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Road Quality and Mean Speed Score

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ABSTRACT: We introduce a novel measure of cross-country road quality based on the travel mean speed between large cities from Google Maps. This measure is useful to assess road infrastructure and access gaps. Our Mean Speed (MS) score is easier to estimate and update than traditional gauges of road network quality which rely on official reports, surveys (i.e., World Economic Forum's Quality of Roads Perception survey), or satellite imaging (i.e., World Bank's Rural Access Index). In a sample of over 160 countries, we find that MS scores range between 38 km/h (23.6 mph) and 107 km/h (66.5 mph). We show that the MS score is a strong proxy for road quality and access.

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WORKING PAPERS

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Contents

I. Introduction

Road connectivity is key for inclusive development (Berg, Deichmann, Liu, and Selod, 2015; Asher and Novosad, 2020). Roads promote access to economic and social services, with positive effects on agricultural and non-agricultural employment and productivity in rural and urban areas (Dash and Sahoo, 2010; Calderón and Servén, 2004; Calderón and Servén, 2010; Calderón, Moral-Benito, and Servén, 2015; Asher and Novosad, 2020) and facilitate internal and external market integration (Jaworski, Kitchens, and Nigai, 2020; OECD, 2020).

Substantial work has been done on estimating country gaps in road infrastructure and access (Fay and Yepes, 2003; Roberts, KC, and Rastogi, 2006; World Bank, 2016; Iimi, Ahmed, Anderson, Diehl, Maiyo, Peralta-Quirós, and Rao, 2016; Mikou, Rozenberg, Koks, Fox, and Peralta Quirós, 2019) and quantifying the impact of roads on GDP (Jaworski, Kitchens, and Nigai, 2020). One focus has been on access under the premise that transport connectivity is supportive for development. Access to improved roads can reduce transport time and costs, increase productivity, and reduce poverty. Indicators of connectivity such as the size of the road network and the Rural Access Index (RAI)—a measure of the proportion of the rural population who live within two kilometers of an all-season road—are often used for infrastructure planning and prioritization.[1] Recognizing the importance of connectivity, the UN 2030 Sustainable Development Goals includes the Rural Access Index (RAI) as a key indicator to track progress in infrastructure development.[2] Originally developed by the World Bank in 2006, RAI provides an understandable and conceptually consistent indicator across countries, remaining the most widely accepted metric for tracking access to transport in rural areas. RAI, however, is costly in time and resources to collect the data, sensitive to the measuring method, and unavailable for some countries. The underlying methodology has changed from surveys to satellite imaging to leverage additional sources of data.

The quality of the road network is also regularly surveyed by the World Economic Forum (WEF) through its Quality of Road Infrastructure (QRI) score, which is used as an indicator of competitiveness across countries. QRI is based on data from a survey of business leaders in 144 countries, who are asked to rate the quality of roads on a scale from 1 (underdeveloped) to 7 (extensive and efficient by international standards).[3] Road quality is multidimensional: from accessibility and surface condition to traffic flow and advanced engineering of tunnels and bridges—all of which factor in mean speed. QRI, however, is subjective and ambiguous by construction. It reflects a potentially biased perception by people surveyed who do not necessarily share the same reference point within countries and even less across countries.[4] Also, the metric is not exogenous and arguably depends on several factors, including travel mean speed. While the mean speed affects the perception of road quality, the *perception* of road quality does not affect mean speed. Thus, the mean speed provides a conceptually robust proxy for the quality of road infrastructure.

[1] See, also, the World Bank's interactive "Rural Access Index Measurement Tool" available at https://rai.azavea.com/.

[2] For instance, the costing of Sustainable Development Goals (SDGs) performed by the International Monetary Fund (IMF) uses RAI as an input variable for the estimating of road stock needed by 2030 (Gaspar, Amaglobeli, García-Escribano, Prady, and Soto, 2019, p. 27).

[3] See Schwab (2019), available at http://www3.weforum.org/docs/WEF_TheGlobalCompetitivenessReport2019.pdf (accessed April 2021).

[4] For example, some people take road quality literally as potholes.

We are not aware of published cross-country measures on how efficient (expeditious) the road network is in moving people and goods within countries.[5] This is surprising, as the economic impact of road infrastructure depends on the speed at which people and goods move and travel time—i.e., the inverse of mean speed—is often used as an indicator for road quality in impact evaluation exercises (DANIDA, 2010; Mackie, Jara-Dıaz, and Fowkes, 2001; Martens and Di Ciommo, 2017). In the United States, managed lanes (priced or otherwise) that fail to maintain a minimum average operating speed of 45 miles per hour (ca. 72 kilometers per hour) 90 percent of the time during peak periods are considered "degraded" (Goodin, Burris, Geiselbrecht, Wood, et al., 2013; Wood, McGee, Geiselbrecht, and Simek, 2020). Travel time can also serve as an econometric instrument. Mean speed is a means to an end to estimate economic outcomes more precisely by reducing endogeneity. For example, Karpowicz, Góes, and García-Escribano (2018) use travel time between cities to proxy the speed of price convergence.

We propose a simple alternative to compare road quality and access across countries. We develop a novel measure of cross-country road quality based on the mean speed between large cities from Google Maps. In a sample of over 160 countries, we find that the mean speeds range between 38 km/h (23.6 mph) and 107 km/h (66.5 mph). We show that the Mean Speed (MS) score is a strong proxy for road quality and access—the MS score is highly correlated with the existing World Bank's Rural Access Index and the WEF's Quality of Road Infrastructure score. MS score complements costly and time-consuming RAI satellite imaging and QRI surveys, produces consistent estimates, and allows for frequent replication by local authorities.

The Google Maps API yields the fastest travel times given "average traffic conditions." These values are arguably upwardly bounded by the quality of vehicles and traffic laws. In this paper, we assume that (i) both road and vehicle quality are correlated with income per capita, i.e., vehicle quality does not bound the mean speed, and (ii) speed limits are a function of traffic fatality, which primarily is a function of road quality, i.e., road quality drives speed limits.

II. Methodology

We identify a list of major cities by country using the United Nations data on city population.[6] We complement the dataset with cities to ensure a minimum of three cities per country. For comparability, we only include cities distant farther than 80 km (50 miles) from the largest city (i.e., travel speed between close cities is biased downwards), and exclude single-city and smaller countries (e.g., Luxembourg) and archipelagos where major cities might not be connected by road (e.g., Fiji, Maldives). We end with a rich dataset of 760 cities in 162 countries across the world, with a minimum of three and maximum of six cities per country. Appendix I presents the list of cities by country in our sample.

Using the Google Maps application program interface (API), we retrieve the geographical coordinates for each city and estimate the distance and travel time by car between the largest city and the other large cities. We estimate a measure of the speed from the largest city to each of the other cities and provide the mean speed

[5] The World Economic Forum's Global Competitiveness Report avouches to compute the average speed of a driving itinerary connecting the 10 or more largest cities but aggregates the results into the road connectivity index (Schwab, 2019, Appendix A: Global Competitiveness Index 4.0 Methodology and Technical Notes, p. 617).

[6] See United Nations Statistics Division, Demographic Statistics Database https://unstats.un.org/unsd/demographic-social/index.cshtml.

as an indicator of road quality for each country. To validate whether the speed is a good proxy for road quality and access, we compare the MS score to traditional indicators such as road density, RAI and RQI.

A. Mean Speed Score

We compute the **Mean Speed [MS] score** as the sum of road distance between the largest city and other large cities by country divided by the travel time—both retrieved from Google Maps through an API as described above—between the largest city and other large cities by country:

$$MS_i = \frac{\sum_{j=2}^{k} distance_{1j}}{\sum_{j=2}^{k} time_{1j}} \tag{1}$$

where i is the country index, j is the index of the largest cities within country excluding the largest one, k is the number of large cities within country i further than 80 km from the largest city, *distance*$_{1j}$ and *time*$_{1j}$ are the distance and fastest travel time by road between the largest city and city j in country i, respectively. Note that the MS score equals the harmonic mean speed: i.e., the travel time weighted by the distance.[7] In other words, the total travel time is the same as if one had traveled the whole distance at that average speed.

