2 (productivity), the autoregressive coefficient obtained through a System-GMM always lies in the interval defined by OLS and FE estimates. This confirms that our sample contains enough information to ensure consistency of our estimators, thus excluding the presence of a finite-sample bias (Bond *et al.*, 2001), in both income and labor productivity estimation.

Second, we ask whether that a System-GMM is the most appropriate estimator given the high persistence of the dependent variable, and our relatively-small sample ( $N = 160$ ). We do so using the fact that if the process were  $AR(1)$ , then OLS estimation for  $\rho$  would have been upward biased, whereas a Within estimator for  $\rho$  would have delivered downward-biased estimates (Nickell, 1981), with a distortion inversely proportional to the econometric sample size. Such extreme cases can provide the boundaries for a consistent estimation of  $\rho$ . Tables D1 and D2 indicate that our estimates for  $\rho$  lie between OLS and Within bounds, suggesting that the System-GMM is an appropriate estimator in our case.

Third, we compare the performance of a System-GMM estimator with that of a Difference-GMM estimator. Figures in Column (3) of both Table D1 and Table D2 reveal that the autoregressive coefficient estimated using a Difference-GMM lies below the Within estimate. This is in line with Bond *et al.* (2001), who suggest that it is “likely that the GMM (diff) estimate is also biased downwards [...], perhaps due to weak instruments”. All this reassures us that a System-GMM estimator should be preferred in our case, for its superior finite-sample properties.

Finally, our estimates show that the first-order auto-regressive coefficient is very close to unity. Therefore, we check for the presence of a unit-root using the the Im-Pesaran-Shin (IPS) test (Im *et al.*, 2003). The test returns a p-value of 0.028 for the labor productivity equation, which gives us a reasonable confidence in rejecting the null hypothesis that our panel exhibits a unit root. In the case of income, instead, the IPS test strongly advises against rejection. Even if the moment condition of the System-GMM should still remain valid in the case of a unit root (providing that there are not  $N$  specific drifts, see Bond *et al.*, 2002), we re-estimate our income regression (with binary centrality indicators) using a different measure of real per-capita GDP, namely the Penn World Tables (7.1) PPP-Converted GDP Per Capita at 2005 constant prices. For this series, the p-value of the IPS test is 0.0381, i.e. the null can safely be rejected. Results are reported in Table D3: even if the overall diagnostics of the GMM are worst in this case (e.g.,  $AR(2)$  is only barely rejected), it is worth noting that the coefficients associated with binary centrality measures are very similar to those in Table 9, both in terms of magnitude and significance.

Dep. Var.	(1)	(2)	(3)	(4)
$\log(y_j^t)$	OLS	System-GMM	Difference-GMM	Fixed Effects
$\log(y_j^{t-1})$	0.992*** (0.001)	0.968*** (0.008)	0.679*** (0.052)	0.929*** (0.016)
$\log(BON_j^t)$	0.014*** (0.002)	0.069*** (0.014)	-0.039* (0.023)	0.013 (0.008)
$\log(OPMOB_j^t)$	0.003*** (0.001)	0.012*** (0.004)	0.064*** (0.020)	0.012*** (0.004)
$\log(OPTRA_j^t)$	-0.001 (0.002)	0.003 (0.011)	0.050** (0.024)	0.011 (0.007)
No. of Observations	2,226	2,226	2,057	2,226
R <sup>2</sup>	0.999			0.955
No. of ID		160	160	160
AR(1) p-value		3.47e-08	0.000104	
AR(2) p-value		0.199	0.356	
Hansen p-value		0.165	0.0540	
No. of Instruments		152	95	

**Table D1:** Coefficient boundaries for dynamic-panel estimation: Country Income with Binary Bonacich Centrality. All regressions contain country and time dummies. Robust SE clustered at country level in parenthesis. Significance Levels: \* $p < 0.1$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ . Column (2): System-GMM, using lag 2 to lag 4 for lagged dependent variable, and lag 2 for network centrality, OPMOB and OPTRA as instruments.

