

Social Capital in the United Kingdom: Evidence from Six Billion Friendships

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Abstract

We construct and publicly release measures of social capital for the United Kingdom using Facebook data covering 20.5 million adults. Low-socioeconomic-status (SES) individuals have far fewer high-SES friends than high-SES individuals do. Areas with more cross-SES friendships and more long ties—friendships between people with no mutual connections—display higher intergenerational mobility, even controlling for other area-level characteristics. Most of the difference in connectedness to high-SES individuals between low- and high-SES individuals is due to differences in friending bias—the tendency of people to befriend others similar to themselves even conditional on the possible friends they are exposed to. Individuals with a greater share of high-SES friends, more close friends, and more mutually supported friendships report higher life satisfaction, greater interpersonal trust, stronger perceived social support, and lower feelings of isolation and disconnection, even after controlling for household income and demographics.

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Social capital describes the strength and structure of social networks that enable communities to coordinate and cooperate for mutual benefit [1]. Social capital is important because we live our lives embedded in social networks and our behaviours and outcomes are shaped by our peers and the resources and information they provide. Labour markets, for example, rely heavily on job referrals [2, 3], and the jobs we search for are shaped by information from our contacts [4]. Even before we apply for a job, our academic results are shaped by those around us [5, 6]. The people around us are also a source of credit and insurance [7, 8], even where financial markets are well-established [9], and even our choice of where to live is shaped by people we know [10–13].

We study social capital in the UK using data on over six billion friendships covering 20.5 million UK adults from Facebook. We construct a number of measures of social capital and relate them to economic mobility (the average adult income of children from low-income families, estimated from income tax filings) and other area-level outcomes. We then relate individual-level measures of social capital to survey responses covering wellbeing, trust, and social connectedness.

Recent work emphasises that social capital is a multifaceted concept, comprised of many distinct components [14]. We focus on the structure of the network of connections between individuals. Two somewhat distinct literatures predict that the structure of a person’s social network shapes their economic opportunities. The first emphasises the individual characteristics of *who* people are connected to: friendships that cross class lines are thought to transmit information, aspirations, norms and referrals that are scarce within disadvantaged communities [2, 4, 15]. The second emphasises the *shape* of the network itself: ties that reach between distinct tightly-knit social groups can transmit information and resources between groups [16–18], while dense bundles of ties can facilitate trust and cooperation within the group [19–23].

Our work builds on recent work by Chetty *et al.* [24], which used data on Facebook friendships within the United States to show that economic connectedness (EC) is strongly related to economic mobility. One contribution of this study is to show that this relationship holds outside the U.S. A low-income child growing up in a local authority at the 90th percentile of the EC distribution (where 57% of their friends would have high SES) can expect to earn approximately 28% (£2,924 per year) more as an adult than a similar child at the 10th percentile (where 44% of their friends would have high SES). This supports the importance of *who* you are connected to, as emphasized by the first literature above. Beyond replicating Chetty *et al.* [24] in a new dataset, the persistence of the EC–mobility relationship suggests that cross-class friendships capture a dimension of social networks relevant to economic opportunity across institutional settings—including in a country with lower residential income segregation [25] and more centralized systems of

health care, schooling, and university admissions than the United States.

A second, distinct aspect of social capital we focus on is the prevalence of “long ties” in an area—friendships between individuals who share no mutual friends [26]. Long ties are disproportionately likely to form outside the most frequent settings in which individuals make friends (such as schools, universities, neighbourhoods and workplaces). While in the U.S. the long-tie ratio is only moderately related to mobility, in the UK this relationship is much stronger. A low-income child at the 90th percentile of the LTR distribution (where 5.5% of friendships are long ties) can expect to earn £2,690 more per year than a similar child at the 10th percentile (where 3.3% are long ties). Indeed, the UK correlation between the LTR and mobility (0.70) is even stronger than that between EC and mobility (0.57). This supports the importance of the broader *shape* of the network, as emphasized by the second literature above. Several patterns in our data suggest this relationship may reflect the role of long ties in facilitating the flow of information, and other studies note that while long ties can promote simple information diffusion they can impede the diffusion of behaviours and norms that require social reinforcement [27–29].