B. Geometric Mean Speed Score

Countries with diverse economic development by region may present a high variation in the speed in different routes. Unlike the arithmetic mean, the geometric mean penalizes outliers, i.e., routes that are much faster or much slower than the country's average.

As an alternative measure, we compute the **geometric Mean Speed [gMS]** score as the geo-metric average of the travel speed between these cities by country:

$$gMS_i = \sqrt[k]{\prod_{j=2}^{k} \frac{distance_{1j}}{time_{1j}}} \tag{2}$$

The geometric MS score displays appealing properties of normal distribution; however, it may be biased for mean speed of roads of different lengths within countries, since short and long routes are equally weighted.

C. Adjusted Mean Speed Score

The harmonic MS and geometric MS scores do not take into account the geography of the country which may drag down speed, like mountains, bays, swamps, and other geographic obstacles. Thus, a mountainous country with good quality roads (e.g., Switzerland) may have a lower MS score than a flat country with average quality roads (e.g., Algeria).

[7] The simple arithmetic mean would overweight the speed of short distances.

To overcome this issue, we adjust the MS score by the distance “as the crow flies”—i.e., the geodesic or straight-line distance—calculated using the geographic coordinates of the city of origin to the city of destination. We divide each travel time by the ratio of actual to crow-flies distance:

$$crow\text{-}flies\ ratio_{1j} = \frac{distance_{1j}}{crow\text{-}flies\ distance_{1j}} \tag{3}$$

I.e., a straight road would have a crow-flies ratio of 1 and a semi-circular road a *crow-flies ratio of π/2*. We winsorize the crow-flies ratio right tail at the 5 percent level to avoid over-adjustments. Finally, we divide the travel time by the square root of the *crow-flies ratio* and calculate the **adjusted Mean Speed [aMS] score** as:

$$MS_i = \frac{\sum_{j=2}^{k} distance_{1j}}{\sum_{j=2}^{k} \frac{time_{1j}}{\sqrt{crow\text{-}flies\ ratio_{1j}}}} \tag{4}$$

The aMS represents a theoretical construct of the MS assuming roads are perfectly flat and straight. By construction, the cumulative distribution function of aMS first-order dominates the cumulative distribution function of MS. It is important to note that high quality roads are more than the quality of the surface of the road: high quality roads overcome geographical obstacles with bridges, tunnels, and bypasses, thus aMS biases road quality upwards. Table 1 presents the summary statistics and Figure 1 plots the histograms of MS, gMS, and aMS scores.

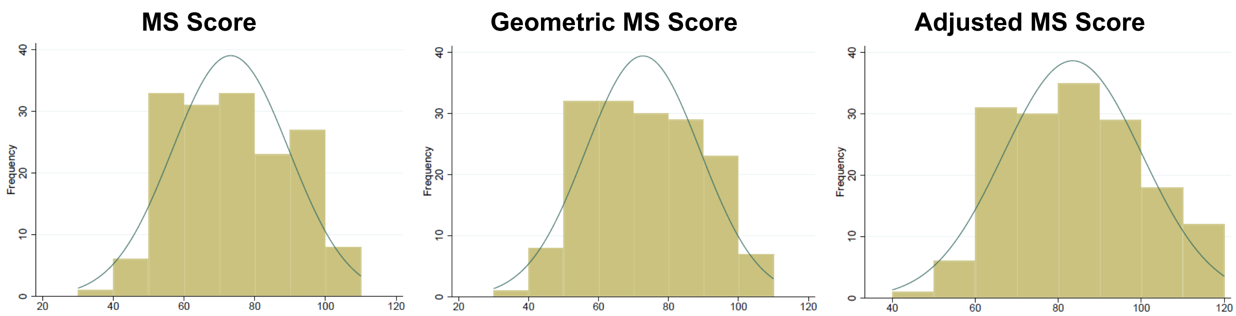
Table 2 presents the computed MS, gMS, and aMS scores by country and Figure 2 illustrates the MS score on the world map. Despite their nuances and advantages in particular cases, MS, gMS, and aMS scores have cross-correlation coefficients above 0.96. We prefer the MS score as it has a straightforward economic interpretation, namely, the expeditiousness in moving people and goods between major agglomerations. Hereafter, we use the MS score in our analyses. In unreported tests, the results are similar with gMS and aMS.

Table 1. Summary Statistics of MS Scores

	Mean	Std. Dev.	25%	50%	75%	Min.	Max.
Mean Speed [MS] score	73	17	60	73	87	38	107
Geometric Mean Speed [gMS] score	73	16	59	73	85	38	107
Adjusted Mean Speed [aMS] score	83	17	70	83	97	48	119
Observations	162						

Note: This table presents summary statistics of the mean speed scores in kilometers per hour between the largest city and other large cities located further than 80 kilometers. **MS score** is the harmonic mean speed, **aMS score** is the terrain-adjusted harmonic mean speed, and **gMS score** is the geometric mean speed. Data are publicly available from Google Maps.

Figure 1. Histograms of Mean Speed Scores



Note: This figure presents the histograms of mean speed scores. Graph 1 (left) plots the histogram of the harmonic Mean Speed [MS] score, calculated as the sum of distances divided by the sum of travel time between the main city and other significant cities further than 80 km. Graph 2 (center) plots the histogram of the geometric Mean Speed [gMS] score, calculated as the geometric mean of the speed between the main city and other significant cities further than 80 km. Graph 3 (right) plots the histogram of the adjusted Mean Speed [aMS] score, calculated as the sum of distances divided by the sum of adjusted travel time between the main city and other significant cities further than 80 km, where the adjusted travel time is the travel time divided by the square root of the ratio of road distance divided by crow-flies distance. The blue line plots the normal distribution for reference. Countries with less than two cities distant more than 80 km by road from the main city—e.g., smaller countries and archipelagos—were dropped. Data are publicly available from Google Maps.

