Social Capital Around the World: Measurement and Correlates

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Abstract

Social interactions across class lines are an important feature of social life that researchers have identified as a potential determinant of outcomes such as upward income mobility, interpersonal trust, prosocial norms, and civic health[1–9]. While cross-class interactions feature prominently in the social science literature, systematic evidence on their prevalence and consequences has been scarce. Here, we construct and analyze the first global measures of economic connectedness—a form of social capital that captures the extent to which individuals form friendships across socioeconomic lines—using data on 596 billion social connections among 2.1 billion Facebook users from 178 countries. Economic connectedness varies both across and within countries and is strongly associated with higher upward income mobility, greater interpersonal and institutional trust, stronger prosocial norms and democratic values, and weaker support for authoritarian and anti-elite political messages. Moreover, cross-country differences in economic connectedness statistically account for the well-documented relationships between inequality and these socio-political outcomes[10–12]. Taken together, our results establish economic connectedness as a key dimension of social capital that predicts a broad range of important societal outcomes. To support further research and policy applications, we publicly release data on the global distribution of economic connectedness at www.socialcapital.org.

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Social scientists have long highlighted the potential role of social capital—the strength of individuals' social networks and communities—in shaping outcomes such as intergenerational income mobility, trust, and civic engagement[13–18]. While empirical evaluations of these theories were historically constrained by the absence of large-scale network data, the rise of digital platforms such as Facebook now makes it possible to study social capital at unprecedented scale. In prior work, we used such data from the United States to build measures of economic connectedness (EC)—a form of bridging social capital that captures how socially connected rich and poor individuals are—and showed that economic connectedness is a strong predictor of upward income mobility[8,9].

In this paper, we take a global perspective. Using data on 596 billion friendships between 2.1 billion Facebook users, we construct national and subnational measures of economic connectedness for 178 countries. Facebook friendships typically reflect offline relationships and have been widely used as proxies for real-world social ties[19–29]. Our measures of economic connectedness allow us to test whether the strong U.S. relationship between EC and upward income mobility generalizes to other settings, and to examine whether EC also predicts other important socio-political outcomes that scholars have linked to social capital. We find that higher EC is associated with greater intergenerational income mobility, higher interpersonal and institutional trust, stronger prosocial norms, and more robust support for democracy. In contrast, there is no strong association between EC and life satisfaction among either rich or poor individuals. In a companion paper[30], we turn to the determinants of economic connectedness, and show that EC is shaped by inequality, residential segregation, population density, and the correlation of income with other social characteristics such as language.

Measuring Economic Connectedness

We measure economic connectedness using data from Facebook, a global online social networking service. Our sample comprises 2.1 billion Facebook users who were active on the platform in the 30 days prior to November 29, 2025, are between 18 and 65 years old, and have at least 25 Facebook friends. We observe users from 178 countries (Methods: 'Sample Construction'). Given substantial cross-country differences in Facebook usage rates, we restrict the main analyses to 133 countries with higher and more representative coverage, though we confirm that our findings hold when including the broader set of countries (Methods: 'Confidence in Measures').

Socioeconomic Status

We estimate the socioeconomic status (SES) of each user in our sample using a machine learning model that was trained to predict SES using features we observe for all users, such as their self-reported educational attainment, phone model, location, and on-platform behavior. As ground truth data to train the model, we use information on the SES of 74,098 users from 64 countries, which was collected via a survey that appeared in users' Facebook news feeds. The SES model performs well on a holdout sample of users, and SES predictions are highly correlated with corresponding subnational measures of income, even in countries not included in the survey (Methods: 'Socioeconomic Status').

With this model, we produce SES estimates for all users in our sample, which we use to compute their SES percentiles within their countries of residence and birth years. We use these SES percentiles as our primary measure of socioeconomic status, allowing us to abstract from differences in average SES across countries and age groups.

EC Stratification and Low-SES EC

To measure economic connectedness in a location, we examine the relationship between individuals' own SES percentiles and the average SES percentiles of their same-country friends (Methods: 'Measuring Economic Connectedness'). Figure 1a shows this relationship for India. If poor and rich Indians had friends of similar SES, the curve would be a horizontal line. In practice, higher-SES Indians have higher-SES friends. For example, Indians at the 25th percentile of the national SES distribution have friends that are on average at the 48.3rd percentile, while Indians at the 75th percentile have wealthier friends, with an average SES at the 62.7th percentile of the national distribution. Since high-SES people generally have more friends[31], the average friend SES percentile is above 50 for much of the population. The relationship between own SES and friends' SES is approximately linear for most of the distribution but becomes convex at the top, suggesting that the highest-SES users in India have especially few connections to low-SES peers.

Figure 1b contrasts economic connectedness in India with that in the U.S. and Denmark. In each country, average friend SES rises with an individual's own SES. However, Denmark exhibits a much flatter curve, indicating relatively more cross-class friendships. By contrast, the U.S. has a steep curve, with low-SES individuals having especially few high-SES friends. These results highlight that while social sorting by SES is common, the strength of this sorting varies substantially across countries.

Figure 1c compares economic connectedness across three Indian states, with SES still measured as a percentile in the national distribution. Since friendships often form locally and regions differ in mean incomes, the curves have a level shift: Indians at the same national SES percentile have lower-SES friends in poorer Bihar than in richer Maharashtra or Andhra Pradesh. For similar reasons, the state-level curves are flatter than the national curve: high- and low-SES people from the same state have more similar networks than when comparing high- and low-SES people across the whole country, since high-SES individuals in the national comparison disproportionately come from richer states where they tend to meet other high-SES people. In addition to the general flattening of state-level curves, their slopes vary: Maharashtra's is steeper, indicating more friendship sorting by SES. As a result, low-SES people in Maharashtra have fewer high-SES friends than in Andhra Pradesh, even though Maharashtra is richer.

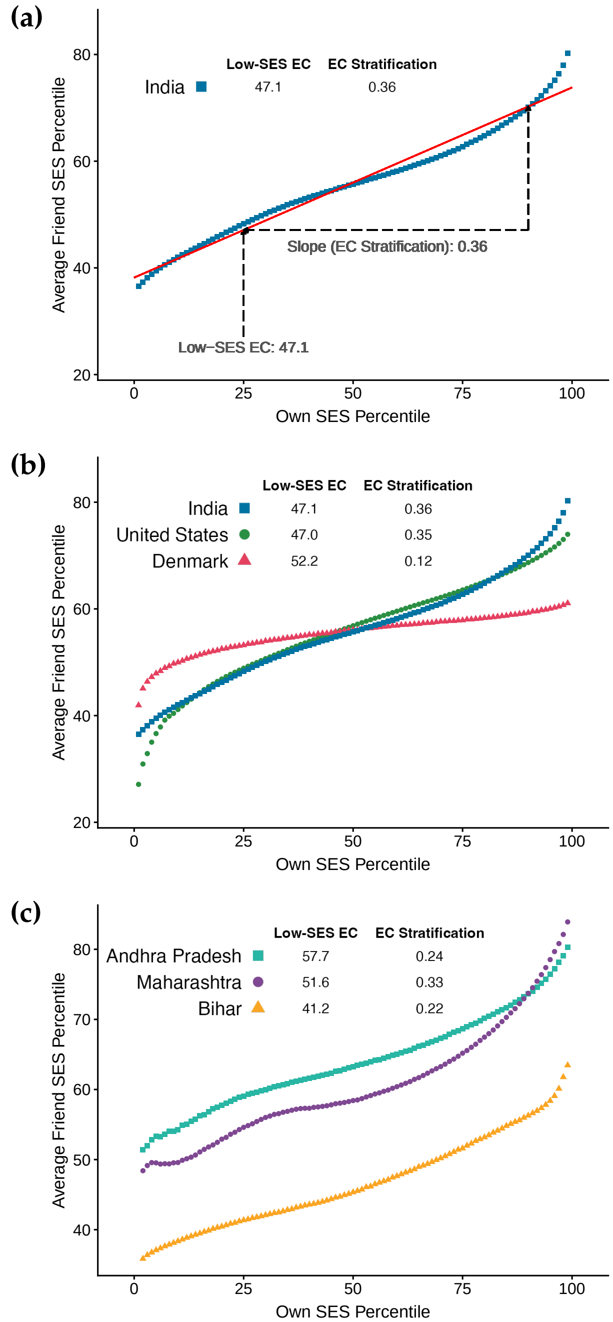


Fig. 1: Measuring Economic Connectedness
a, Binscatter (conditional mean) of average friend SES percentiles versus individuals' own SES percentiles for India. EC stratification is the slope of an OLS regression of average friend SES percentile against individual SES percentile in the underlying individual-level data. Low-SES EC is the corresponding predicted value of friend SES percentile for individuals at the 25th percentile of own SES. **b**, Binscatter of average friend SES percentile versus individuals' own SES percentile for India, the United States, and Denmark. **c**, Binscatter of average friend (national) SES percentile versus individuals' own (national) SES percentile for three Indian states: Andhra Pradesh, Maharashtra, and Bihar.

To make economic connectedness comparable across locations, we summarize it using two regression-based measures (Methods: 'Measuring Economic Connectedness'). Specifically, for each country or region, we estimate a linear regression of the average SES percentile of a person's friends against their own SES percentile (Fig. 1a).

Our first measure, *EC stratification*, is the slope of this regression. A steep slope means that high-SES people mainly befriend other high-SES people and low-SES people mainly befriend other low-SES people; a flatter slope means that friendship networks of high- and low-SES individuals in a location are more similar in their SES composition, generally indicating more cross-class ties.

Our second measure, *low-SES EC*, is the regression-predicted average friend SES percentile for someone at the 25th percentile of their country's SES distribution. Higher values mean that low-SES individuals have more high-SES friends, and variation in low-SES EC across regions reflects both the availability of high-SES peers and the extent of EC stratification (Extended Data Fig. 2a).

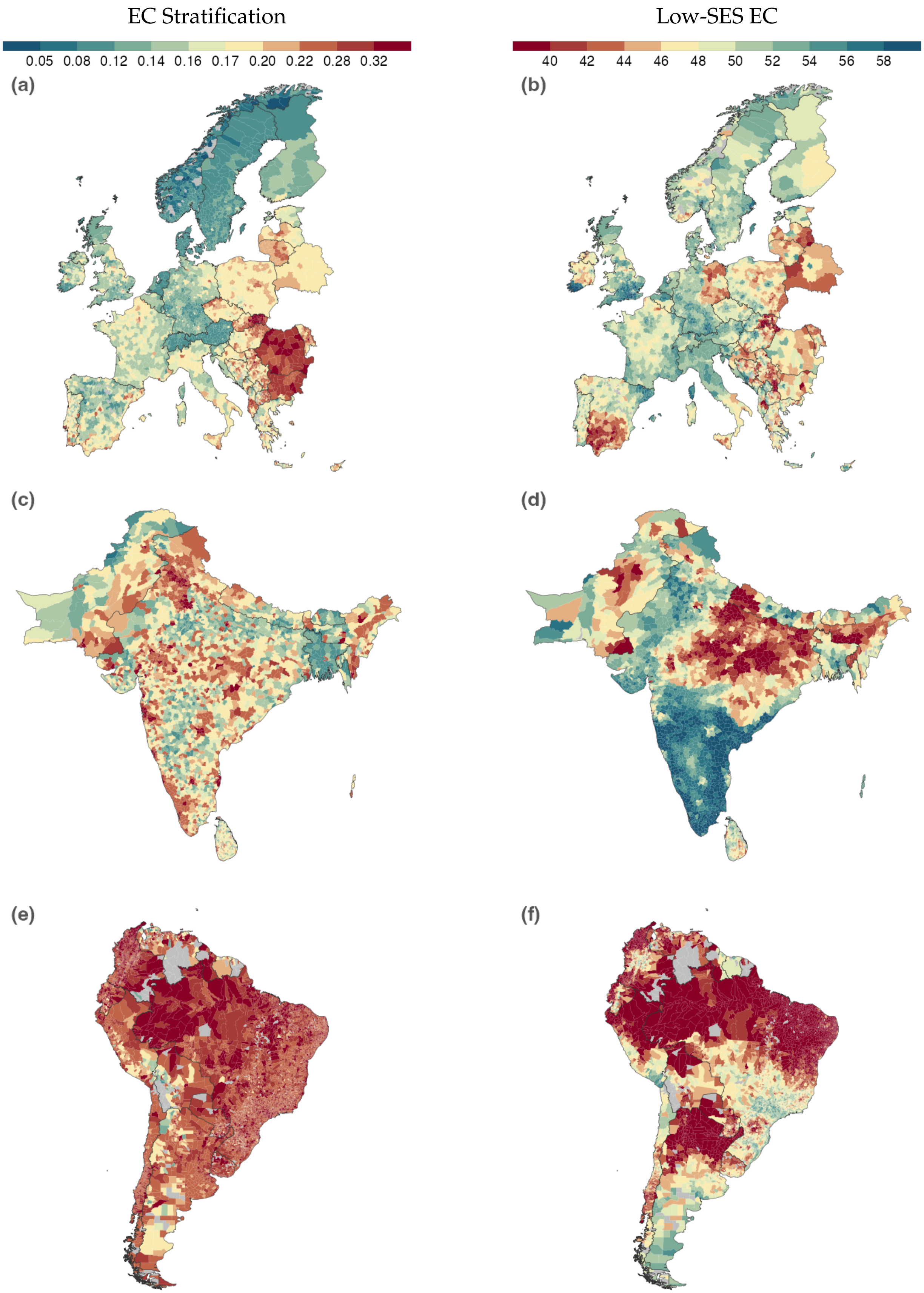
EC Around the World

Figure 2 maps the distribution of subnational measures of economic connectedness across global administrative area (GADM) regions (Methods: 'Locations'). Across these regions, the average EC stratification is 0.24, with a 5–95 percentile range of 0.14–0.35; the average low-SES EC is 48.1, with a 5–95 percentile range of 43.8–51.5 (Extended Data Table 2). About 58.9% of the across-region variation in EC stratification and 27.9% of the variation in low-SES EC occur across countries rather than within them, illustrating that heterogeneity in economic connectedness reflects regional patterns inside nations as much as cross-country differences.