Dep. Var.	(1)	(2)	(3)	(4)
$\log(y_j^t)$	OLS	System-GMM	Difference-GMM	Fixed Effects
$\log(y_j^{t-1})$	0.991*** (0.002)	0.980*** (0.007)	0.710*** (0.054)	0.926*** (0.017)
$\log(BON_j^t)$	0.015*** (0.003)	0.053*** (0.014)	-0.023 (0.022)	0.013 (0.009)
$\log(OPMOB_j^t)$	0.003** (0.001)	0.003 (0.005)	0.061*** (0.019)	0.011** (0.005)
$\log(OPTRA_j^t)$	0.001 (0.002)	0.009 (0.010)	0.025 (0.024)	0.009 (0.008)
No. of Observations	2,130	2,130	1,968	2,130
R <sup>2</sup>	0.999			0.936
No. of ID		153	153	153
AR(1) p-value		0.000	0.000	
AR(2) p-value		0.976	0.802	
Hansen p-value		0.202	0.0249	
No. of Instruments		152	95	

**Table D2:** Coefficient boundaries for dynamic-panel estimation: Country Productivity with Binary Bonacich Centrality. All regressions contain country and time dummies. Robust SE clustered at country level in parenthesis. Significance Levels:  $*p < 0.1$ ,  $**p < 0.05$ ,  $***p < 0.01$ . Column (2): System-GMM, using lag 2 to lag 4 for lagged dependent variable, and lag 2 for network centrality, OPMOB and OPTRA as instruments.



Dep. Var.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\log(y_j^{t-1})$	0.988*** (0.009)	0.993*** (0.010)	0.995*** (0.009)	0.989*** (0.009)	0.994*** (0.009)	0.996*** (0.009)	0.990*** (0.009)	0.994*** (0.009)	0.994*** (0.008)
$\log(ND_j^t)$		0.029** (0.012)			0.040*** (0.011)			0.034*** (0.010)	
$\log(BON_j^t)$	0.052*** (0.017)			0.064*** (0.014)			0.055*** (0.014)		
$\log(KATZ_j^t)$			0.089** (0.036)			0.120*** (0.031)			0.098*** (0.028)
$\log(OPMOB_j^t)$	0.006 (0.006)	0.007 (0.006)	0.007 (0.006)	0.003 (0.005)	0.004 (0.005)	0.004 (0.006)	0.002 (0.005)	0.003 (0.005)	0.003 (0.005)
$\log(OPTRA_j^t)$	-0.005 (0.015)	-0.014 (0.014)	-0.016 (0.013)	-0.003 (0.015)	-0.011 (0.014)	-0.015 (0.014)	0.002 (0.014)	-0.003 (0.014)	-0.004 (0.013)
No. of Observations	2,233	2,233	2,233	2,233	2,233	2,233	2,233	2,233	2,233
No. of ID	161	161	161	161	161	161	161	161	161
AR(1) p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
AR(2) p-value	0.015	0.015	0.015	0.016	0.016	0.016	0.016	0.016	0.016
Hansen p-value	0.063	0.066	0.077	0.174	0.222	0.228	0.996	0.990	0.995
No. of Instruments	127	127	127	152	152	152	218	218	218

**Table D3:** Using an alternative country-income definition to test the effect of country *binary* centrality on income. Country income: Per capita GDP (ppp) 2005 constant US\$ from PWT7.1. Dynamic Panel: 1995-2010. System GMM Estimates. All regressions contain country and time dummies. Endogenous variables: lagged dependent variable, centrality indicator, openness to mobility and trade. In all regressions we use two-year lags as instrument for endogenous regressors. Columns 4-6: we employ also  $t-4$  lag for the lagged dependent variable. Columns 7-9: we use all available instruments for the lagged dependent variable. Robust SE clustered at country level in parenthesis. Significance levels: \* $p < 0.1$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ .

## E Disaggregating Temporary Mobility Flows: Business Travels

In this Appendix, we provide some robustness checks concerning alternative definitions of temporary bilateral-mobility flows. In our analysis, we have reported regression results where mobility flows are computed using travel flows related to both business and tourism purposes. Of course, as discussed in AD, travel flows for business purposes only should be preferred. However, UNWTO data report tourism-business breakdowns solely for country-aggregate figures, and not for outbound bilateral flows.