Table 2. Mean Speed Scores by Country

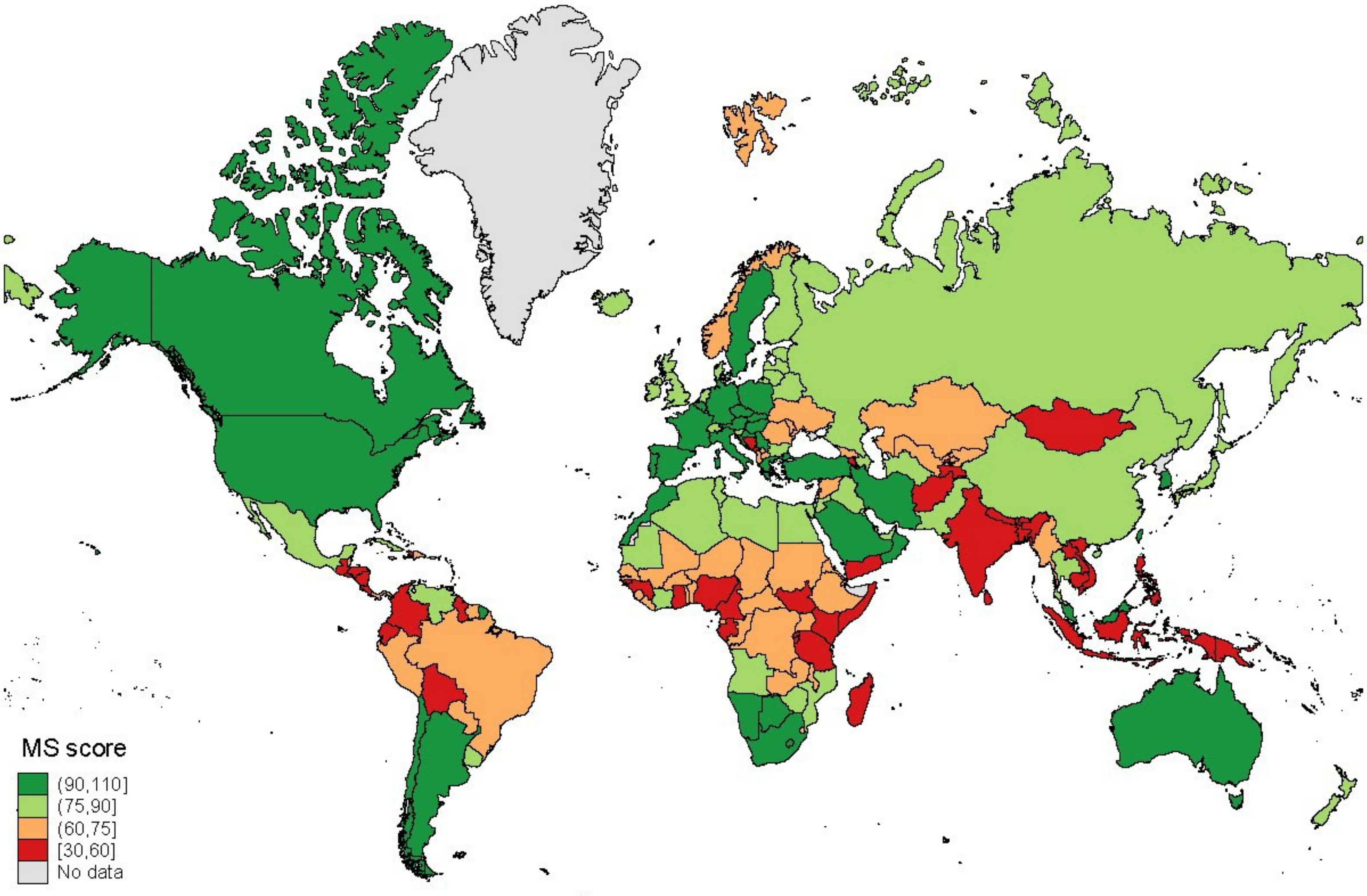
Country	MS	gMS	aMS
Bhutan	38	38	51
Nepal	40	40	50
Timor-Leste	40	40	53
Bangladesh	41	41	48
Haiti	41	40	50
Nicaragua	46	51	54
Rwanda	47	47	60
Bolivia	50	49	62
Sri Lanka	50	52	56
Guinea	50	49	61
Burundi	51	51	66
Vietnam	51	50	61
Madagascar	51	50	63
Trinidad and Tobago	51	50	63
Tajikistan	52	54	68
Philippines	52	53	60
Gambia	53	52	60
Guatemala	53	53	67
Costa Rica	55	54	66
Indonesia	55	63	63
Nigeria	55	56	61
Yemen	55	50	65
Cambodia	55	54	64
Ghana	56	56	63
El Salvador	56	56	62
Mongolia	56	54	66
Honduras	56	55	72
Cameroon	56	52	72
Tanzania	57	49	66
Afghanistan	57	55	63
Bosnia and Herzegovina	57	57	70
Armenia	57	58	70
Colombia	57	55	72
Kenya	57	55	62
India	58	58	63
Somalia	58	57	69

Country	MS	gMS	aMS
South Sudan	59	60	67
Papua New Guinea	59	58	67
Guyana	59	59	74
Montenegro	59	59	75
Lesotho	60	60	76
Ecuador	60	62	74
Laos	60	59	73
Lebanon	60	61	67
Guinea-Bissau	60	60	73
Gabon	60	60	71
Ethiopia	61	59	77
Kyrgyz Republic	61	63	77
Central African Republic	61	62	73
Jamaica	61	61	71
Democratic Republic of the Congo	62	61	77
Eritrea	62	59	82
Peru	62	62	73
Togo	63	62	66
Congo, Republic of	63	62	73
Burkina Faso	63	62	68
Benin	63	62	70
Chad	63	62	68
Uganda	64	63	69
Georgia	64	65	75
Sierra Leone	64	62	75
Albania	65	65	80
Kosovo	65	66	74
Suriname	65	65	74
Liberia	66	65	74
Moldova	67	68	74
Belize	67	66	79
Paraguay	67	67	73
Niger	69	69	78
Djibouti	69	69	91
Eswatini	69	68	82
Senegal	71	70	80
Uzbekistan	71	68	83
Myanmar	71	69	80
Syria	72	71	78
Kazakhstan	72	71	81
Brazil	72	72	81
Mali	72	73	84
Panama	72	72	87
Sudan	72	73	83
Romania	73	72	83
Zambia	73	71	81
Norway	73	74	88
Equatorial Guinea	74	76	86
Dominican Republic	74	75	82
North Macedonia	74	74	89
Malawi	75	74	86
Ukraine	75	76	83
Russia	76	77	83
Cyprus	76	76	93
Jordan	77	74	87
Thailand	77	73	86
Latvia	77	77	82
Iceland	77	77	97
Mauritania	77	78	85
Angola	78	78	86
Cuba	78	79	82
Mozambique	78	77	97
Tunisia	78	78	86
Côte d’Ivoire	78	79	84
Puerto Rico	78	77	95

Country	MS	gMS	aMS
Denmark	78	79	87
Iraq	79	79	84
Turkmenistan	79	81	90
Azerbaijan	80	82	89
United Arab Emirates	80	82	90
Estonia	81	80	85
Japan	81	81	92
Qatar	82	81	86
Uruguay	82	81	88
New Zealand	83	84	95
Egypt	83	83	90
Zimbabwe	83	83	92
Finland	83	83	89
Venezuela	83	83	95
Israel	84	84	99
Kuwait	85	85	97
Belarus	85	85	91
Pakistan	86	86	94
Switzerland	87	85	97
Netherlands	87	87	98
United Kingdom	87	84	95
Bulgaria	88	87	95
Brunei Darussalam	88	88	101
Algeria	88	88	99
Ireland	88	87	95
Lithuania	89	88	93
Libya	90	85	110
China	90	91	98
Slovenia	90	88	100
Mexico	90	85	99
Argentina	91	92	95
Botswana	91	91	96
Taiwan	91	89	100
Malaysia	92	92	101
Poland	92	90	98
Chile	92	86	101
Belgium	92	91	98
Greece	93	92	115
Korea	93	93	100
Turkey	93	90	109
Slovak Republic	93	94	105
Sweden	94	93	102
Iran	94	94	106
Serbia	94	93	106
Italy	95	95	113
Morocco	95	95	103
Australia	96	96	106
Austria	96	95	107
Hungary	96	96	104
Germany	97	96	107
Czech Republic	98	93	109
Croatia	98	97	117
Namibia	99	99	114
South Africa	100	99	106
Oman	102	100	111
Spain	103	102	115
France	105	105	114
Canada	106	103	119
Saudi Arabia	106	106	112
Portugal	106	106	114
United States	107	107	114

Note: This table presents the mean speed scores by country. MS is the harmonic mean speed score; gMS is the geometric mean speed score; and aMS is the adjusted harmonic mean speed score. Countries are sorted by MS score. Tiny countries, archipelagos, and cities within 80 km by road from the city of reference are omitted. Data are publicly available from Google Maps.

Figure 2. MS Scores on the World Map



Note: The boundaries, colors, denominations, and any other information shown on the maps do not imply, on the part of the International Monetary Fund, any judgment on the legal status of any territory or any endorsement or acceptance of such boundaries.

III. Mean Speed Score as Informative Road Metric

A. Relationship with Other Measures

We validate the MS score against GDP per capita, road density, the QRI, and the RAI. The aim of this section is to present a simple metrics for analysis, rather than unraveling the causality channels.

GDP per capita in 2018 in US dollars comes from the World Economic Outlook Database (IMF, 2019). **Road density** is calculated as the road length in kilometers from the World Factbook (CIA, "Roadways," accessed June 2020) divided by the country area in squared kilometers from the World Development Indicators (World Bank, 2019).