The left panel of Figure 2 shows the regional variation in EC stratification. Levels are relatively low across Western Europe, especially in Nordic and German-speaking countries, but higher in Eastern Europe, particularly in Romania, Bulgaria, and eastern Slovakia (Fig. 2a). In South Asia, EC stratification is low across Bangladesh and Bhutan, but it varies sharply within India, where it is particularly high in urban areas (Fig. 2c). South America has almost uniformly high EC stratification, with the exceptions of some regions in Bolivia, Peru, and Argentina (Fig. 2e). The United States also exhibits high EC stratification nationwide (Fig. 2g). In sub-Saharan Africa, EC stratification is mostly low except in Namibia and South Africa, consistent with the enduring legacy of Apartheid (Fig. 2i). In the Middle East, the six GCC states rank among the most stratified globally—partly reflecting social divides between migrant workers and wealthier locals—while Yemen and Iraq display lower levels of EC stratification (Fig. 2l).

Spatial variation in low-SES EC is determined by differences in both average SES and EC stratification. Within countries, low-SES EC is often smallest in the poorest regions, such as eastern Germany (Fig. 2b), northern India (Fig. 2d), northeastern Brazil (Fig. 2f), and the southern United States (Fig. 2h). Variation in EC stratification also shapes low-SES EC. For example, in India, Thane is somewhat richer the nearby more rural Murbad, yet Thane's higher EC stratification leads to a smaller value of low-SES EC (Extended Data Fig. 2b). Similar patterns arise when comparing other richer cities with nearby poorer but less socially stratified rural areas.

These maps show how EC varies across regions, providing a new perspective on the global distribution of cross-class social ties. Our EC estimates reflect real variation rather than sampling noise (Extended Data Table 3). The spatial patterns are robust to alternative data construction choices, such as restricting EC measures to only include a person's top-10 or top-100 same-country friends, modifying the SES model and EC estimation procedure, and expanding the sample (Extended Data Table 4). They are also similar when measuring EC at other levels of geographic aggregation (Extended Data Table 2). We next explore how these EC differences predict economic and socio-political outcomes long associated with social capital.


EC Stratification
0.05 0.08 0.12 0.14 0.16 0.17 0.20 0.22 0.28 0.32
Low-SES EC
40 42 44 46 48 50 52 54 56 58
(a)
(b)
(c)
(d)
(e)
(f)

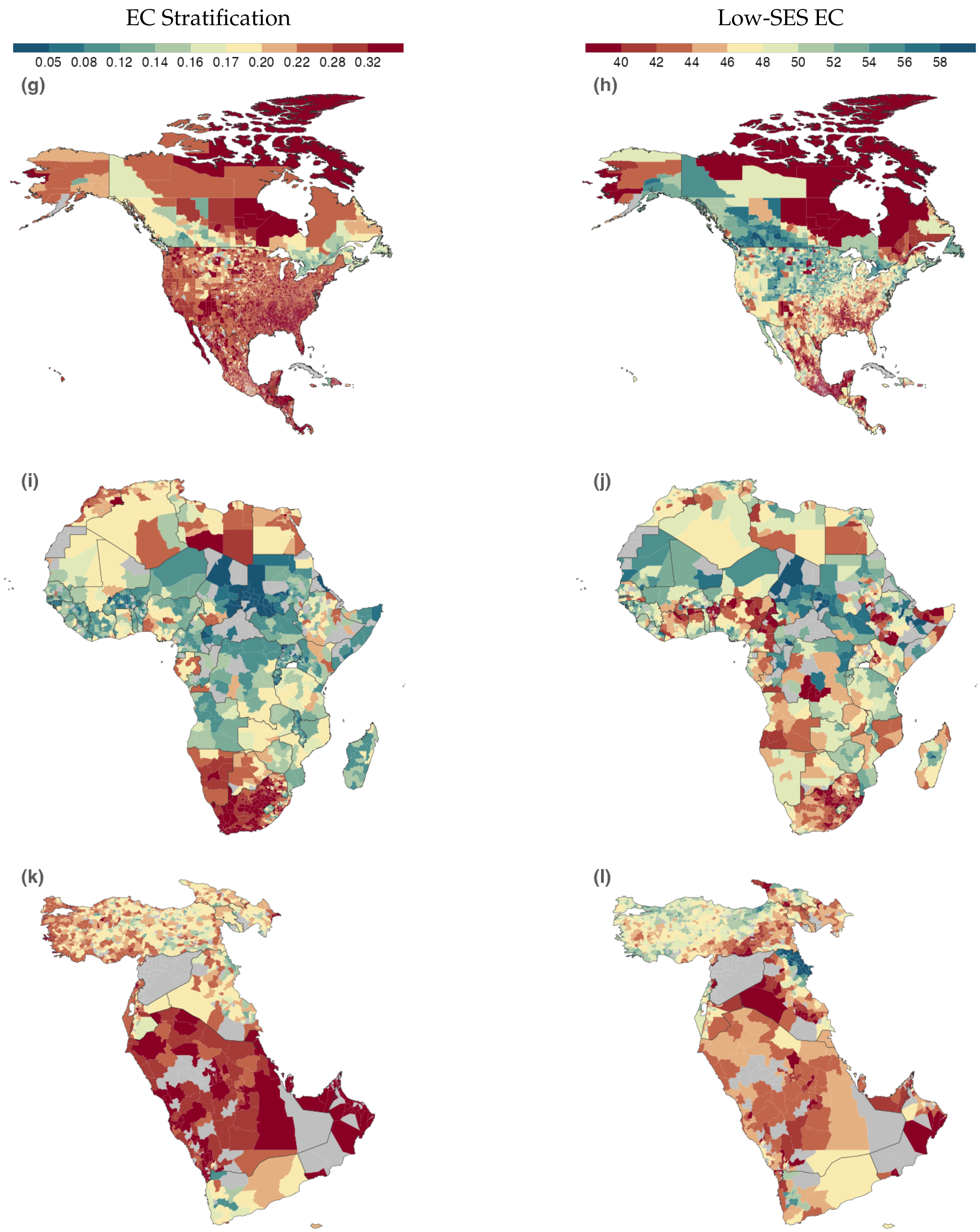


Fig. 2: Economic Connectedness Around The World

EC stratification and low-SES EC across GADM regions, with common scale. EC stratification is defined as the slope from regressing average friend (national) SES percentile on individuals' own (national) SES percentile. Low-SES EC is defined as the expected average friend (national) SES percentile for an individual at the 25th (national) SES percentile. Low-population regions in gray. **a, b,** Europe. **c, d,** South Asia. **e, f,** Africa. **g, h,** North America. **i, j,** South America. **k, l,** West Asia/Middle East. Maps for additional regions are in Extended Data Fig. 1. Maps with region-specific scales are in the Supplementary Information.

EC and Upward Mobility

In earlier work, we showed that economic connectedness in the U.S. is strongly associated with upward income mobility: in counties where low-SES individuals have more high-SES friends, they also have a higher chance of rising up the income distribution[8,9]. Ongoing work documents similar patterns in England[32], and recent U.S. evidence establishes a causal link between friendships with higher-SES peers in high school and later-life success[33]. These results are consistent with theories of how high-SES friends can foster advancement by serving as role models, sharing information, and providing access to resources such as job referrals[18,34], but the exact mechanism remains elusive.

We now explore the extent to which the relationship between economic connectedness and intergenerational mobility generalizes beyond the U.S., both across countries and, where data permit, across regions within countries. Establishing where this link holds—and where it does not—can provide insights into the mechanisms through which cross-class friendships support mobility.

We first examine the relationship between economic connectedness and country-level measures of intergenerational income mobility from the World Bank[35]. These measures capture the extent to which a child's income depends on that of their parents, and thus measures the degree to which income disparities persist across generations. We relate this measure of mobility to EC stratification, which captures differences in access to high-SES friends across the socioeconomic spectrum. As shown in Figure 3a, the cross-country correlation between intergenerational income mobility and EC stratification is strongly negative (ρ = -0.55). Column 1 of Table 1a presents the corresponding regression estimate: countries with more economically segregated networks tend to exhibit substantially lower intergenerational income mobility. For instance, Scandinavian countries combine low EC stratification with high mobility, whereas Colombia, Brazil, India, and the U.S. have both higher EC stratification and lower mobility.

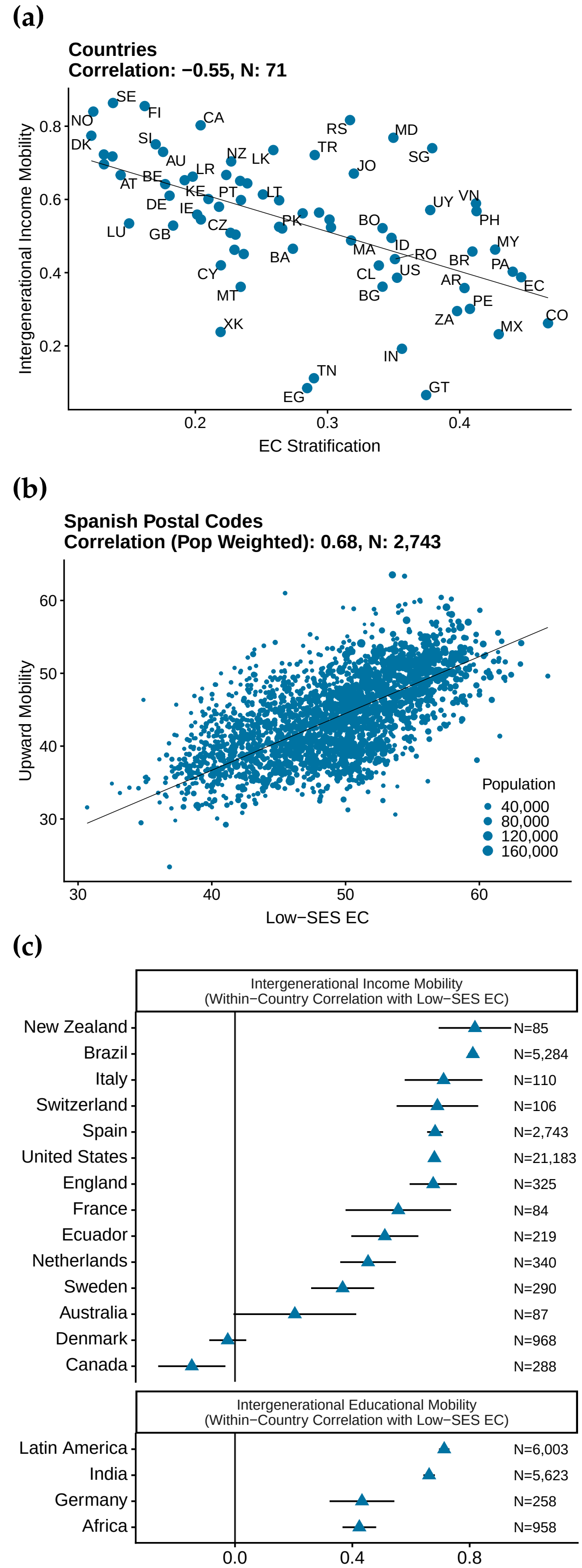


Fig. 3: EC and Upward Mobility

a, 1 − Intergenerational elasticity of earnings vs. EC stratification across countries. **b**, Expected adult income percentile rank for children born to parents in the lower half of the income distribution vs. low-SES EC for Spanish postal codes. **c**, Within-country correlation between upward mobility and low-SES EC, with 95% confidence intervals.