Here, we report some examples of cross-section and dynamic-panel exercises using bilateral flows computed by multiplying all outbound total bilateral flows by constant business-travel shares reported for country aggregates. Tables E1-E2 contain results about the effect of country *binary* centrality in the ITHMN for business purposes on income. Overall, all our foregoing results are confirmed. Notice that, since business flows are a subset of total flows, the two binary versions of the ITHMN (i.e. for total vs business-only flows) can only differ if a link present in the total-flow network disappears in the business-only one. This is actually the case for many country-pair combinations. Notwithstanding this mismatching, centrality in the business-only ITHMN still appears to be an important factor in explaining country income.

Similar results hold for country productivity and, what is more, for the weighted version of the business-only ITHMN (the whole set of results are available from the Authors upon request). All this indicates that total bilateral flows are a good proxy for those flows of people that are behind the mechanisms through which the sharing of ideas and diffusion of tacit knowledge actually occur.

Dep. Var.	log(real GDP per-capita)					
	(1)	(2)	(3)	(4)	(5)	(6)
log(OPMOB)	0.269*** (0.070)	0.113 (0.144)	0.280*** (0.070)	0.138 (0.135)	0.281*** (0.072)	0.146 (0.131)
log( <i>ND</i> )			0.401*** (0.125)	0.443** (0.183)		
log( <i>BON</i> )	0.549*** (0.165)	0.658** (0.266)				
log( <i>KATZ</i> )					1.047*** (0.331)	1.072** (0.449)
log(OPTRA) <sub>1990–2000</sub>	0.193* (0.100)		0.183* (0.100)		0.186* (0.102)	
log(OPTRA)		0.344 (0.353)		0.293 (0.328)		0.266 (0.316)
<i>INST</i> <sub>1990–1999</sub>	0.038 (0.037)	0.036 (0.040)	0.038 (0.036)	0.039 (0.040)	0.041 (0.036)	0.044 (0.039)
TROPICS	-0.433*** (0.161)	-0.446** (0.181)	-0.442*** (0.160)	-0.450** (0.177)	-0.449*** (0.158)	-0.452*** (0.174)
LATITUDE	-0.550 (0.481)	-0.563 (0.492)	-0.553 (0.490)	-0.533 (0.503)	-0.547 (0.490)	-0.503 (0.507)
LANDLOCKED	-0.147 (0.113)	-0.216* (0.117)	-0.147 (0.114)	-0.231* (0.118)	-0.146 (0.113)	-0.243** (0.117)
log(RENT)	0.169*** (0.046)	0.197*** (0.048)	0.169*** (0.047)	0.196*** (0.048)	0.170*** (0.046)	0.198*** (0.048)
Constant	10.367*** (0.659)	11.854*** (1.122)	7.201*** (0.881)	8.094*** (0.654)	8.235*** (0.688)	9.262*** (0.421)
No. of Observations	135	131	135	131	135	131
Kleibergen-Paap F stat	12.19	3.20	12.45	4.59	12.03	4.81
Stock-Yogo critical values <sup>†</sup>	7.03/4.58		7.03/4.58		7.03/4.58	

**Table E1:** Temporary business mobility flows. The Effect of Country *Binary* Centrality on Income. Cross-Section 2SLS estimation, second stage. Year 2000. log(OPTRA)<sub>1990–2000</sub> refers to the log of trade openness averaged over the period 1990-2000 (data are from Penn World Tables 7.1), INST is the average Polity-2 score in the same period. OPTRA and OPMOB are instrumented using gravity predictions. Robust Standard Errors in parenthesis. \*, \*\*, \*\*\* significance at the 10, 5 and 1 percent level. *Note.* (<sup>†</sup>): Critical values for 10% and 15% max IV size.