The World Economic Forum compiles the executives' perception of the **Quality of Road Infrastructure (QRI)** score through their response to the question: "In your country, what is the quality (extensiveness and condition) of road infrastructure?," where 1 is "extremely poor—among the worst in the world" and 7 is "extremely good—among the best in the world" (Schwab, 2019, Appendix A). Albeit quantified, it is a qualitative index in nature. The QRI score used in our analysis is the 2017–18 weighted average or latest period available, for total of 152 countries. We supplemented the data with "The 2019 Legatum Prosperity Index"[8] for 18 countries not reported in Schwab (2019)—i.e., Afghanistan, Belarus, Central African Republic, Republic of Congo, Cuba, Djibouti, Eritrea, Guinea-Bissau, Equatorial Guinea, Iraq, Niger, Papua New Guinea, Sudan, Somalia, South Sudan, Togo, Turkmenistan, and Uzbekistan—scored on the same scale.[9]

Rural Access Index (RAI) is the share of rural population with access to an all-weather road within two kilometers. RAI was originally survey based. The latest versions of RAI are estimated based on geographic information systems (GIS) models of the distribution of rural population, and geospatial models of rural roads, including their location and type (Mikou, Rozenberg, Koks, Fox, and Peralta Quiros, 2019).[10] In our estimations, we use the World Bank's RAI as the primary source (141 countries), complemented with Mikou, Rozenberg, Koks, Fox, and Peralta Quiros's (2019) RAI estimation for primary and secondary roads (16 instances), United Nations (2015, three instances), and The 2019 Legatum Prosperity Index (11 instances) when the World Bank's RAI was not reported, for a total of 172 countries.[11] RAI and quality of roads are empirically ($\rho = 0.56$) and conceptually weakly correlated: a country may have a high RAI but low quality of roads and vice versa (e.g., Timor-Leste's RAI equals 90 and QRI equals 2.2, while Namibia's RAI equals 57 and QRI equals 5).[12] As a result, we assembled balanced cross-sectional data for all 162 countries in our sample.

[8] See: "The 2019 Legatum Prosperity Index," www.prosperity.com.

[9] These countries are at the low spectrum of the score. Therefore, omitting them would have made our estimates from the matched countries upwardly biased. Unfortunately, there is no official data for Kosovo.

[10] Mikou, Rozenberg, Koks, Fox, and Peralta Quirós (2019) estimates are available at http://documents.worldbank.org/curated/en/75946155024 2864626/pdf/WPS8746.pdf. The figure for the Russian Federation comes from Roberts, KC, and Rastogi (2006), available at https://openknowledge.worldbank.org/bitstream/handle/10986/17414/360060TP100Rural0access0index01PUBLIC1.pdf.

[11] Mikou, Rozenberg, Koks, Fox, and Peralta Quiros (2019) estimated the RAI using open data. The correlation of their and the World Bank's RAI is low, though: 0.40 for primary and secondary roads, and 0.31 and 0.30 when tertiary and tracks are included, correspondingly.

[12] In a few cases where variables were not available for specific countries (e.g., GDP or road network length for Cuba, Kosovo, and Syria), we procured them from various alternative sources and then cross-checked them with other data and similar counties.

Table 3 presents the summary statistics of QRI, RAI, GDP per capita, and road density.

Table 3. Summary Statistics of GDP per Capita, Road Density, QRI, and RAI

	Mean	Std. Dev.	25%	50%	75%	Min.	Max.
GDP per capita 2018 (USD)	13,572.59	18,873.62	1,539.90	5,268.20	16,415.19	307.46	82,756.02
Road density	0.42	0.71	0.03	0.13	0.38	0	4.13
Quality of road infrastructure	3.86	1.05	3.04	3.8	4.53	2.01	6.37
Rural Access Index	64.36	25.47	43	69	84	5	100
Observations	161						

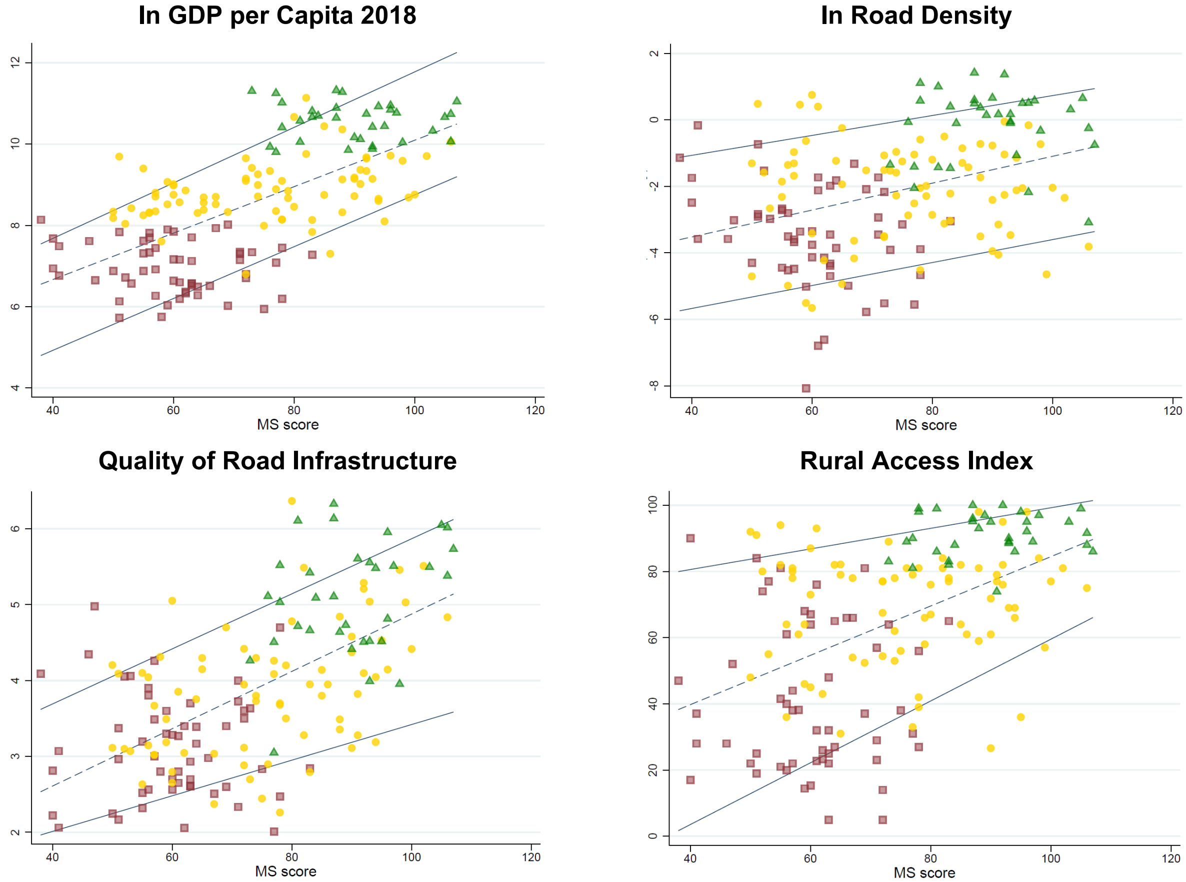
Note: This table presents summary statistics of key variables. **GDP per capita** is the GDP in 2018 in US dollars divided by the population in 2018. **Road density** is calculated as the road length in kilometers divided by the area in square kilometers. **Quality of road infrastructure** is the World Economic Forum compilation of executives' perception of the quality of road infrastructure, ranging from 1–bad to 7–excellent. **RAI** is the share of rural population with an all-weather road within two kilometers.

Alternative measures highlight distinct interpretive road network features. The RAI speaks to the extent to which rural households can reach local markets and other facilities and services, while MS score focuses on the road expeditiousness between major urban centers. While these measures partially overlap and correlate, it is conceivable that a country can undertake infrastructure investments that dramatically increase one measure without changing the others. Furthermore, these variables are endogenous, simultaneous, and autocorrelated. For example, rural access, road density, and road quality contribute to higher GDP per capita, while higher GDP per capita allows for investment in road network extension and quality.