Table 1: Correlates of Economic Connectedness: Cross-Country Regressions

(a) Intergenerational Mobility

	Intergenerational Income Mobility			Intergenerational Educational Mobility		
	(1)	(2)	(3)	(4)	(5)	(6)
EC Stratification	-0.551***		-0.491***	-0.541***		-0.599***
	(0.085)		(0.124)	(0.090)		(0.119)
Inequality		-0.430***	-0.086		-0.300***	0.090
		(0.099)	(0.130)		(0.111)	(0.121)
Observations	71	71	71	84	84	84
Adjusted R^2	0.294	0.173	0.287	0.284	0.079	0.280

(b) Interpersonal and Institutional Trust, Prosocial Norms

	Trust Most People		Confidence in Courts		Cheating on Taxes is Justifiable		Votes are Counted Fairly	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
EC Stratification	-0.683***	-0.685***	-0.344***	-0.301	0.402***	0.373**	-0.604***	-0.421***
	(0.102)	(0.133)	(0.122)	(0.200)	(0.107)	(0.158)	(0.085)	(0.144)
Inequality		0.004		-0.051		0.044		-0.036
		(0.085)		(0.162)		(0.155)		(0.122)
Rule of Law Index				0.018				
				(0.133)				
Clean Election Index								0.404***
								(0.088)
Observations	73	73	72	71	73	73	73	72
Adjusted R^2	0.459	0.451	0.105	0.080	0.150	0.139	0.356	0.472

(c) Political Attitudes, Preference for Redistribution, and Life Satisfaction

	Importance of Democracy		Support for Un-checked Leadership		Incomes Should be Equalized		Overall Life Satisfaction	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
EC Stratification	-0.503***	-0.311**	0.733***	0.584***	-0.328***	-0.547***	-0.124	-0.136
	(0.091)	(0.152)	(0.061)	(0.133)	(0.090)	(0.133)	(0.110)	(0.172)
Inequality		-0.008		0.023		0.340**		0.275*
		(0.137)		(0.107)		(0.139)		(0.145)
Democracy Index		0.320**		-0.232**				0.285*
		(0.129)		(0.104)				(0.152)
Observations	73	72	73	72	73	73	73	72
Adjusted R^2	0.242	0.284	0.531	0.548	0.095	0.151	0.001	0.101

This table reports estimates from regressions of country-level outcomes on EC stratification. EC stratification is the slope from regressing the average SES percentile of an individual's friends on the individual's own SES percentile. We restrict to countries with green data-quality flags (Methods: 'Confidence in Measures'). Panel A uses intergenerational income and educational mobility data from the World Bank's Global Database on Intergenerational Mobility (see SI Section 1.2). Inequality is measured using Gini coefficients drawn from the World Bank, the Standardized World Income Inequality Database, and All the Ginis (see SI Section 1.6). Panel A employs lagged measures of inequality to approximate the levels of inequality individuals were exposed to during childhood. In Panels B and C, which examine present-day sociopolitical outcomes, we use contemporary inequality data. Panels B and C use country-level aggregates of survey responses from the Joint European Values Study/World Values Survey (see SI Section 1.5.1). The Clean Election Index, Rule of Law Index, and Democracy Index are expert-coded measures from the V-Dem dataset, averaged over 2018-2024 (see SI Section 1.7). All dependent and independent variables are standardized to have mean zero and unit variance. Robust standard errors in parentheses. Significance Levels: *10%, **5%, ***1%.

Prior work has attributed cross-country differences in upward income mobility to higher levels of inequality in low-mobility countries[10,36,37]. In column 2 of Table 1a, we replicate this "Great Gatsby Curve"[38] relationship—recently described as "one of the most visible stylized facts in contemporary inequality research"[39]—and confirm the strong negative correlation between inequality (Gini coefficient) and upward mobility ($\rho = -0.43$).

One of several theories to explain the Great Gatsby Curve proposes that inequality lowers mobility by fostering the segregation of social groups, which limits the exposure of low-SES individuals to role models and sources of information from higher socioeconomic strata[40–42]. In column 3 of Table 1a, we test a key prediction of this theory and estimate the effects of EC stratification and inequality jointly. The coefficient on inequality becomes small and statistically insignificant, while the effect of EC stratification remains strong. Put differently, holding inequality fixed, higher EC stratification is associated with lower mobility; conversely, holding EC stratification fixed, inequality is no longer associated with mobility. This finding suggests that the Great Gatsby Curve relationship between inequality and mobility may indeed be mediated by the frequency of cross-class friendships, raising the possibility that inequality affects mobility less through direct resource constraints and more by shaping the social networks that enable children to move up the income distribution.

Columns 4–6 of Table 1a repeat the analysis using World Bank measures of intergenerational educational mobility[43], defined as the dependence of a child's educational rank (relative to her cohort) on that of her parents. The results mirror those for income mobility: educational mobility declines with EC stratification ($\rho = -0.54$), and once EC stratification is accounted for, inequality no longer explains cross-country variation in educational mobility.

Researchers increasingly use administrative datasets to measure spatial differences in intergenerational income mobility within countries[44–46]. Where such data are available, we test whether variation in economic connectedness is related to income mobility across regions (Methods: 'Subnational Measures of Mobility'). These studies typically estimate upward income mobility as the average national income rank in adulthood of children whose parents were at the 25th percentile of the national income distribution. We examine whether this measure correlates with subnational variation in low-SES EC, which captures access to high-SES friends among lower-SES individuals.

Figure 3b shows a strong positive relationship between low-SES EC and upward income mobility across Spanish postal codes ($\rho = 0.68$): places where low-SES individuals have more high-SES friends are places where children born into low-SES families have higher adult incomes. Similar patterns emerge within most countries with regional data on upward income mobility (Fig. 3c, Supplementary Fig. SI-13), including developed countries such as Italy and France, and middle-income countries such as Brazil and Ecuador. We also find that regional measures of upward educational mobility are strongly correlated with low-SES EC across India, Germany, Latin America, and Africa (Supplementary Fig. SI-14).

The exceptions to this pattern are Australia, Denmark, and Canada, where higher economic connectedness is not strongly associated with higher upward income mobility. In all three countries, spatial variation in upward mobility is only weakly related to average incomes—a departure from the patterns seen in other settings with regional mobility data. This finding suggests that in countries where local resources themselves are less predictive of children's prospects, the benefits that typically come from accessing resources or information through richer friends may also be less important. A central task for future work is to better understand which features of these countries—such as their public education systems or social safety nets—explain why they show no strong link between local economic resources or economic connectedness and children's upward mobility.

EC and Socio-Political Outcomes

While prior empirical work on economic connectedness has emphasized its relationship with upward income mobility, social scientists have long argued that societies with more cross-class interactions may also differ along other important dimensions. For example, researchers have proposed that cross-group and cross-class connections can increase trust, reduce prejudice, and facilitate democratic engagement[1,2,4,15]. In this section, we use our novel data to explore the empirical relationships between EC stratification and a range of such socio-political outcomes around the world. While our findings are purely correlational, they nevertheless can provide evidence in support of—or against—many of these influential theories.

Interpersonal and Institutional Trust

A long line of research suggests that cross-class ties can reduce prejudice and increase interpersonal trust and institutional confidence[2,15,47]. Using data from the Joint European Values Study/World Values Survey (Methods: 'Socio-Political Outcomes'), we find that across a wide range of countries, higher EC stratification is indeed strongly correlated with lower trust in other people (ρ = -0.68; Fig. 4; Table 1b). These pattern holds for both high- and low-income survey respondents: where cross-class connections are stronger, people across the income spectrum are more likely to agree that others can generally be trusted (Extended Data Fig. 4). Analyses using data from the Gallup World Poll and the International Social Survey Programme yield similar results, confirming the strong link between economic connectedness and interpersonal trust (Extended Data Fig. 5).

While prior work found that inequality predicts lower interpersonal trust[11,48,49], Table 1b shows that, once EC stratification is controlled for, the effect of inequality is no longer significant. These patterns suggest that—similar to the Great Gatsby Curve—inequality might correlate with lower interpersonal trust largely because it fosters more segregated social networks[30].

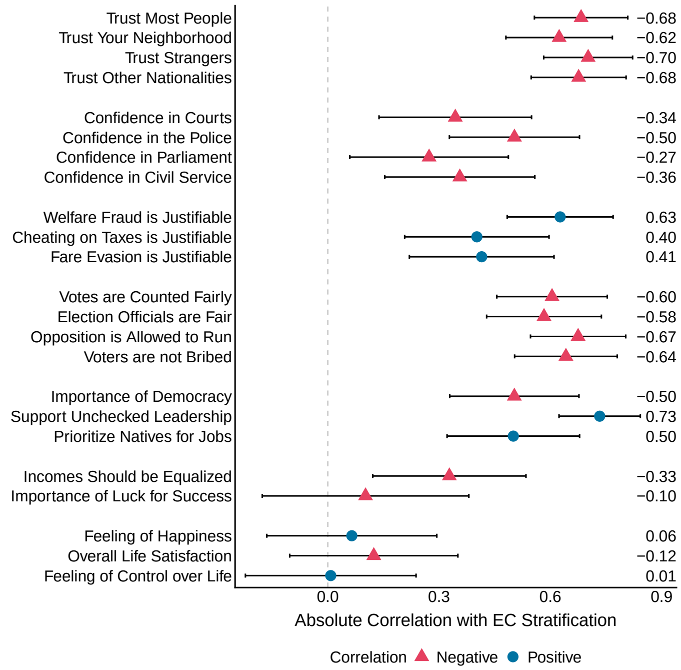


Fig. 4: EC Stratification and Civic, Political, and Social Attitudes and Beliefs
This figure shows the absolute value of correlation coefficients between EC stratification and country-level average responses to the Joint European Values Study/World Values Survey; the sign of each relationship is indicated by the marker (blue circles for positive correlations, pink triangles for negative correlations). Error bars denote 95% confidence intervals. Corresponding scatter plots are shown in Extended Data Fig. 3.

In addition to interpersonal trust, higher EC stratification also correlates with lower confidence in core state institutions, including the judiciary, law enforcement, legislative bodies, and the civil service (Fig. 4). These relationships persist, though with reduced statistical significance, after controlling for objective measures of the rule of law as well as measures of inequality (Table 1b, Methods: 'Socio-Political Outcomes'). Thus, the structure of social networks appears to predict not only how much citizens trust one another, but also whether they extend such trust to state institutions.

Prosocial Norms

Cross-class connectedness is also associated with stronger support for prosocial norms, even after controlling for inequality (Fig. 4, Table 1b). For example, in countries with high EC stratification, both high- and low-income individuals are more likely to condone cheating on taxes or evading public transit fares (Extended Data Fig. 4). These patterns are consistent with sociological theories that emphasize the role of cross-group interactions in broadening trust and extending norms of reciprocity beyond one's immediate circle[2,13,14,50].

Political Functioning & Attitudes

We also find that EC stratification is negatively correlated with expert assessments of the democratic performance of countries, as measured by multiple V-Dem indices (ρ = -0.56; Extended Data Fig. 6, Methods: 'Socio-Political Outcomes'). This finding is consistent with work highlighting the importance of cross-group ties for democratic functioning[5,6,14,51]. In addition, higher EC stratification is strongly associated with more negative perceptions of electoral integrity and fairness of the political process, even after accounting for objective institutional quality: among countries with similar scores on V-Dem's Clean Election Index, citizens perceive elections as fairer where cross-class connections are stronger (Table 1b).

We also find that in countries where networks are more segregated by SES, both high- and low-SES individuals are less likely to agree that democracy is important ($\rho \approx$-0.50, Extended Data Fig. 4). As before, controlling for expert assessments of the actual performance of democracy only somewhat attenuates the relationship between EC stratification and a belief in the importance of democracy (Table 1c). One interpretation is that personal ties across the SES spectrum improve the perceptions of other groups and thus make the principle of equal political voice more appealing[2,52–56].

These patterns suggest that network segregation influences democratic trust and support beyond its potential effects on the actual quality of institutions. Consistent with this interpretation, cross-class ties also predict lower receptivity to populist, authoritarian, and nativist views (Fig. 4). For example, in societies where friendships are more segregated by SES, citizens are more likely to prefer a "strong leader who does not have to bother with parliament and elections" and to support prioritizing natives in employment. These patterns remain even after controlling for income inequality and institutional quality (Table 1c). Evidence from the Ipsos Populism Survey shows that EC stratification is also associated with anti-elite sentiments, distrust of mainstream media and experts, and beliefs that the economy is rigged to benefit the rich (Extended Data Fig. 5). These findings are consistent with theories highlighting the erosion of social integration as a driver of populist politics[7].

Taken together, these findings suggest that the structure of social networks might shape both democratic trust and performance, as well as the appeal of authoritarian and anti-elite messages. Moreover, inequality's association with these outcomes disappears once EC stratification is controlled for, consistent with its effects operating through reduced cross-class interaction.

Preferences for Redistribution

EC stratification is also negatively related to support for redistribution as measured by agreement with the statement that "incomes should be made more equal," both on average (ρ = -0.33) and separately among rich and poor individuals (Extended Data Fig. 4). This relationship strengthens once we control for inequality: while higher inequality is associated with more support for redistribution, at any given level of inequality, societies with more cross-class connections show substantially greater support for income equalization (Table 1c).

By contrast, EC stratification is not strongly related to beliefs about the causes of inequality. For example, it does not predict support for the idea that success depends on hard work rather than luck (Fig. 4). Although attributing success to luck rather than effort is itself associated with stronger preferences for redistribution (Supplementary Table SI-13), such beliefs do not appear to be the mechanism linking economic connectedness to views on redistribution. Instead, a more plausible channel is the well-documented effect of cross-group friendships in fostering empathy and more favorable outgroup perceptions[47,54–56].

Subjective Well-Being

We find no systematic relationship between EC stratification and individuals' assessments of their own life satisfaction or overall well-being (Fig. 4), for either rich or poor respondents (Extended Data Fig. 4). This is true both in univariate regressions and in those controlling for inequality and indicies of democratic performance (Table 1c). This result suggests that EC segregation is associated primarily with outcomes in the political and civic domain, while not having a clear relationship with people's sense of happiness. The absence of such a relationship pushes against a simple psychological channel—such as reduced life satisfaction among the socially isolated—as a potential mechanism linking EC stratification to lower support for democracy and higher receptivity to populism.

Discussion

This study makes several contributions to the literature on the role of social capital in shaping economic and social outcomes. By assembling novel measures of economic connectedness and linking them to intergenerational mobility, trust, and civic health, we provide the first systematic evidence on how cross-class interactions are associated with societal outcomes at a global scale.

One contribution of our work is to expand our understanding of the determinants of upward income mobility. Earlier research in the United States found that individuals from lower socioeconomic backgrounds achieve better adult outcomes when they have more high-SES friends. We show that this relationship is not confined to the U.S. context, but emerges across many—though not all—institutional environments. We also contribute to a broader understanding of the drivers of the Great Gatsby Curve, highlighting that the segregation of social networks by SES may be a key mechanism linking inequality and mobility.