Dep. Var.	$\log(y_j^t) = \log(\text{real GDP per capita})$								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\log(y_j^{t-1})$	0.972*** (0.009)	0.978*** (0.008)	0.980*** (0.008)	0.966*** (0.008)	0.971*** (0.007)	0.971*** (0.008)	0.968*** (0.007)	0.973*** (0.006)	0.973*** (0.007)
$\log(BON_j^t)$	0.076*** (0.015)			0.074*** (0.014)			0.074*** (0.013)		
$\log(ND_j^t)$		0.052*** (0.013)			0.054*** (0.011)			0.055*** (0.011)	
$\log(KATZ_j^t)$			0.154*** (0.036)			0.158*** (0.034)			0.161*** (0.031)
$\log(OPMOB_j^t)$	0.007 (0.006)	0.009* (0.005)	0.010* (0.006)	0.011** (0.005)	0.012** (0.005)	0.012** (0.005)	0.008* (0.004)	0.008* (0.004)	0.009* (0.005)
$\log(OPTRA_j^t)$	0.001 (0.013)	-0.012 (0.013)	-0.014 (0.014)	0.007 (0.011)	-0.003 (0.011)	-0.004 (0.012)	0.006 (0.010)	-0.003 (0.010)	-0.004 (0.011)
No. of Observations	2,226	2,226	2,226	2,226	2,226	2,226	2,226	2,226	2,226
No. of ID	160	160	160	160	160	160	160	160	160
AR(1) p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
AR(2) p-value	0.224	0.202	0.182	0.234	0.218	0.197	0.230	0.213	0.194
Hansen p-value	0.049	0.052	0.047	0.177	0.138	0.152	0.993	0.997	0.997
No. of Instruments	127	127	127	152	152	152	218	218	218

**Table E2:** Temporary business mobility flows. The Effect of Country *Binary* Centrality on Income. Dynamic Panel: 1995-2010. System GMM Estimates. All regressions contain country and time dummies. Endogenous variables: lagged dependent variable, centrality indicator, openness to mobility and trade. In all regressions we use two-year lags as instrument for endogenous regressors. Columns 4-6: we employ also  $t - 4$  lag for the lagged dependent variable. Columns 7-9: we use all available instruments for the lagged dependent variable. Robust SE clustered at country level in parenthesis. Significance levels: \* $p < 0.1$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ .

## References

- Bonacich, Phillip. (1987). Power and Centrality: A Family of Measures. *American Journal of Sociology*, **92**(5), 1170–1182.
- Bond, Stephen Roy, Hoeffler, Anke, & Temple, Jonathan. 2001 (Nov.). *GMM Estimation of Empirical Growth Models*. CEPR Discussion Papers 3048. Center for Economic Policy Research.
- Bond, Stephen, Nauges, Céline, & Windmeijer, Frank. (2002). *Unit roots and identification in autoregressive panel data models: A comparison of alternative tests*. 10th International Conference on Panel Data, Berlin, July 5-6, 2002 C5-4. International Conferences on Panel Data.
- Colizza, V., Flammini, A., Serrano, M. A., & Vespignani, A. (2006). Detecting rich-club ordering in complex networks. *Nature Physics*, **2**, 110–115.
- Fagiolo, G., & Mastrorillo, M. (2013a). International Migration Network: Topology and modeling. *Physical Review E*, **88**, 012812.
- Gallup, John L., Mellinger, Andrew D., & Sachs, Jeffrey D. (1999). *Geography datasets*. Center for International Development at Harvard University.
- Im, Kyung So, Pesaran, M. Hashem, & Shin, Yongcheol. (2003). Testing for unit roots in heterogeneous panels. *Journal of Econometrics*, **115**(1), 53–74.
- Katz, Leo. (1953). A new status index derived from sociometric analysis. *Psychometrika*, **18**, 39–43.
- Marshall, M., & Jagers, K. (1999). *P<sup>o</sup>lity iv project: Political regime characteristics and transitions, 1800-2007*. Center for international development and conflict management, University of Maryland.
- Opsahl, Tore, Colizza, Vittoria, Panzarasa, Pietro, & Ramasco, José J. (2008). Prominence and control: the weighted rich-club effect. *Physical Review Letters*, **101**(16), 168702.
- Nickell, Stephen J. (1981). Biases in Dynamic Models with Fixed Effects. *Econometrica*, **49**(6), 1417–26.