Figure 3 presents the results of OLS and quantile regressions of the natural logarithms of GDP per capita, road density, quality of road infrastructure survey score, and the Rural Access Index on the MS score. There is a strong and positive relationship between GDP per capita and road density and the MS score. This relationship rises exponentially for wealthier countries and countries with more dense road networks. Put differently, a marginal improvement in the MS score is associated with a higher GDP per capita and higher road density for advanced economies than for low-income developing countries.[13] There is also a strong and positive relationship between the quality of roads and RAI, on the one hand, and the MS score, on the other hand. This relationship is stronger for the countries with low RAI.

[13] Jaworski, Kitchens, and Nigai (2020) estimate that the US interstate highway system contributes to ca. 4 percent of GDP, a quarter of which through foreign trade.

Figure 3. OLS and Quantile Best Fit Lines of MS Score and GDP per Capita, Road Density, Quality of Road Infrastructure, and Rural Access Index



Note: This figure presents the OLS and quantile regression best fit lines of Mean Speed [MS] score on the natural logarithm of the GDP per capita in 2018 in US dollars (top-left graph), the natural logarithm of road density defined as road length in kilometers divided by country area in squared kilometers (top-right graph), the quality of road infrastructure survey score ranging from 1-poor to 7-excellent (bottom-left), and the Rural Access Index, which measures the share of rural population which have access to an all-weather road within two kilometers (bottom-right graph). The top and bottom solid blue lines represent the 90th and 10th quantile fit lines, correspondingly; the dashed middle blue line represents the OLS fit line. Round red squares represent low-income developing countries (LIDC), yellow circles represent emerging market economies (EME), and green triangles represent advances economies (AE). Countries with less than two cities distant more than 80 km by road from the main city—e.g., smaller countries and archipelagos—were dropped.

B. Contest between Road Network Measures

As argued previously, road quality is multidimensional. The perception of the quality of road infrastructure is foremost a function of road access, road density, and mean speed. Which of these variables has the highest predictive power regarding the QRI? To answer to this question, we run single and simultaneous *horse races* of road network variables.

Since the RQI survey score is a continuous variable, we encode it as “1–low” if the quality of roads survey score is below 3; “2–medium” if it ranges between 3 and 5; and “3–high” if it is above 5. To complete the sample, we classified Kosovo—which does not have a QRI score—as “2–medium” along with neighboring countries: Albania, Montenegro, North Macedonia, and Serbia. Table 4 presents the results of ordered logistic regressions of encoded RQI on RAI, road density, and MS score.

Table 4. Ordered Logistic Regressions of Road Quality on Road Network Characteristics

	(1)	(2)	(3)	(4)
RAI	0.0494***			0.0227**
	-0.00781			-0.0099
Road density		0.609***		0.315**
		-0.104		-0.129
MS score			0.0727***	0.0547***
			-0.0118	-0.0132
Observations	162	162	162	162
Pseudo R^2	0.162	0.135	0.151	0.246

Note: This table presents the results of ordered logistic regressions of road quality on road network characteristics. The dependent variable is the quality of road infrastructure encoded as “1–low” if the survey value is below 3; “2–medium” if it ranges between 3 and 5; and “3–high” if it is above five. **RAI** is the share of rural population with an all-weather road within two kilometers in percentage points**. Road density** is the natural logarithm of road length in kilometers divided by the area in square kilometers. **MS score** is the harmonic mean speed between the major city and other large cities. Data are from the UN, IMF, World Bank, and World Economic Forum. The sample contains balanced data for 162 countries. Heteroskedasticity-robust standard errors are reported in parenthesis; $*$ denotes significance at 10%, $**$ significance at 5%, and $***$ significance at 1%.

The results accentuate that the MS score is economically meaningful and statistically significant, and more resilient than other covariates to explain the quality of roads perception. While the coefficients associated with RAI and road density fall by 54 and 48 percent from univariate to multivariate regressions (cf. models 1–2 versus model 4), correspondingly, the coefficient for MS score fall only by 25 percent (cf. model 3 versus model 4).

Similarly, a country’s road network characteristics—access, density, and speed—contributes to its income level. Which road network variable is most strongly correlated with income? In a similar fashion as with QRI, we encode the three income levels according to the IMF’s World Economic Outlook: “1” for LIDC, “2” for EME, and “3” for AE.[14]

Table 5 presents the results of ordered logistic regressions of income levels on RAI, road density, and MS score. The MS score outperforms other road network variables in their explanatory power of country

[14] The classification of countries by income levels used by the IMF follows a waterfall process. The main criteria to sort countries into advanced economies and emerging market and developing economies are: (i) income per capita, (ii) export diversification, and (iii) degree of integration into the global financial system. Further, within the emerging market and developing economies the LIDCs are countries that have per capita income levels below a certain threshold (currently set at US$2,700 in 2016 as measured by the World Bank’s Atlas method), structural features consistent with limited development and structural transformation, and insufficiently close external financial linkages to be widely seen as emerging market economies. See https://www.imf.org/external/pubs/ft/weo/2019/02/weodata/groups.htm. For this exercise, we also classified Cuba and Kosovo to the group of Emerging Market Economies on the basis of their GDP per capita.

development. While RAI and road density coefficients fall by 35 and 40 percent, respectively, the MS score coefficient only adjusts downwards by 8 percent.

Table 5. Ordered Logistic Regressions of Income Levels on RAI, Road Density, and MS Score

	(1)	(2)	(3)	(4)
RAI	0.0891***			0.0575***
	-0.011			-0.0126
Road density		0.928***		0.554***
		-0.122		-0.158
MS score			0.103***	0.0946***
			-0.0134	-0.017
Observations	162	162	162	162
Pseudo R^2	0.342	0.244	0.25	0.506

Note: This table presents the results of ordered logistic regressions of income levels on road network characteristics. The dependent variable is the IMF's World Economic Outlook country classification by income encoded as "1–Low-Income Developing Countries," "2–Emerging Market Economies," and "3–Advanced Economies." **RAI** is the share of rural population with an all-weather road within two kilometers in percentage points. **Road density** is the natural logarithm of road length in kilometers divided by the area in square kilometers. **MS score** is the harmonic mean speed between the major city and other large cities. Data are from the UN, IMF, and World Bank. The sample contains balanced data for 162 countries. Heteroskedasticity-robust standard errors are reported in parenthesis; * denotes significance at 10%, ** significance at 5%, and *** significance at 1%.

Taken together, these results suggest that MS score is a relevant independent dimension which is less collinear, more stable, and more strongly correlated with road quality and income than other road network variables.

IV. Mean Speed Score for Welfare Calculations

The MS score can be used to enhance the cost-benefit analysis of a road investment (cf. OECD, 2020). Assuming *arguendo* that a public administration in an emerging economy is considering building a bypass or alternative road to alleviate traffic that would increase the MS score in the network from the median MS score of 73 by one standard deviation to 90 (Table 1).

For simplicity, let us assume that the bypass is 100 km long and that the cost of paving two lanes, in line with the World Bank's estimates, is US$1,000,000 per km (Mikou, Rozenberg, Koks, Fox, and Peralta Quiros, 2019).[15] Further, the bypass would shorten the average 50-km commuting time by ca. 8 minutes each way (i.e.,

[15] Mikou, Rozenberg, Koks, Fox, and Peralta Quiros (2019) estimate that the cost of paving two lanes ranges between US$843,000 in South Asia to US$1,588,000 in Eastern Europe and Central Asia.

from 41 minutes to 33 minutes)[16] for 100,000 commuters. At an hourly GDP per capita of US$3.30,[17] the road investment would pay back in ca. five years.[18]

Cost-benefit calculations become simpler for ex-post evaluations using pre- and post-investment MS scores for a defined area. For specific purposes, the MS score can be calibrated to local and regional networks, and to ranges of distances (e.g., 20–50 km).

V. Public Investment Management

The MS score is an output variable of a complex public investment and management process. But what goes into its *production function*?