Beyond economic outcomes, our results suggest that higher levels of cross-class connectedness are systematically associated with greater interpersonal and institutional trust, stronger endorsement of prosocial norms, and more favorable attitudes towards democratic institutions. These findings provide support for theories that emphasize the importance of bridging social ties in sustaining not only economic opportunity but also civic health and institutional legitimacy.

As with any empirical study, our findings come with caveats. First, our evidence is correlational: while the observed relationships align with theories proposing causal effects of cross-class connectedness on the outcomes we study, our analysis does not establish such causality.

Second, Facebook usage rates vary across countries. While average SES estimates align well with external income benchmarks, EC estimates from countries with limited and more selected coverage should be interpreted with caution (Methods: 'Confidence in Measures').

Third, although our SES model performs well across the countries in the training data, spatial variation in its ability to distinguish low- and high-SES individuals could affect measured economic connectedness. In our context, such variation would attenuate the estimated relationships between EC stratification and outcomes of interest, without invalidating the conclusion that economic connectedness predicts them. Nonetheless, caution is warranted when using the data in contexts where such attenuation may pose greater concerns.

Fourth, while economic connectedness is associated with a range of outcomes, it is unlikely to be the only dimension of social capital that matters. Other forms of associational life—such as bonding ties within communities or bridging ties along dimensions other than SES—are likely also relevant.

Fifth, survey-based indicators of attitudes may partially capture cultural or contextual differences in reporting, which complicates cross-country comparisons. Moreover, our primary analysis is based on the World Values Survey; while we confirm several patterns in other surveys, differences across survey instruments and contexts mean that alternative datasets may yield somewhat different results. These limitations suggest caution in interpreting the magnitudes of the observed relationships, while reinforcing the value of complementary research strategies capable of establishing causality and mechanisms more directly. We hope that by releasing our measures of economic connectedness, we can stimulate such research.

Looking forward, our companion paper examines the determinants of economic connectedness and shows that variation in EC stratification across countries and regions is systematically linked to inequality, residential segregation, population density, and the alignment of socioeconomic status with other social markers such as language[30]. By complementing the evidence in this study with such an analysis of the institutional, cultural, and economic conditions that predict network segregation, we aim to provide a more comprehensive account of how economic connectedness is formed, and how it might be influenced to promote upward mobility, trust, and broader social cohesion.

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Methods

Sample Construction

Our analyses in this paper are based on the population of Facebook users whose accounts were active in the 30 days before November 29, 2025 and who were between 18 and 65 years of age on that date. We additionally require that individuals have more than 25% of their friends in the country in which they live and remove users with fewer than 25 friends within their country of residence. In total, our sample consists of 2.1 billion users.

Extended Data Table 1 reports summary statistics for the full sample. The average user has 654 Facebook friends—with 10th–90th percentile range of 63 to 1,691 friends—and 586 within-country friends, with a 10th–90th percentile range of 54 to 1,523 friends. 43.1% of users are female. The sample spans diverse economic contexts: the 10th–90th percentile range across users of country-level GDP per capita is $2,000–$54,000.

Locations

We observe an estimate of each user's home location, based on a proprietary model that combines signals such as self-reported home location, the IP addresses used to connect to Facebook, and on-platform activity. We match estimated locations to shapefiles to assign users to countries and regions.

Our maps show the distribution of EC across GADM (Database of Global Administrative Areas) regions. We mostly use second-level administrative boundaries, corresponding to counties in the U.S. and NUTS3 regions in Europe. For countries with small populations or limited Facebook usage, we aggregate to first-level units or the national level. In countries where sample sizes are large even at finer scales, we disaggregate to third-level units (Supplementary Information Section 2.2).

Since many subnational measures of intergenerational mobility are defined over geographic units that do not align with GADM boundaries, we also map users to other geographic regions, spatially joining their estimated home locations with the relevant boundary definitions (Supplementary Information Section 1.3). This allows us to produce estimates of EC that match the granularities of the external datasets on upward mobility.

Friendship Links

Facebook friendships are undirected connections between two users established with the consent of both users. Users can have up to 5,000 friends at a time. These connections typically reflect offline relationships and have been widely used as proxies for real-world social ties in prior work[8,9,20–29]. In this paper, we restrict all analyses to friendships between individuals residing in the same country.

To capture variation in tie strength, we rank each user's friendships using a proprietary model that incorporates features such as mutual friends and interaction frequency. Measures of economic connectedness calculated using only a user's top-10 or top-100 friends are highly correlated with baseline measures using all friends ($\rho \approx 1.00$ across countries and $\rho \approx 0.98$ across GADM1 regions; Extended Data Table 4). This suggests that the inclusion of more marginal friendships does not meaningfully affect our results.

Socioeconomic Status

To estimate the socioeconomic status (SES) of the individuals in our sample, we build a machine learning model that predicts users' SES based on their self-reported demographics, location, phone type, and on-platform behavior. We train this model on data on key aspects of the socioeconomic status of individuals who responded to a survey conducted by Facebook.

On-Platform Survey. Ground-truth data on users' SES was collected by Facebook via a survey inserted into users' news feeds. The survey was conducted in two waves, the first running from July 12th, 2023 to July 26th, 2023, and the second from September 4th, 2024 to September 18th, 2024. The survey was translated in 50 languages, and users were shown the survey in the language in which they were estimated to be most fluent. We include responses from individuals answering more than half the questions, leaving us with 74,098 respondents from 64 countries covering various geographies and levels of development (see below).

The survey collected information on individuals' incomes—by asking them to select one of five country-specific income quintiles, created using data from the World Inequality Database—as well as information on whether they:

1. Own or rent a car
2. Have a computer at home
3. Own a smart phone
4. Own a television
5. Own stocks, bonds, or mutual funds
6. Fly in a plane at least once a year
7. Have savings to cover 3 months of expenses
8. Have reliable electricity at home
9. Have regular running water at home

The survey interface and user disclosures are shown in Supplementary Information Section 2.1.

Questions 6 and 7 were only asked in the following countries: Algeria, Argentina, Australia, Austria, Belgium, Brazil, Bulgaria, Canada, Colombia, Croatia, Cyprus, Czechia, Denmark, Ecuador, Finland, France, Germany, Greece, Hungary, Iraq, Ireland, Italy, Japan, Kazakhstan, Luxembourg, Malta, Mexico, the Netherlands, Peru, Poland, Portugal, Romania, Saudi Arabia, Slovakia, Slovenia, South Africa, South Korea, Spain, Sweden, Thailand, Turkey, the United Kingdom, the United States, Uzbekistan, and Vietnam.

Questions 8 and 9 were only asked in the following countries: Angola, Bangladesh, Benin, Bolivia, Cameroon, the Democratic Republic of the Congo, Egypt, Ethiopia, Ghana, India, Indonesia, Ivory Coast, Kenya, Morocco, Nigeria, Pakistan, the Philippines, Tanzania, and Zambia.

SES Target Construction. We construct a single SES index from the survey responses and use it as the target variable in training the machine learning model. Specifically, the responses to the various survey questions are combined using principal component analysis (PCA) as follows.

We first code the access-to-resource questions as 1/0, while income quintiles are mapped to the natural logarithm of a random dollar value chosen with uniform probability within the bounds of the corresponding income quintile. For the open-ended top and bottom quintiles, we set the outer bounds at twice the 80th percentile and half the 20th percentile, respectively. We then standardize each variable across respondents, and impute missing values for each respondent using a k-nearest-neighbors algorithm, where missing values are set as the median value of a user's five nearest neighbors on the questions they did answer. Finally, we extract the first principal component from these standardized responses. Each respondent's survey-based SES is then calculated by projecting their transformed responses onto this first component. Since principal components are defined only up to sign, we orient the index such that higher values correspond to greater resources and income.

We validate the SES index by mapping respondents to locations and comparing spatial variation in the survey-derived average SES with administrative benchmarks. At the country level, average SES is highly correlated with log GDP per capita ($\rho = 0.93$). Within countries, the index tracks regional household incomes, closely mirroring state-level patterns in the U.S. and NUTS2-level variation in Europe (Supplementary Fig. SI-1).

Model Training. We train a gradient-boosted tree to predict the SES index using features observed for all individuals in the sample. These predictors fall into three categories: (1) user demographic information; (2) Facebook activity variables; and (3) aggregate SES measures for a user's location.

Demographic information includes self-reported educational attainment (high school, college, graduate school), and self-reported marital status. Facebook usage information includes details on the devices used to access Facebook (e.g., phone model and price), mobile carrier, and donations and marketplace usage on the platform. Location-based predictors include estimates of average area-level incomes as well as information on the country-level Human Development Index and GDP per capita. Importantly, we do not use information from an individual's friends to predict their SES. This design ensures that prediction errors are not mechanically correlated across friends, which would bias our estimates of SES-homophily. A full list of predictors and their relative feature importance is provided in Supplementary Information Section 2.1.

We then use the trained model to generate SES predictions for all individuals in the sample. Supplementary Fig. SI-8 shows maps of the average absolute SES predictions by region.

Model Validation. We validate the SES model by aggregating predictions to the regional level and comparing them against official statistics on income and GDP from the World Bank, Eurostat, the U.S. Census Bureau, and the OECD (Extended Data Fig. 7). The model performs well, yielding high correlations across all geographic granularities considered. Because our index is designed to capture a broader concept of SES than income alone, a perfect correlation is neither expected nor desirable. Nonetheless, the consistently strong correlations with income-based benchmarks provide reassurance about the validity of the SES predictions. In our companion paper[30] we show that our individual-level SES estimates also aggregate to measures of national and regional inequality that track administrative data where available, indicating that we capture both average incomes and their distribution across people.

To further assess the quality of our SES predictions in countries without survey data, we implement a leave-one-out cross-validation procedure. For each country in turn, we re-estimate the model while excluding all respondents from that country. We then predict the SES of all respondents from the excluded country. As shown in Supplementary Table SI-8, the model continues to perform well: our ability to predict the SES of survey respondents remains high even when their country of residence is entirely omitted from the training data.

The gradient-boosted tree used in our main analysis is only one way of combining SES proxies used as predictors into a single index. To verify that our results are not dependent on this modeling choice, we construct an alternative SES measure using phone price alone as a simple proxy. This approach requires neither survey data nor a trained prediction model, yet it yields EC measures that are strongly correlated with those from our baseline model at both the country and GADM-region levels (Extended Data Table 4).

One possible concern with our approach is that including subnational SES proxies, such as average local incomes, as model features could cause predicted SES values to shrink towards regional means. This might mechanically exaggerate spatial SES clustering and inflate estimated SES homophily in settings where individuals make many local friends. To test for this, we re-estimate the model while excluding all subnational geographic predictors, instead using (i) only individual-level features or (ii) individual-level plus country-level features. The resulting EC measures remain highly correlated with those from the baseline model (Extended Data Table 4), indicating that our findings are not mechanically driven by regional shrinkage.

SES Rank Construction. We use the model's absolute SES predictions to create SES percentile ranks of each user within their country and birth year.

Measuring Economic Connectedness

For each individual i, we first compute the average SES percentile of their friends (average friend percentile, or AFP) within their country of residence:

$$\text{AFP}_i = \frac{\sum_{j \in N(i)} \text{SES}_j}{|N(i)|},$$

where $N(i)$ is the set of same-country friends of user i and SES_j is the SES percentile of friend j. Since high-SES individuals generally have more Facebook friends—and therefore appear as alters for more individuals—the average AFP_i across individuals in a country is substantially above 50 (see Supplementary Fig. SI-4).

To obtain measures of economic connectedness, we estimate regression 1 of average friend SES percentile on one's own SES percentile for all users located in region c:

$$\text{AFP}_i = \alpha_c + \beta_c \times \text{SES}_i + \varepsilon_i. \quad (1)$$

The slope coefficient $\widehat{\beta}_c$ measures EC stratification, and captures how much social network composition differs across the SES distribution. We also construct a measure of low-SES EC by evaluating the fitted regression line at the 25th percentile of the national SES distribution: $\hat{\alpha}_c + \widehat{\beta}_c \times 25$.

Our measures of EC are robust to several alternative construction approaches. In the first such approach, we compute, for each location, the average friend rank for local residents in each decile of the national income distribution, and then estimate regression 1 on these decile-level averages (or percentile-level averages for countries and GADM1 regions). This method, which equal-weights national SES deciles rather than weighting by the number of individuals in each decile in a region, produces EC measures that are highly correlated with our baseline estimates (Extended Data Table 4). Likewise, defining low-SES EC as the equal-weighted average AFP across the bottom five deciles, and EC stratification as the difference in equal-weighted average AFP between the top and bottom five deciles, also yields similar estimates to our baseline approach (Extended Data Table 4). Taken together, these analyses indicate that our EC estimates are not overly sensitive to nonlinearities in the relationship between SES_i and AFP_i.

We estimate economic connectedness at multiple levels of geographic aggregation. Since individuals generally sort spatially by SES and friends are disproportionately made locally, average EC stratification varies systematically with the level of aggregation. Specifically, EC stratification is consistently larger at higher levels of aggregation, and national EC stratification always exceeds the population-weighted mean of region-level EC stratification within the same country (Extended Data Table 2 and Supplementary Fig. SI-3). This difference is more pronounced in countries with greater regional disparities in average SES, such as India. This is because in regions where most people have low SES, the networks of the few high-SES people resemble those of the low-SES people—everybody has many low-SES friends—and EC stratification is low. Similarly, in regions with mainly high-SES people, both low- and high-SES people have high AFP_i, similarly leading to low EC stratification. However, estimates of EC stratification at the country level are disproportionately determined by comparing the networks of low-SES people in low-average-SES places to those of high-SES people from high-average-SES places, leading to higher EC stratification. Nevertheless, the overall spatial distribution of economic connectedness is highly robust to the choice of aggregation (Extended Data Table 2).