The Public Investment Management Assessment (PIMA) database (IMF, 2015 and 2018)[19] surveys over 60 countries and evaluates 15 institutions involved in the three key stages of the public investment cycle: (i) planning of sustainable investment across the public sector, (ii) allocation of investment to the right sectors and projects, and (iii) implementation of investments projects to deliver productive and durable public assets—for a total of 45 variables. Each institution is assessed on institutional strength (the organization, policies, rules and procedures on paper) and effectiveness (the degree to which the intended purpose is being achieved in practice or there is a clear useful impact).

For the matched countries in the MS and PIMA datasets, the MS score is strongly correlated with good public investment management practices along 14 dimensions; only investment protection during budget implementation is orthogonal to MS. These correlations are only indicative as there is a selection bias into the PIMA dataset. Future work can focus on the principal components of that go into the *production function* of the MS score.

VI. Discussion and Conclusion

The quality of roads is a function of various factors and difficult to encapsulate in a single statistic. We develop a computationally-efficient method to proxy countries' road quality based on the harmonic mean speed between the major cities. We argue that the mean speed [MS] score captures a quintessential economic characteristic of road network quality: the ability to move people and goods expeditiously between cities. The MS score covers 162 countries worldwide—excepting only small countries and archipelagos with short road networks—more than any other comprehensive measure of road quality.

We show that there is a strong and positive relationship between the MS score and both GDP per capita and road density. Quantile regressions provide evidence that these relationships rise exponentially for wealthier

[16] The one-way commute times before and after the road upgrade are: (i) 60 minutes × 50 km ÷ average speed 73 km/h = 41.1 minutes versus (ii) 60 minutes × 50 km ÷ 90 km/h = 33.3 minutes.

[17] I.e., at the median annual GDP per capita in our sample of US$5,268 (Table 2) and assuming 1,600 working hours per year.

[18] The undiscounted payback period equals US$100 million investment in the bypass ÷ (US$3.30 median hour rate × 16 minutes two-way shorter commute ÷ 60 minutes × 250 working days × 100,000 commuters).

[19] Cf. IMF's web page on PIMA: https://infrastructuregovern.imf.org/content/PIMA/Home/PimaTool/What-is- PIMA.html (accessed February 2021).

countries. Furthermore, the MS score outperforms other variables describing road network characteristics in predicting the perception of road quality and correlates more strongly with country income level than road access and road density.

We acknowledge two caveats of the MS score. First, the MS score reflects the fastest times in a day (usually at night), thus it may not necessarily correlate with mean speed during high economic activity for locations with high congestion variation (i.e., two countries with similar MS score may have different mean speeds during commute times). Future work will be guided towards collecting the high-low and variance MS scores.

Second, the MS score draws on speed between a minimum of three and a maximum of six cities. Since small countries have fewer large cities than large countries and large cities tend to be better connected, the city count truncation may bias upwards the MS estimate towards large countries. Thus, countries should be compared with peers by size and population rather than unconditionally across the board.

The MS score can be used as an instrument of road investment efficiency and for cost-benefit analysis of road investments. The MS score provides a robust instrumental variable for the quality of road infrastructure: (i) it strongly affects the perception of road quality (cf. Figure 3 and Table 4) and (ii) it is unlikely to suffer from the same measurement problems as the other connectivity indicators. The MS score is easy to replicate locally and can be run periodically to create rich panel data. Further applications and extensions include the quantification of different transport policies, sub-national and regional rankings, travel time between major cities in different countries,[20] determinants of efficient investment in infrastructure, and event studies (e.g., the effects of natural disasters).

[20] E.g., as a compliment to the accessibility framework presented by (Dijkstra, Poelman, and Ackermans 2019).

Appendix I. List of Countries and Cities

The table below lists the cities by country in our sample used to compute the Mean Speed [MS] score. The first city by country in the list is the city of reference (start), usually the largest metropolitan area; the remaining cities are the destinations in alphabetical order. Distance is the distance between the city of reference and the destination. Cities in all capital letters are state capitals. Tiny countries, archipelagos, and cities within 80 km by road from the city of reference are omitted. Data are publicly available from Google Maps.

Country	City	Distance
Afghanistan	KABUL	
	Herat	817
	Kandahar	497
	Kunduz	336
	Mazari Sharif	427
Albania	TIRANA	
	Kukes	145
	Sarande	279
	Shkoder	103
	Vlore	152
Algeria	ALGIERS (EL DJAZAIR)	
	Batna	427
	El Djelfa	297
	Stif	268
	Wahran	413
Angola	LUANDA	
	Benguela	542
	Huambo	604
	Lubango	898
	Malanje	381
Argentina	BUENOS AIRES	
	Cordoba	696
	Mendoza	1050
	Rosario	297
	Salta	1466
Armenia	YEREVAN	
	Gosh	118
	Gyumri (Leninakan)	120
	Kapan	303
	Vanadzor (Kirovakan)	116
Australia	Sydney	
	Adelaide	1375
	Brisbane	916
	Melbourne	878
	Perth	3934
Austria	WIEN	
	Graz	199
	Innsbruck	476
	Linz	184
	Salzburg	296
Azerbaijan	BAKU	
	Balakan	394
	Ganja	360
	Lankaran	248
	Mingachevir	317
Bangladesh	DHAKA	
	Chittagong	248
	Khulna	271
	Mymensingh	112
	Rajshahi	248
Belarus	MINSK	
	Gomel	311

Country	City	Distance
	Grodno	280
	Mogilev	198
	Vitebsk	291
Belgium	BRUXELLES (BRUSSEL)	
	Arlon	193
	Bastogne	153
	Liege (Luik)	97
	Malmedy	150
	Ostend	111
Belize	BELIZE CITY	
	Corozal	136
	Punta Gorda	270
	San Igancio	115
Benin	Cotonou	
	Bohicon	125
	Djougou	458
	Kandi	628
	Parakou	414
Bhutan	THIMPHU	
	Gelephu	244
	Jakar	258
	Phuntsholing	147
	Samdrup Jongkhar	420
Bolivia	Santa Cruz	
	Cochabamba	480
	El Alto	851
	LA PAZ	853
	Oruro	688
Bosnia and Herzegovina	SARAJEVO	
	Banja Luka	190
	Mostar	129
	Tuzla	119
Botswana	GABORONE	
	Francistown	433
	Selibe Phikwe	406
	Serowe	310
Brazil	Rio de Janeiro	
	BRASILIA	1202
	Belo Horizonte	441
	Fortaleza	2587
	Salvador	1632
Brunei Darussalam	BANDAR SERI BEGAWAN	
	Kuala Belait	113
	Seria	101
Bulgaria	SOFIA	
	Burgas	383
	Plovdiv	146
	Ruse	309
	Varna	441
Burkina Faso	OUAGADOUGOU	
	Bobo Dioulasso	356
	Koudougou	117
	Ouahigouya	182
	Solenzo	333
Burundi	BUJUMBURA	
	Gitega	99
	Ngozi	125
Cambodia	PHNOM PENH	
	Battambang	293
	Kampong Cham	124
	Serei Saophoan	422
	Siem Reap	318
Cameroon	Douala	
	Bafoussam	258
	Bamenda	321
	Garoua	1370