Measures of Intergenerational Mobility

We compile national and subnational data on intergenerational mobility. At the national level, we use the World Bank's Global Database on Intergenerational Mobility (GDIM), which provides harmonized estimates of income and educational mobility across countries[35,57]. Income mobility is measured as one minus the intergenerational income elasticity—the slope from regressing children's log incomes on those of their parents—while educational mobility is defined as one minus the correlation between parental and child years of schooling.

At the subnational level, we use estimates of upward income mobility from Australia, Brazil, Canada, Denmark, Ecuador, England, France, India, Italy, the Netherlands, New Zealand, Spain, Sweden, Switzerland, the United States[44,46,58–69]; and estimates of upward educational mobility from India, Germany, Africa, and Latin America[43,70–72]. These typically capture the expected adult income or educational attainment of children born to parents at the bottom of the respective national distributions.

Further details on definitions, sources, and units of analysis are provided in Supplementary Information Sections 1.1-1.4.

Socio-Political Outcomes

To study the relationships between EC and socio-political outcomes, we use data from several large-scale survey programs. Our main source is the Joint European Values Study/World Values Survey (EVS/WVS), which measures attitudes toward trust, democracy, redistribution, and civic norms across 92 countries and territories, based on survey responses from 156,658 individuals. We complement this data with information from the Gallup World Poll, which spans more than 140 countries; the Ipsos Populism Report, which covers 31 countries; and the International Social Survey Programme, whose 2017 and 2019 modules collected data from 32 and 34 countries, respectively. Variable definitions and survey details are provided in Supplementary Information Section 1.5.

Other Data

Inequality. Our primary measure of inequality is the Gini index, taken from the World Bank's Poverty and Inequality Platform. Where these data are unavailable, we use estimates from the Standardized World Income Inequality Database (SWIID) and the 'All the Ginis' dataset (Supplementary Information Section 1.6).

Quality of Democracy. To capture institutional quality, we use indices from the Varieties of Democracy (V-Dem) project, averaging country-level scores over 2018–2024. The V-Dem data are based on expert assessments by thousands of country specialists, with multiple coders rating each country-year and statistical models used to reconcile disagreements. We work with the project's flagship indices, including assessments of election integrity, rule of law, and several dimensions of the overall performance of democracy (Supplementary Information Section 1.7).

Population. We estimate populations for each geography by aggregating 1km $\times$ 1km population grid cells from LandScan[73]. These population estimates, which we use to weight regressions of subnational mobility against EC, show high correlations with administrative population data where available (Supplementary Information Section 1.8).

Confidence in Measures

The 178 countries in our full sample represent 80.4% of the global population, and the 2.1 billion users aged 18 to 65 in our sample represent 54.1% of the population in that age range within these countries. However, the share of individuals using Facebook varies across countries, raising concerns about the representativeness of our measures. For example, in developing countries, limited internet access might disproportionately exclude low-SES individuals, leading us to measure EC only among relatively wealthier residents. Despite this limitation, Facebook provides the most comprehensive global social network data, and we find it captures meaningful variation in SES and EC. We therefore construct and release data for all countries where Facebook is available, while providing a country-level confidence measure to guide interpretation.

This confidence measure is based on two signals: (i) the Facebook coverage rate, defined as the share of a country's population that logged into Facebook in the 30 days before November 29, 2025, and (ii) the accuracy of our SES index, measured as the percent error of the predicted mean SES relative to log GDP per capita. 25 countries with low coverage and/or low SES accuracy are coded "red"; 20 countries with intermediate coverage/accuracy are coded "orange"; and 133 countries with high coverage/accuracy are coded "green" (see Extended Data Fig. 7a). Except for the maps or where otherwise noted, all exhibits in this paper are restricted to the green countries, for which the high population coverage and the close alignment between average SES in our sample and GDP per capita suggest that SES-specific selection into our sample is not a first-order concern.

In Supplementary Table SI-10 and Supplementary Figs. SI-12, SI-15, and SI-16, we reproduce our core results when also including the "orange" and "red" countries, finding results similar to those drawn from the narrower sample.

Privacy and Ethics

Our analyses focus on patterns at the community level rather than on individual users. We used a server-side script that automatically processed the raw data, stripped it of personal identifiers, and produced the aggregated region-level measures that we analyze in this paper. The raw data generated for this project, including any individual-level predictions, were promptly deleted once the aggregation was complete. To supplement these measures, we incorporated publicly available aggregate statistics, but we did not link any external individual-level data to the Facebook data. All analyses were conducted solely for the purposes of this research, and no outputs, including any individual-level predictions, were used by Meta for any other purpose. The study was approved under NYU IRB-FY2018-1399.

Data Availability & Differential Privacy

To facilitate further research on social capital, we release country- and region-level aggregate statistics on economic connectedness and its predictors. To protect user privacy while maintaining statistical reliability, we do not release information for cells containing fewer than 500 individuals, and apply methods from the differential privacy literature that introduce calibrated noise to the publicly available aggregates. These privacy-protected data are accessible via the Humanitarian Data Exchange and at www.socialcapital.org.

The population-weighted correlations between country- and region-level measures of EC stratification and low-SES EC in the raw data and the privacy-protected data are all above 0.999. Except for Extended Data Table 3, all exhibits are based on the publicly available privacy-protected measures of EC. As a result, the reported correlations can be interpreted as (slight) lower bounds on the correlations one would observe before the addition of privacy preserving noise. We provide more information about the noise we add to each column in the public data in Supplementary Information Section 3.

Code Availability

The code that supports the findings of this study is available at www.socialcapital.org.

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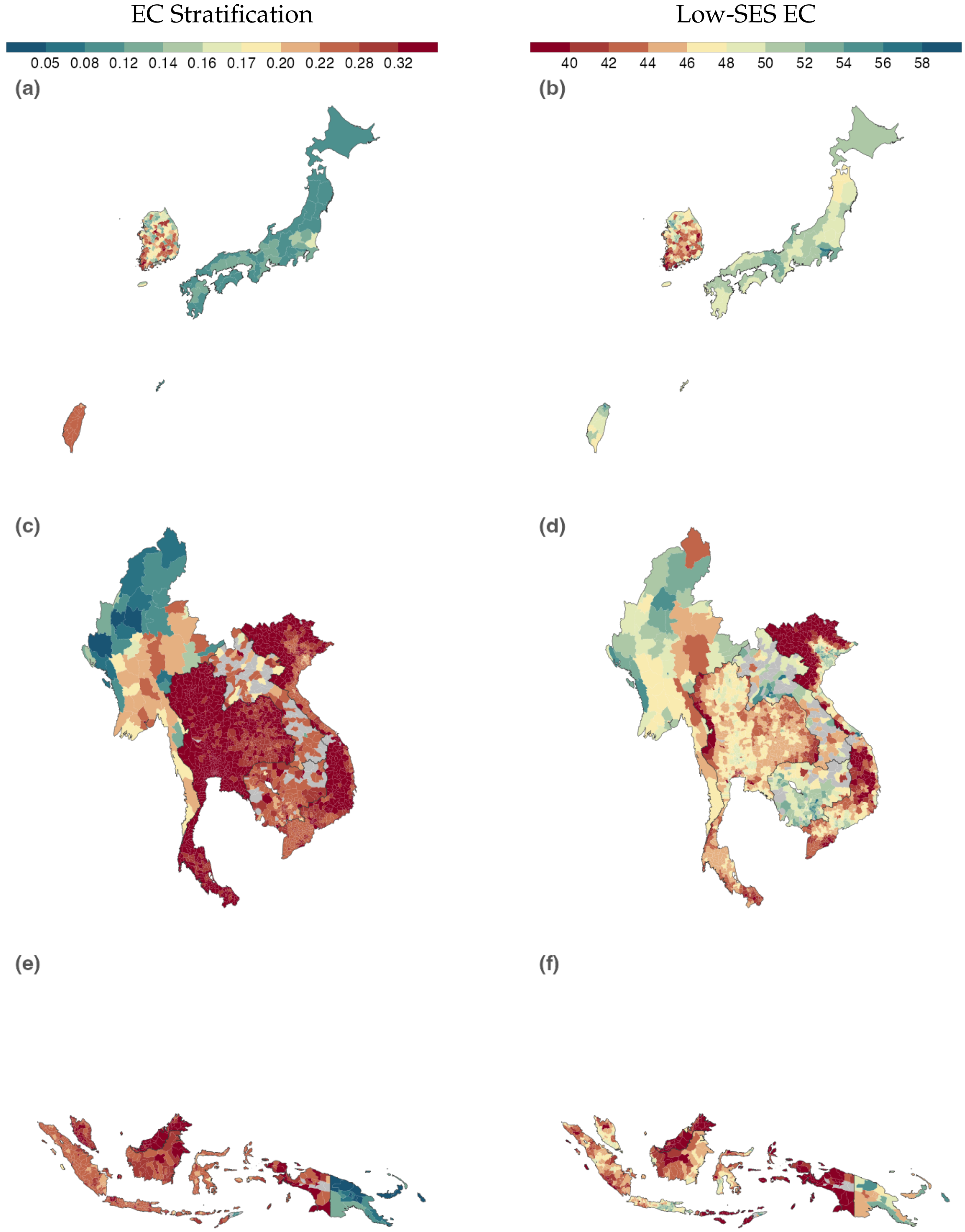
Author Contributions

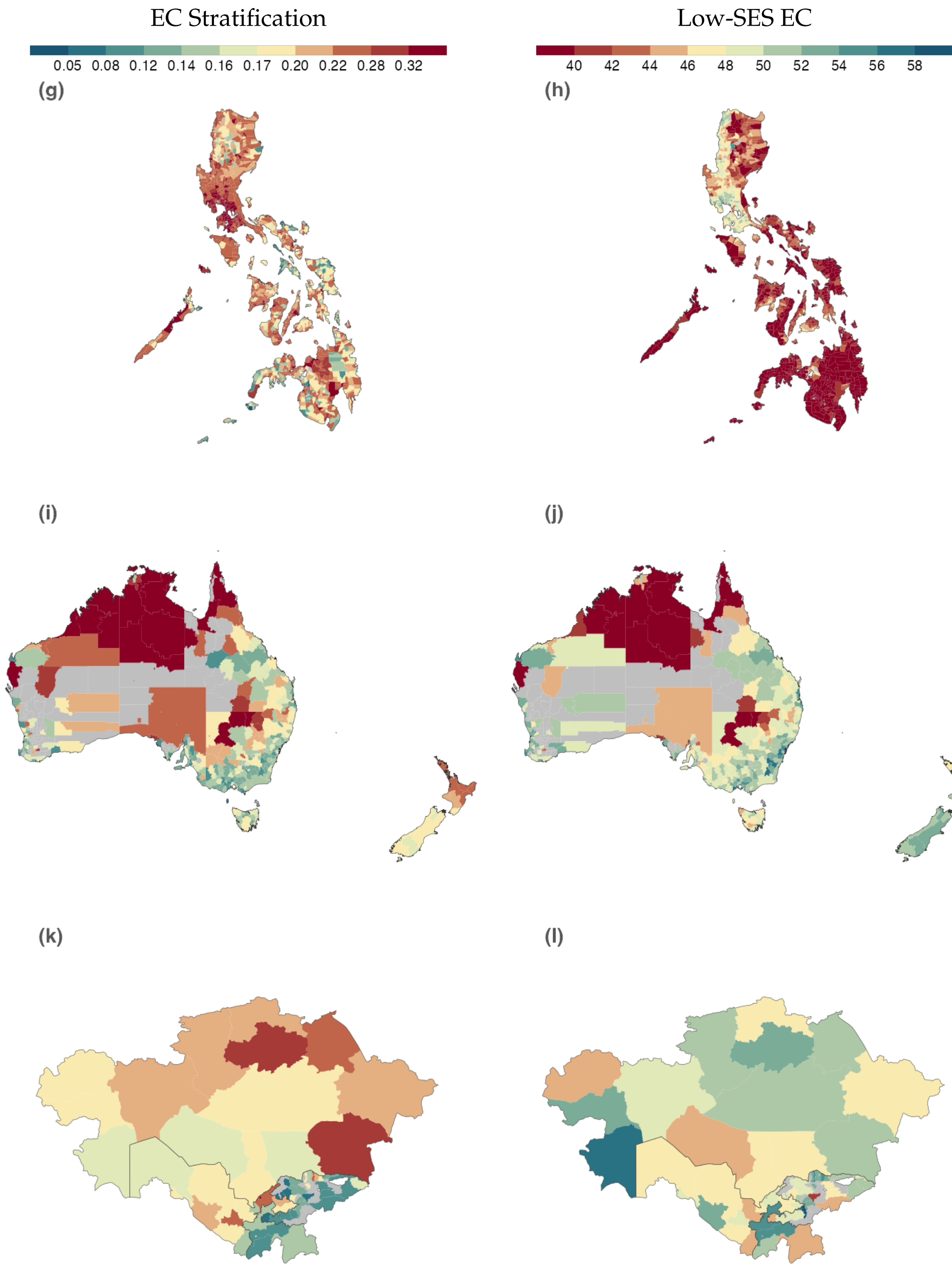
D.J., A.K., T.K., and J.S. were joint principal investigators on this project and designed the study, supervised all analyses, analyzed data, and wrote the paper. M.K. analyzed data, prepared figures, drafted sections of the paper, and provided conceptual contributions. M.B. led the collaboration between the external researchers and the Meta research team.

Competing Interests

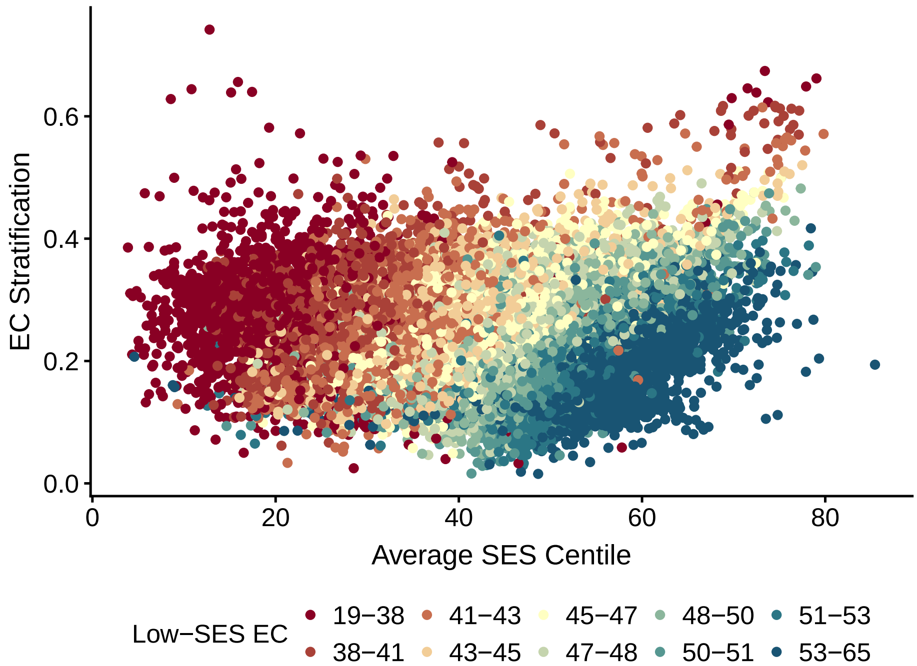
In 2018, T.K. and J.S. received an unrestricted gift from Facebook to NYU Stern. Opportunity Insights receives core funding from the Chan Zuckerberg Foundation (CZI). CZI is a separate entity from Meta, and CZI funding to Opportunity Insights was not used for this research. M.B. and D.J. are employees of Meta Platforms. M.K., T.K., and J.S. are contract affiliates through Meta's contract with Harvard University. In the past, A.K., T.K., and J.S. were contract affiliates through Meta's contract with PRO Unlimited. This work was produced under an agreement between Meta and Harvard University specifying that Harvard shall own all intellectual property rights, titles and interests (subject to the restrictions of any journal or publisher of the resulting publications).

Extended Data Figures

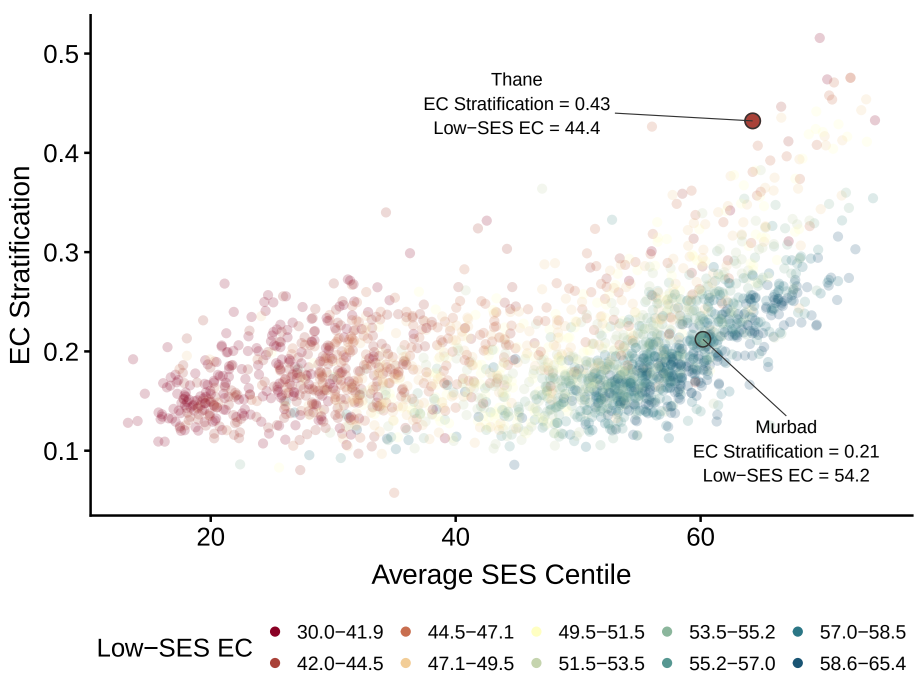




Extended Data Fig. 1: Economic Connectedness Around The World
EC stratification and low-SES EC across GADM regions, with common scale. EC stratification is defined as the regression slope of average friend (national) SES percentile versus individuals' own (national) SES percentile. Low-SES EC is defined as the expected average friend (national) SES percentile for an individual at the 25th (national) SES percentile. Low-population regions in gray. **a, b,** East Asia. **c, d,** Southeast Asia. **e, f,** Maritime Southeast Asia. **g, h,** Philippines. **i, j,** Australia & New Zealand. **k, l,** Central Asia. Maps with region-specific scales are in the Supplementary Information.

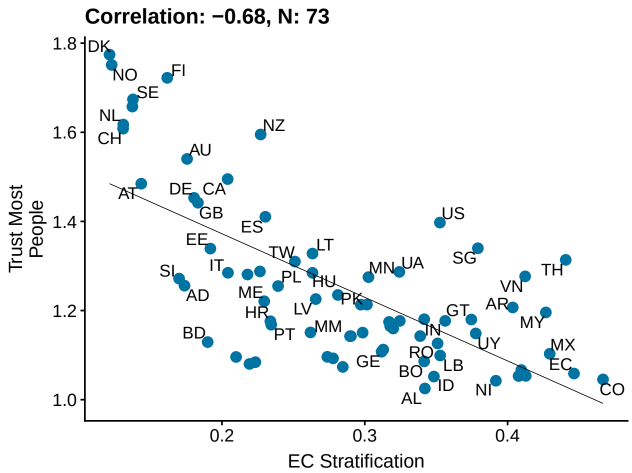


(a) Subnational Regions Around the World

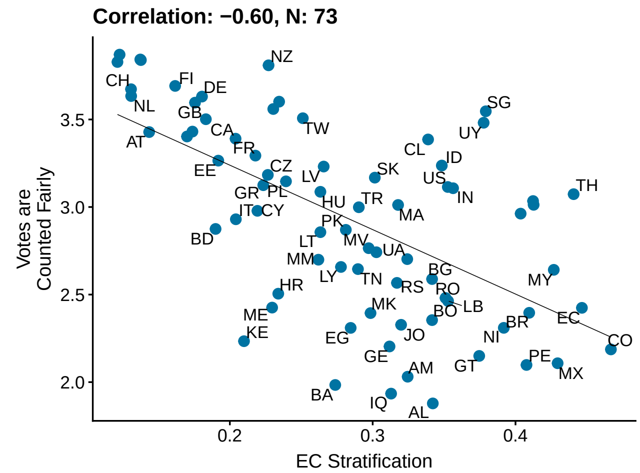


(b) Subnational Regions in India

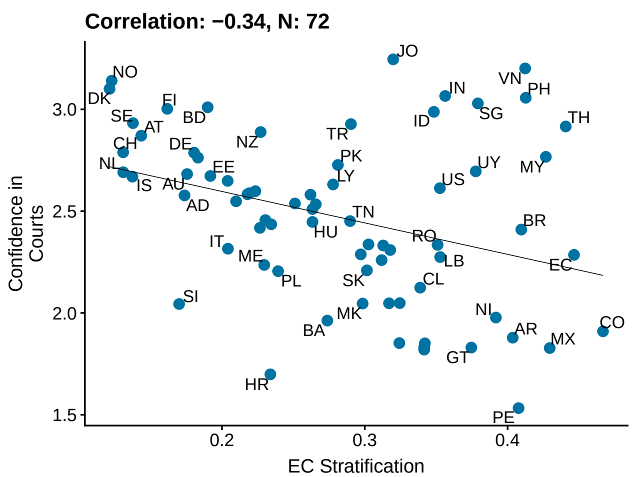
Extended Data Fig. 2: EC Stratification, Average SES, and Low-SES EC
a, Average SES percentile plotted against EC stratification for global GADM regions worldwide. Points represent individual regions, colored by decile of low-SES EC; the legend indicates the range of low-SES EC within each decile. **b,** Average SES percentile plotted against EC stratification for GADM regions in India. Points represent individual regions, colored by decile of low-SES EC.