Country	City	Distance
	YAOUNDE	266
Canada	Toronto	
	Edmonton	3472
	Montreal	541
	Ottawa	456
	Vancouver	4373
Central African Republic	BANGUI	
	Bambari	377
	Berb´erati	520
	Bouar	435
	Carnot N'DJAME´NA	425
Chad		
	Ab´ech´e	748
	K´elo	379
	Moundou	480
	Sarh	561
Chile	SANTIAGO	
	Antofagasta	1336
	Temuco	679
	Valparaiso	116
	Vina del Mar	122
China	Shanghai	
	BEIJING (PEKING)	1214
	Chongqing	1684
	Guangzhou	1436
	Wuhan	839
Colombia	BOGOTA , D.C.	
	Barranquilla	1001
	Cali	461
	Cartagena	1072
	Medellin	415
Congo, Republic of	BRAZZAVILLE	
	Dolisie	361
	Kindamba	144
	Nkayi	281
	Pointe-Noire	515
Costa Rica	SAN JOSE	
	Liberia	210
	Limon	159
	San Carlos	156
Croatia	ZAGREB	
	Osijek	283
	Rijeka	160
	Split	409
	Zadar	285
Cuba	HAVANA	
	Guant´anamo	910
	Holgu´ın	736
	Pinar del Rio	164
	Santiago de Cuba	867
Cyprus	NICOSIA	
	Famagusta	82
	Limassol	85
Czech Republic	PRAHA	
	Brno	205
	Liberec	110
	Ostrava	371
	Plzen	95
Cˆote d'Ivoire	Abidjan	
	Bouake	343
	Daloa	379
	Korhogo	565
	YAMOUSSOUKRO	236
Democratic Republic of the Congo	KINSHASA	
	Kananga	1121
	Kisangani	2324

Country	City	Distance
	Lubumbashi	2291
	Mbuji-Mayi	1297
Denmark	KOBENHAVN	
	Alborg	304
	Arhus	187
	Esbjerg	298
	Odense	168
Djibouti	DJIBOUTI	
	Ali Sabieh	151
	Dikhil	173
	Obock	120
Dominican Republic	SANTO DOMINGO	
	Las Matas de Farfan	221
	Monte Cristi	272
	Puerto Plata	231
	Punta Cana	194
	Santiago de los Caballeros	155
Ecuador	Guayaquil	
	Cuenca	197
	Machala	182
	QUITO	425
	Santa Elena	130
Egypt	CAIRO	
	Alexandria	218
	Port Said	197
El Salvador	SAN SALVADOR	
	San Miguel	138
	Usulutan	115
Equatorial Guinea	BATA	
	Aconibe	192
	An˜isoc	161
	Ebebiy´ın	221
Eritrea	ASMARA	
	Assab	1062
	Keren	94
	Massawa	118
Estonia	TALLINN	
	Narva	212
	Parnu	128
	Tartu	185
	Voru	252
Eswatini	MBABANE	
	Lavumisa	176
	Lomahasha	143
	Nhlngano	130
Ethiopia	ADDIS ABABA	
	Bahir Dar	490
	Gondar	656
	Hawassa	279
	Mek’ele	934
Finland	HELSINKI	
	Kuusamo	798
	Oulu	607
	Tampere	180
	Turku	168
	Utsjoki Village	1262
France	PARIS	
	Lyon	466
	Marseille	774
	Nantes	385
	Toulon	839
Gabon	LIBREVILLE	
	Franceville	737
	Moanda	680
	Oyem	371

Country	City	Distance
Gambia	BANJUL	
	Bansang	269
	Farafenni	117
	Fatoto	353
	Sintet	135
Georgia	TBILISI	
	Batumi	374
	Gori	89
	Kutaisi	230
Germany	BERLIN	
	Frankfurt am Main	545
	Hamburg	289
	Koln	573
	Munchen	585
Ghana	Kumasi	
	ACCRA	249
	Ashiaman	268
	Tamale	382
	Tema	276
Greece	ATHINAI	
	Larissa	355
	Patrai	211
	Thessaloniki	502
Guatemala	CUIDAD DE GUATEMALA	
	Coban	211
	Huehuetenango	232
	Puerto Barrios	292
	Quetzaltenango	201
Guinea	CONAKRY	
	Kankan	638
	Labe	353
	Nzerekore	864
Guinea-Bissau	BISSAU	
	Bafatá	141
	Catió	285
	Gabú	191
Guyana	GEORGETOWN	
	Bartica	674
	Linden	108
	New Amsterdam	111
Haiti	PORT-AU-PRINCE	
	Cape-Haitien	199
	Jacmel	94
	Les Cayes	200
	Port-de-Paix	218
Honduras	TEGUCIGALPA	
	Choloma	349
	Danli	94
	La Ceiba	394
	San Pedro Sula	267
Hungary	BUDAPEST	
	Debrecen	231
	Miskolc	186
	Nyiregyhaza	231
	Szeged	175
Iceland	REYKJAVIK	
	Akureyri	388
	Fjardabyggd	668
	Hof, Iceland	342
India	Mumbai	
	Ahmedabad	531
	Bangalore	984
	Delhi	1422

Country	City	Distance
	Hyderabad	709
Indonesia	JAKARTA	
	Bandung	151
	Medan	1913
	Surabaya	783
Iran	TEHRAN	
	Esfahan	448
	Mashhad	900
	Shiraz	932
Iraq	BAGHDAD	
	Erbil	365
	Mosul	401
Ireland	DUBLIN	
	Cork	259
	Galway	208
	Limerick	203
	Waterford	171
Israel	JERUSALEM	
	Beersheba	118
	Eilat	314
	Haifa	150
	Mitzpe Ramon	203
Italy	ROMA	
	Milano	573
	Napoli	226
	Palermo	924
	Torino	690
Jamaica	KINGSTON	
	Montego Bay	170
	Savanna-la-Mar	192
Japan	TOKYO	
	Kumamoto	1188
	Niigata	318
	Osaka	499
	Sendai	370
Jordan	AMMAN	
	Al-Jafr	222
	Aqaba	333
	At-Tafilah	184
	Irbid	90
	Kerak	130
Kazakhstan	Almaty	
	Astana	1214
	Aktobe Province	2184
	Karaganda	1002
	Shimkent	682
Kenya	NAIROBI	
	Eldoret	324
	Kisumu	351
	Mombasa	488
	Nakuru	171
Korea	SEOUL	
	Busan	391
	Daegu	279
	Daejeon	157
	Gwangju	293
Kosovo	PRISTINA	
	Gjakova	89
	Pec	85
	Prizren	85
Kuwait	Salmiya	
	Abdali	125
	Al Wafrah	103
	Al-Nuwaiseeb	97

Country	City	Distance
Kyrgyz Republic	BISHKEK	
	Karakol	403
	Naryn	316
	Osh	610
	Talas	291
Laos	VIENTIANE	
	Luang Prabang	324
	Paxce	670
	Savannakhet	462
	Thakhek	337
Latvia	RIGA	
	Daugavpils	223
	Liepaja	218
	Rezekne	238
	Ventspils	189
Lebanon	BEIRUT	
	Qaa	132
	Qoubaiyat	138
	Tripoli	82
	Tyre	83
Lesotho	MASERU	
	Qachas Nek	224
	Quthing	176
	Rafolatsane	294
Liberia	MONROVIA	
	Buchanan	142
	Ganta	265
	Gbarnga	198
Libya	TRIPOLI	
	Al Baida	1226
	Al Khums	122
	Benghazi	1022
	Misrata	210
Lithuania	VILNIUS	
	Kaunas	103
	Klaipeda	307
	Panevezhis	137
	Shauliai	213
Madagascar	ANTANANARIVO	
	Antsirabe	171
	Fianarantsoa	413
	Mahajanga	572
	Toamasina	355
Malawi	LILONGWE	
	Blantyre City	312
	Chitipa	665
	Mzuzu	355
	Zomba	288
Malaysia	KUALA LUMPUR	
	Johor Bahru	329
	Kuantan	237
	Majlis Perbandaran Ipoh	205
Mali	BAMAKO	
	Kayes	618
	Koutiala	392
	Segou	235
	Sikasso	375
Mauritania	NOUAKCHOTT	
	Atar	439
	Kaedi	411
	Kiffa	599
	Nouadhibou	480
Mexico	MEXICO, CIUDAD DE	
	Guadalajara	551