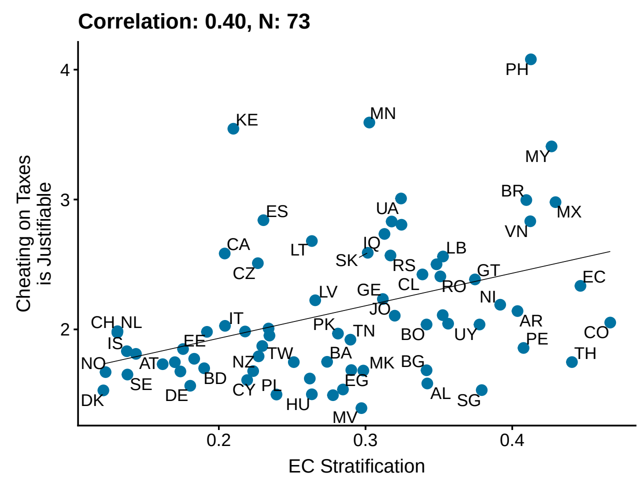
(a) Trust Most People



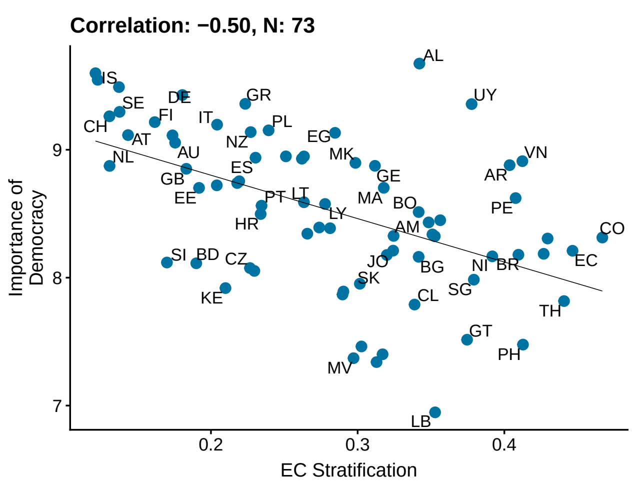
(b) Votes are Counted Fairly



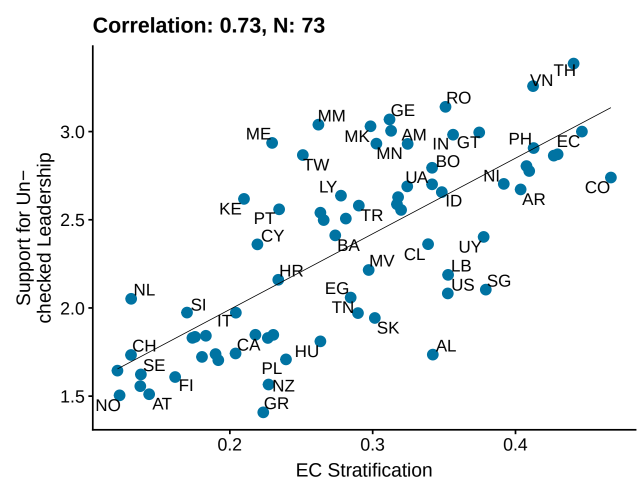
(c) Confidence in Courts



(d) Cheating on Taxes is Justifiable



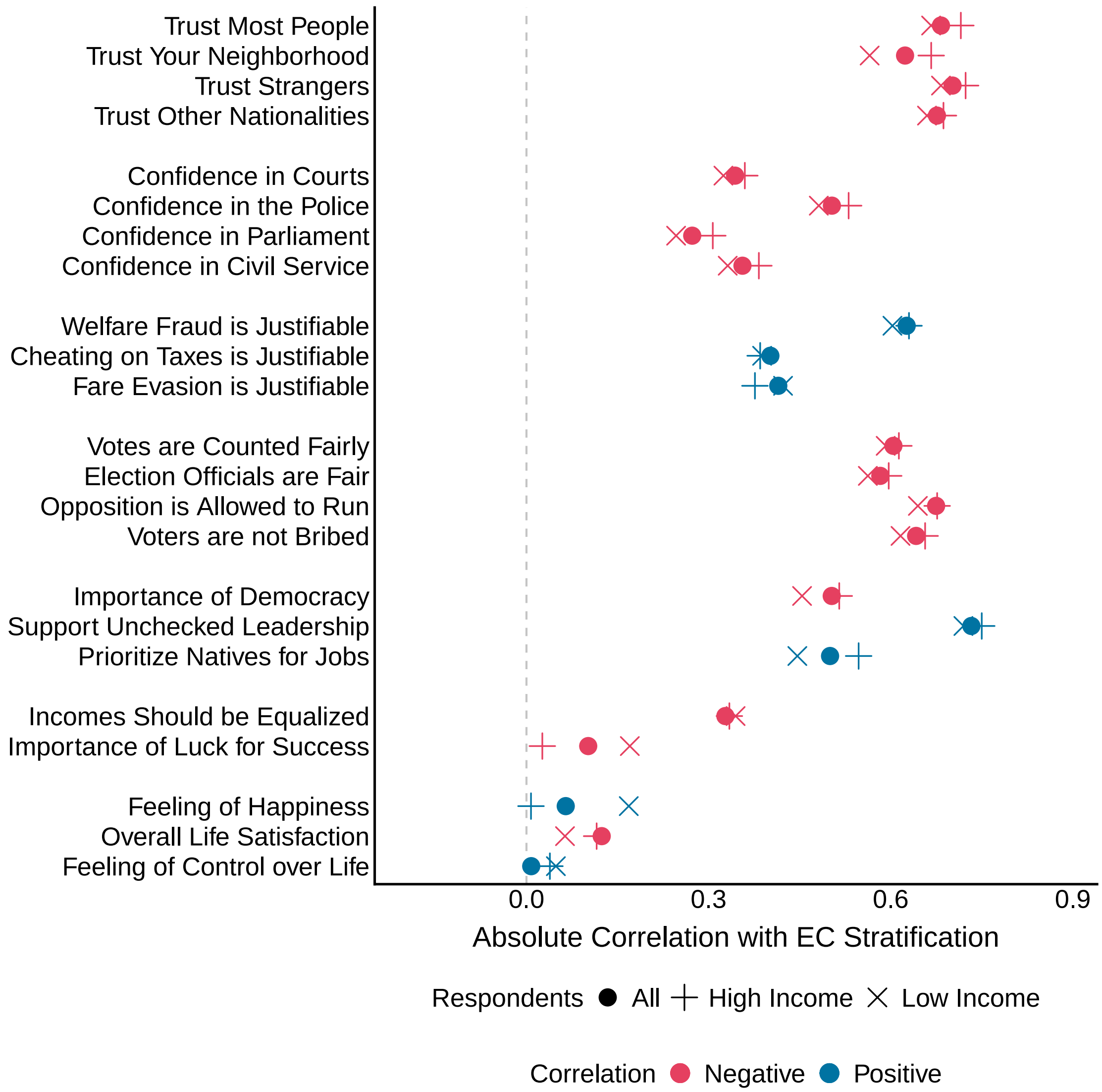
(e) Importance of Democracy



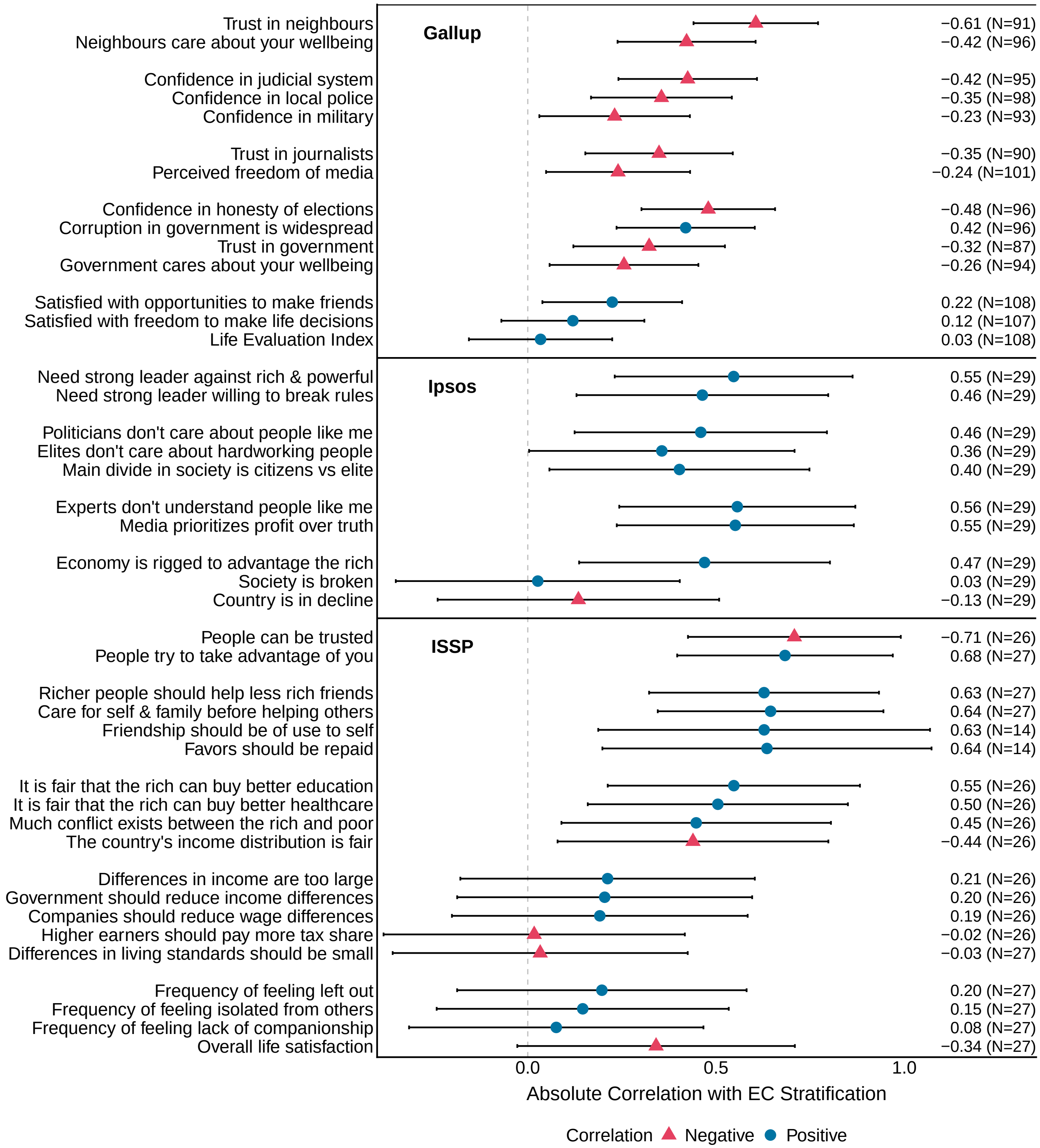
(f) Support for Unchecked Leadership

Extended Data Fig. 3: EC Stratification and Socio-Political Outcomes

Scatter plots display relationships between EC stratification and country-level measures of various socio-political outcomes. Data on outcomes are from the Joint European Values Study/World Values Survey. Scatter plots for additional socio-political outcomes are in Supplementary Figs. SI-17–SI-20.

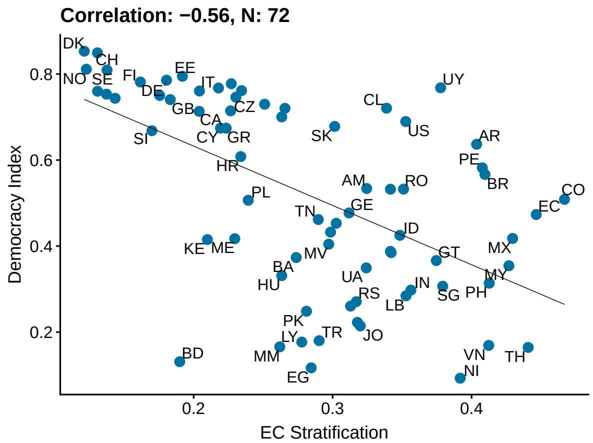


Extended Data Fig. 4: EC Stratification and Socio-Political Outcomes by Self-Reported Income
This figure plots the absolute value of the correlation coefficient between EC stratification and country-level outcomes from the Joint European Values Study/World Values Survey (EVS/WVS), separately for high-income respondents, low-income respondents, and all respondents pooled. Respondents are categorized as high or low income based on whether their household income decile as reported in the Joint EVS/WVS dataset is in the top or bottom half of the full distribution. The WVS responses include a subjective assessment of household income decile while the EVS responses report a national decile of the net household income distribution. Correlations are shown in absolute value to facilitate comparison of magnitudes. The direction of the relationship is indicated by the marker color: blue denotes positive correlations and pink denotes negative correlations. Markers represent different respondent groups: circles for all respondents pooled, plus signs for high-income respondents, and crosses for low-income respondents.

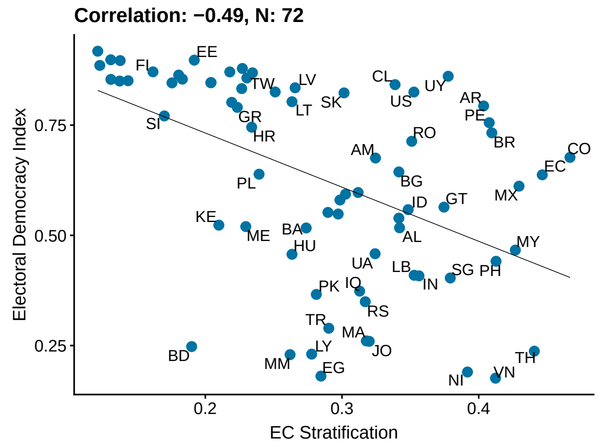


Extended Data Fig. 5: EC Stratification and Socio-Political Outcomes from the Gallup World Poll, the Ipsos Populism Report, and the International Social Survey Programme

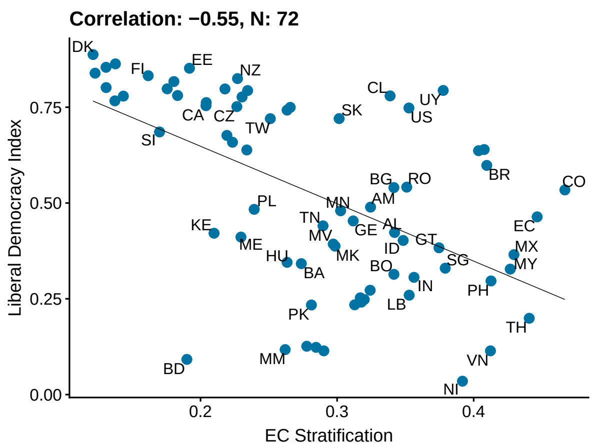
This figure shows the absolute value of correlation coefficients between EC stratification and country-level outcomes from three survey sources: the Gallup World Poll, the Ipsos Populism Report, and the International Social Survey Programme (ISSP). Correlations are shown in absolute value to facilitate comparison of magnitudes. The direction of the relationship is indicated by the marker: blue circles denote positive correlations and pink triangles denote negative correlations. Error bars represent 95% confidence intervals.



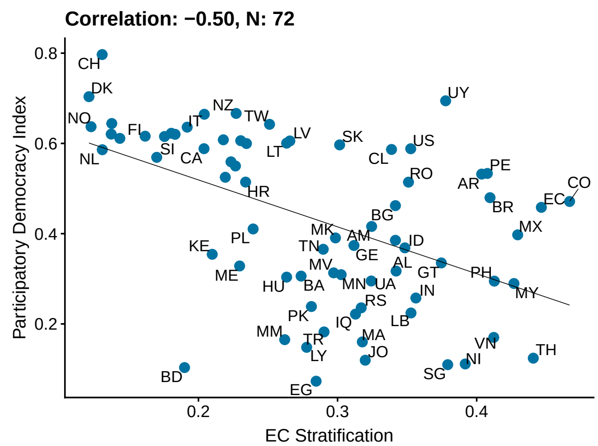
(a) Democracy Index



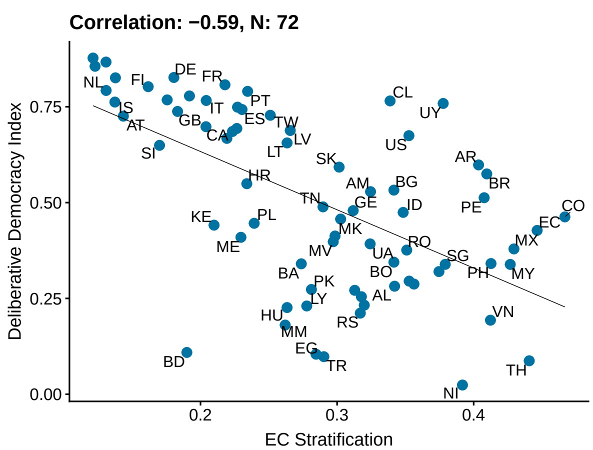
(b) Electoral Democracy Index



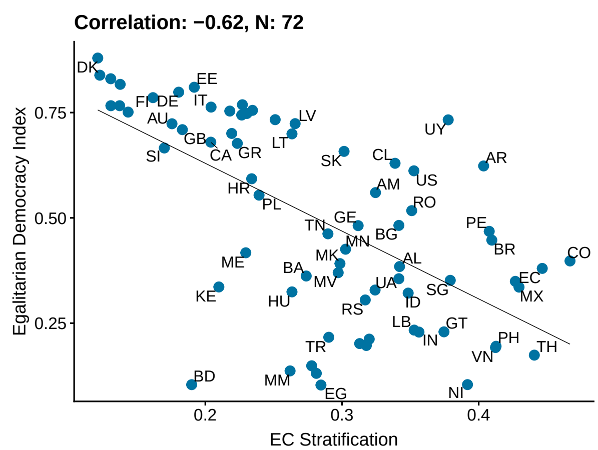
(c) Liberal Democracy Index



(d) Participatory Democracy Index

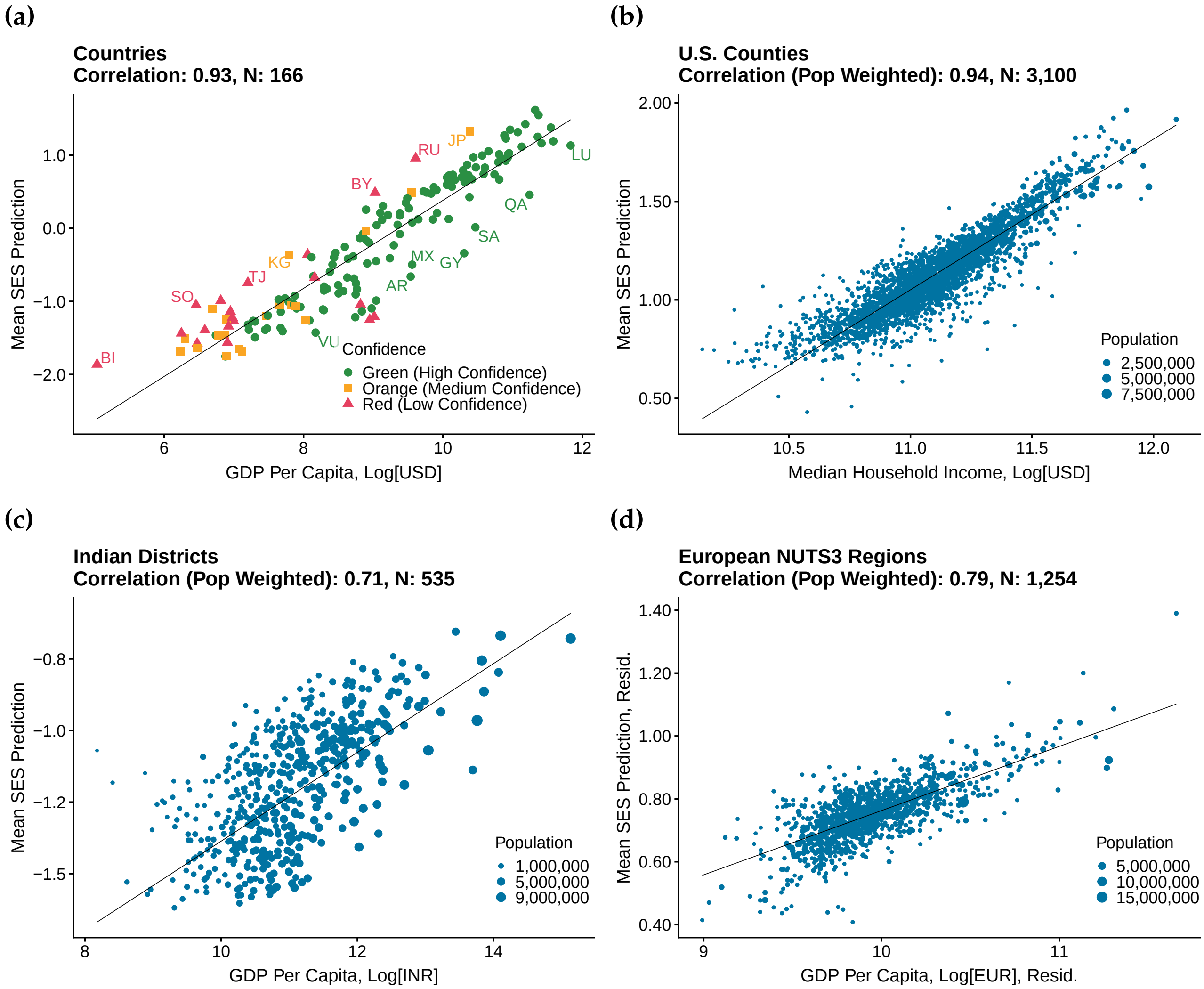


(e) Deliberative Democracy Index



(f) Egalitarian Democracy Index

Extended Data Fig. 6: Varieties of Democracy Indices vs. EC Stratification Across Countries
These figures present scatter plots illustrating the relationship between EC stratification and democracy indices, as measured by the Varieties of Democracy (V-Dem) dataset. Panel A uses a composite democracy index, calculated as the arithmetic mean of V-Dem's five core democracy indices. Panels B through F use each of the five individual democracy indices separately. Country-level indices are averaged over the years 2018-2024. The sample includes only countries with "green" data quality and those used in the analysis of socio-political outcomes in Table 1.



Extended Data Fig. 7: SES Model Correlations with Regional Average Incomes

a, Mean SES prediction of individuals living in a country versus Log[GDP per capita] in 2023 (in current U.S. dollars). Country-level GDP data are from the World Bank. **b**, Mean SES prediction of individuals living in a U.S. county versus median household income in 2023 (current U.S. dollars). County-level income estimates are from the 2023 5-Year American Community Survey (ACS). Top- and bottom-coded household income estimates from the ACS (affecting very small counties) are excluded. **c**, Mean SES prediction of individuals living in an Indian district versus Log[GDP per capita] in 2013, expressed in constant 2004 rupees. Gross regional product for Indian districts is from the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT). **d**, Mean SES prediction of individuals living in a European NUTS3 region versus Log[GDP per capita] in 2019, expressed in current euros, controlling for country fixed effects. GDP per capita estimates for NUTS3 regions are from Eurostat. Figure excludes French overseas territories. Reported correlations are unweighted in **a**, and weighted by estimated population of region for **b**, **c**, and **d**.

Extended Data Tables

Extended Data Table 1: Sample Summary Statistics

Variable	Mean	SD	P1	P10	P25	P50	P75	P90	P99
Total Friends	654	821	29	63	138	349	824	1,691	3,866
Same Country Friends	586	747	28	54	118	309	739	1,523	3,742
Percentage Female	43.1								
GDP PC (USD)	15,940	23,939	623	2,067	2,481	4,876	13,790	54,343	82,769

This table reports summary statistics for the Facebook users in the sample. Reported measures include total number of friends, number of same-country friends, the proportion of female users, and the GDP per capita in the country of the user.

Extended Data Table 2: Economic Connectedness — Summary Statistics by Geography

Summary Statistics

(a) EC Stratification

Level	Mean	P5	P10	P25	P50	P75	P90	P95	N
Country-Level (Equal Weights)	0.28	0.13	0.16	0.21	0.27	0.35	0.41	0.44	133
Country-Level (Pop. Weighted)	0.33	0.18	0.20	0.28	0.35	0.36	0.41	0.43	133
GADM1 (Pop. Weighted)	0.28	0.16	0.17	0.24	0.28	0.34	0.36	0.39	2,416
GADM2 (Pop. Weighted)	0.25	0.13	0.16	0.23	0.23	0.31	0.32	0.35	32,016
GADM3 (Pop. Weighted)	0.24	0.13	0.17	0.22	0.22	0.30	0.33	0.34	78,050
GADM-Best (Pop. Weighted)	0.24	0.14	0.16	0.22	0.22	0.31	0.33	0.35	29,259

(b) Low-SES EC

Level	Mean	P5	P10	P25	P50	P75	P90	P95	N
Country-Level (Equal Weights)	48.52	43.93	44.71	46.73	48.83	50.71	51.80	52.26	133
Country-Level (Pop. Weighted)	47.23	43.46	44.73	45.51	47.09	48.16	50.37	51.04	133
GADM1 (Pop. Weighted)	47.84	43.92	45.34	46.50	48.40	48.40	50.30	51.27	2,416
GADM2 (Pop. Weighted)	48.06	43.77	45.28	46.75	48.53	48.79	50.63	51.54	32,016
GADM3 (Pop. Weighted)	48.16	44.89	45.61	46.75	48.53	48.91	50.22	51.13	78,050
GADM-Best (Pop. Weighted)	48.09	43.77	45.28	46.75	48.64	48.91	50.32	51.50	29,259

Correlation Matrices

(c) EC Stratification

	Country-Level	GADM1 Mean	GADM2 Mean	GADM3 Mean	GADM-Best Mean
Country-Level	1.00				
GADM1 Mean	0.96	1.00			
GADM2 Mean	0.94	0.99	1.00		
GADM3 Mean	0.93	0.98	0.99	1.00	
GADM-Best Mean	0.94	0.98	0.99	0.99	1.00

(d) Low-SES EC

	Country-Level	GADM1 Mean	GADM2 Mean	GADM3 Mean	GADM-Best Mean
Country-Level	1.00				
GADM1 Mean	0.97	1.00			
GADM2 Mean	0.96	0.99	1.00		
GADM3 Mean	0.95	0.97	0.99	1.00	
GADM-Best Mean	0.96	1.00	0.99	0.98	1.00

This table reports summary statistics and correlation matrices for EC measures across countries and regions with green data-quality flags, at multiple levels of geographic aggregation. **a, b,** Summary statistics for EC stratification and Low-SES EC, respectively. For each variable, we report the mean, percentiles (5th, 10th, 25th, 50th, 75th, 90th, and 95th), and sample size (N) across multiple geographic aggregation levels. These levels include: (i) country-level statistics with equal weighting across countries, (ii) country-level statistics weighted by country populations, and (iii) regional statistics at GADM1, GADM2, GADM3, and GADM-Best levels, where regions are weighted by their populations. **c, d,** Correlation matrices for EC stratification and Low-SES EC, respectively. Each matrix reports unweighted correlation coefficients between country-level measures constructed either directly, or by calculating population-weighted averages of the same measure across regions in a country. Supplementary Table SI-9 reports summary statistics and correlation for all available countries.

Extended Data Table 3: Split Sample Correlations

	EC Stratification		Low-SES EC	
	Unweighted	Weighted	Unweighted	Weighted
Country	1.000	1.000	0.999	1.000
GADM1 Regions	0.996	1.000	0.998	1.000
GADM1 Regions (Resid.)	0.970	0.986	0.984	0.993

This table reports split-sample correlations for EC measures at three different granularities. We randomly divide the analytic sample into two halves forming two distinct friendship graphs. Low-SES EC and EC stratification are calculated over the two friendship graphs for countries and GADM1 regions. GADM1 Regions (Resid.) refers to the split-sample correlation after residualizing EC measures on country fixed-effects. Each cell reports the unweighted pairwise correlation between the two split samples as well as the correlation weighted by population.

Extended Data Table 4: EC Construction Robustness - Correlation with Baseline Model

Panel A: EC Stratification

	Country		GADM1 Regions		GADM1 Regions (Resid.)	
	Unweight.	Weighted	Unweight.	Weighted	Unweight.	Weighted
Other SES Measures						
Individual Features	0.930	0.872	0.941	0.925	0.918	0.929
Individual & Country Features	0.907	0.781	0.907	0.868	0.918	0.907
Phone Price	0.861	0.779	0.831	0.769	0.766	0.768
Other Sample Restrictions						
Expanded Sample	0.980	0.994	0.981	0.992	0.977	0.984
Top Friendships						
Top-10 Friends	0.989	0.990	0.970	0.979	0.952	0.956
Top-100 Friends	0.995	0.993	0.985	0.991	0.971	0.971
Other EC Constructions						
National SES Quantile Regression	1.000	0.999	0.953	0.961	0.834	0.865
Direct Quantile Method	0.998	0.998	0.970	0.954	0.755	0.707

Panel B: Low-SES EC

	Country		GADM1 Regions		GADM1 Regions (Resid.)	
	Unweight.	Weighted	Unweight.	Weighted	Unweight.	Weighted
Other SES Measures						
Individual Features	0.887	0.810	0.915	0.915	0.914	0.915
Individual & Country Features	0.913	0.814	0.925	0.904	0.913	0.925
Phone Price	0.840	0.643	0.789	0.813	0.816	0.839
Other Sample Restrictions						
Expanded Sample	0.973	0.991	0.992	0.995	0.993	0.993
Top Friendships						
Top-10 Friends	0.939	0.954	0.975	0.977	0.981	0.984
Top-100 Friends	0.988	0.993	0.986	0.995	0.986	0.989
Other EC Constructions						
National SES Quantile Regression	1.000	1.000	0.988	0.982	0.983	0.987
Direct Quantile Method	0.999	0.999	0.990	0.982	0.961	0.966

This table reports unweighted and population-weighted correlations for EC measures built using our primary methodology and alternative approaches. Panel A reports correlations for EC stratification, Panel B for Low-SES EC. For each measure, we report correlations across (i) countries, (ii) GADM1 regions, and (iii) GADM1 regions after residualizing on country fixed effects. Four variations of construction methodology are shown. The first set of variations uses three alternative SES measures based on: (i) a machine learning model trained without geographic features, labeled "Individual Features"; (ii) a machine learning model trained without subnational geographic features, labeled "Individual & Country Features", and (iii) an individual's phone price as our measure of SES, labelled "Phone Price". The second variation drops the restriction which excludes from our sample individuals with fewer than 25% of their friends within their country of residence. The third set of variations calculates EC with measures of AFP among the top-10 (or top-100) friendships for each individual. Friendship strength is ranked using a proprietary algorithm developed by Facebook. The fourth set of variations uses alternative methods to estimate EC, using (i) an approach that equal-weights SES deciles (or percentiles) in the regression rather than weighting by population, and (ii) by directly calculating Low-SES EC as the average of the AFP in the bottom five deciles, and EC stratification as the difference between the average AFPs between the top and bottom five deciles of the distribution.