Country	City	Distance
	Juarez	1793
	Monterrey	910
	Puebla-Tlaxcala	121
Moldova	CHISINAU	
	Balti	135
	Cahul	167
	Ribnita	105
	Soroca	156
Mongolia	ULAANBAATAR	
	Darkhan-Uul	245
	Hovsgol	866
	Selenge	378
Montenegro	PODGORICA	
	Bijelo Polje	121
	Pljevlja	175
Morocco	CASABLANCA	
	Agadir	466
	Fez	294
	Marrakech	242
	Tánger	338
Mozambique	MAPUTO	
	Beira	1216
	Chimoio	1147
	Nampula	2075
Myanmar	Yangon	
	Hpa-an	289
	Mandalay	626
	NAY PYI TAW	367
Namibia	WINDHOEK	
	Henties Bay	357
	Omaruru	208
	Swakopmund	352
	Walvis Bay	396
Nepal	KATHMANDU	
	Bharatpur	149
	Biratnagar	377
	Pokhara	201
Netherlands	AMSTERDAM	
	Enschede	162
	Groningen	183
	Maastricht	215
	Nijmengen	121
New Zealand	Auckland	
	Grisbone	480
	Hamilton	124
	WELLINGTON	644
Nicaragua	MANAGUA	
	Bluefields	354
	Chinandega	138
	Leon	97
	Puerto Cabezas	517
Niger	NIAMEY	
	Agadez	951
	Maradi	661
	Tahoua	551
	Zinder	891
Nigeria	Lagos	
	Benin City	315
	Ibadan	130
	Kaduna	771
	Kano	978
North Macedonia	SKOPJE	
	Bitola	174
	Gevgelija	154

Country	City	Distance
	Kriva Palanka	100
	Struga	174
Norway	OSLO	
	Bergen	463
	Kristiansand	318
	Stavanger	547
	Trondheim	494
Oman	As Seeb	
	Salalah	1012
	Sohar	183
Pakistan	Karachi	
	Faisalabad (Lyallpur)	1114
	Gujranwala	1267
	Lahore	1211
	Rawalpindi	1392
Panama	CIUDAD DE PANAMA	
	David	445
	Las Tablas	284
	Yaviza	282
Papua New Guinea	PORT MORESBY	
	Abau	221
	Kerema	303
	Kupiano	185
	Maopa	157
	Vuru	157
Paraguay	ASUNCION	
	Ciudad del Este	320
	Encarnacion	367
	Hernandarias	337
	Mariscal Estigarribia	522
	Salto del Guaira	407
Peru	LIMA	
	Arequipa	1012
	Chiclayo	774
	Cusco	1102
	Trujillo	558
Philippines	Quezon City	
	Baguio	240
	Laoag	479
	Naga	393
	Tuguegarao	475
Poland	WARSZAWA	
	Krakow	294
	Lodz	130
	Poznan	310
	Wroclaw	348
Portugal	LISBOA	
	Braga	364
	Porto	314
	Vila Nova de Gaia	308
Puerto Rico	SAN JUAN	
	Aguadilla Pueblo	132
	Boqueron	190
	Mayaguez	191
	Ponce	117
Qatar	DOHA	
	Abu Samra	96
	Al Ruwais	110
	Dukhan	84
	Zubara Fort	104
Romania	BUCURESTI	
	Cluj-Napoca	453
	Iasi	389
	Sibiu	279

Country	City	Distance
	Timisoara	548
Russia	MOSCOW	
	Ekaterinburg	1786
	Nizhny Novgorod	422
	Novosibirsk	3357
	St. Petersburg	706
Rwanda	KIGALI	
	Butare	124
	Gisuma	229
	Rubavu	138
Saudi Arabia	RIYADH	
	Ad-Dammam	409
	Al-Madinah	839
	Jiddah	954
	Makkah	869
Senegal	DAKAR	
	Ballou	716
	Kaolack	191
	Mbour	96
	St Louis	289
	Tambacounda	466
Serbia	BEOGRAD (BELGRADE)	
	Kragujevac	139
	Nis	237
	Novi Sad	94
	Subotica	190
Sierra Leone	FREETOWN	
	Bo	239
	Kambia	126
	Kenema	306
	Makeni	186
Slovak Republic	BRATISLAVA	
	Kosice	404
	Liptovsky Mikulas	287
	Poprad	328
	Zilina	203
Slovenia	LJUBLJANA	
	Koper	106
	Maribor	130
	Metlika	98
	Murska Sobota	179
Somalia	MOGADISHU	
	Borama	1522
	Bosaso	1395
	Galkayo	721
	Hargeisa	1289
South Africa	Johannesburg	
	Cape Town	1403
	Durban	568
	Port Elizabeth	1051
	Upington	794
South Sudan	JUBA	
	Ezo	579
	Raga	963
	Wau	645
Spain	MADRID	
	Barcelona	621
	Sevilla	535
	Valencia	357
	Zaragoza	314
Sri Lanka	COLOMBO	
	Batticaloa	320
	Galle	145
	Jaffna	360

Country	City	Distance
	Trincomalee	265
Sudan	OMDURMAN	
	El-Obeid	409
	Kassala	637
	Nyala	1210
	Port Sudan	839
Suriname	PARAMARIBO	
	Matapi	376
	Moengo	108
	Nieuw Nickerie	229
	Pokigron	185
Sweden	STOCKHOLM	
	Goteborg	469
	Linkoping	200
	Malmo	613
Switzerland	Zurich	
	Basel	84
	Geneve	277
	Lausanne	221
	Lugano	207
Syria	Aleppo	
	Ar Raqqah	210
	DAMASCUS	356
	Homs	185
	Latakia	175
Taiwan	NEW TAIPEI	
	Kaohsung	346
	Taichung	151
Tajikistan	DUSHANBE	
	Khorog	522
	Khujand	303
	Kulob	196
	Panjakent	234
Tanzania	Dar es Salaam	
	DODOMA	443
	Mwanza	1129
	Tanga	331
	Zanzibar	92
Thailand	BANGKOK	
	Chiang Mai	690
	Chon Buri	84
	Nakhon Ratchasima	259
	Songkhla	968
Timor-Leste	DILI	
	Maliana	153
	Suai	176
Togo	LOMÉ	
	Atakpamé	161
	Kara	414
	Kpalimé	128
	Sokodé	340
Trinidad and Tobago	PORT OF SPAIN	
	Icacos	134
	Mafeking	98
	Toco	89
Tunisia	TUNIS	
	El Kef	168
	Gafsa	363
	Monastir	169
	Sfax	267
Turkey	ISTANBUL	
	Adana	935
	Ankara	450
	Bursa	154

Country	City	Distance
	Izmir	479
Turkmenistan	ASHKHABAD	
	Balkanabat	425
	Dashoguz	599
	Tashauz	599
	Turkmenabat	620
Uganda	KAMPALA	
	Fort Portal	296
	Gulu	334
	Mbarara	270
	Mbarara	270
Ukraine	KYIV	
	Dnepropetrovsk	477
	Donets'k	732
	Kharkiv	526
	Odessa	475
United Arab Emirates	DUBAI CITY	
	Abu-Dhabi City	139
	Fujairah	147
	RAK City	106
United Kingdom	LONDON	
	Birmingham	202
	Glasgow	663
	West Midlands	188
	West Yorkshire	326
United States	New York (NY)	
	Chicago (IL)	1272
	Houston (TX)	2618
	Los Angeles (CA)	4490
	Phoenix (AZ)	3873
Uruguay	MONTEVIDEO	
	Chuy	326
	Melo	398
	Rivera	504
	Salto	492
Uzbekistan	TASHKENT	
	Andizhan	353
	Namangan	294
	Nukus	1136
	Samarkand	308
Venezuela	CARACAS	
	Barquisimeto	365
	Ciudad Guayana	671
	Maracaibo	696
	Valencia	167
Vietnam	HO CHÍ MIN CITY	
	Can Tho	171
	Da Nang	852
	Ha Noi	1611
	Hai Phong	1672
Yemen	SANA'A	
	Adan	385
	Al-Hudaydah (Hodeidah)	251
	Al-Mukalla	799
	Ta'izz	269
Zambia	LUSAKA	
	Chipata	568
	Kasama	855
	Kitwe	358
	Ndola	317
Zimbabwe	HARARE	
	Bulawayo	442
	Gweru	276
	Mutare	266

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