The bivariate correlations between EC and the LTR and economic mobility are extremely large (0.57 and 0.70 respectively). For context, these are roughly as large as the correlations of mobility with secondary-school (GCSE) attainment (0.60) and with average area disposable income (0.56). They are substantially larger than the absolute correlations of mobility with employment rates (0.19), unemployment rates (0.11), and the share of single-parent households (0.19), larger than the share of black individuals (0.48), and larger than measures of early-stage educational attainment (between 0.27 and 0.53). EC and the LTR also represent distinct forms of social capital: both remain strongly predictive of mobility in multivariable regressions incorporating all our social capital measures, and both remain strong predictors after controlling for other area-level characteristics such as income, educational attainment, and demographics.

Following Chetty *et al.* [30], we then decompose the EC gap between low- and high-SES individuals into three components: differences in the settings where individuals make friends (friending shares), differences in exposure to high-SES individuals within settings, and differences in friending bias (connectedness within settings conditional on exposure). Differences in friending shares account for around 9% of the gap, and differences in exposure for roughly 32%; the majority (59%) is attributable to friending bias. The prominence of friending bias highlights an advantage of our data, which directly observes friendships and interactions, over the mobile-phone co-location data also popular in this literature [31–34]. Relatedly, we find that long ties are especially likely to form *outside* the settings in which individuals usually make friends.

Finally, we complement our area-level analysis with an individual-level survey on life sat-

isfaction, interpersonal trust, perceived social support, and feelings of social disconnection, administered to 5,472 UK Facebook users between June and July 2024. We link 3,770 respondents to individual-level social capital measures from Facebook’s social graph, including the share of high-SES friends, the number of friends, clustering coefficients, and long-tie ratios. Ours is one of the first studies to combine individual-level social capital metrics derived from large-scale network data with individual measures of subjective wellbeing.

We find that individuals with a greater share of high-SES friends, more friends and close friends, and a lower fraction of long ties report higher life satisfaction, greater interpersonal trust, stronger social support, and lower feelings of isolation. These associations are robust to controlling for age, gender, and self-reported household income. The bivariate correlations between our social capital measures and wellbeing outcomes are comparable in magnitude to the bivariate correlations between self-reported income and the same outcomes. These results support both of the theoretical literatures described earlier and provide particular evidence for models in which denser connections within groups can support greater levels of trust and cooperation [19–23]. In particular, while long ties are associated with lower levels of trust, less clustered networks in themselves are *not* predictive of lower levels of trust, which is a prediction of the particular model of favour exchange and cooperation in networks of Jackson *et al.* [21].

We make all of the area-level social capital and mobility metrics we construct publicly available on the [Humanitarian Data Exchange](#) to facilitate further research. We formally define all of our social capital metrics in Appendix A.2, and our economic mobility metrics in Appendix A.6. Our mobility estimates are the first UK-wide estimates of intergenerational mobility for granular areas, including the first estimates of intergenerational economic mobility for areas in Scotland and Northern Ireland.

Results

Our analytic sample consists of 20.5 million UK Facebook users aged 25–64 with at least 100 friends. We assign each user a predicted SES rank within their birth cohort using a machine-learning model trained on and validated against an on-platform income survey.

Individual-Level Social Capital in the UK

Figure 1a shows that individuals with higher SES also have higher-SES friends on average: a 1 percentage point increase in an individual’s national SES rank is associated with a 0.17 percentage

point increase in the average SES rank of their friends. The association is stronger for close friends on the platform (a slope of 0.21), suggesting that income homophily is stronger for close friends.

Figure 1b further illustrates UK homophily. Among individuals in the bottom SES decile, roughly 20% of their friends are also in the bottom decile, while only 5% are in the top decile.

Individuals with above-median SES for their birth cohort (henceforth “high-SES”) have both more friends and a higher proportion of high-SES friends than below-median (“low-SES”) individuals, and so have dramatically more high-SES friends in total (Figure 1c).

We also examine how network cohesiveness varies by SES using two measures: the *clustering coefficient*, which is the fraction of pairs of an individual’s friends who are also friends with each other [35], and the *long-tie ratio*, which is the proportion of friends with whom the individual shares no mutual connections [26]. Note that the long-tie ratio is equivalent to 1 subtract the *support ratio*, as defined by Jackson *et al.* [21]. Higher-SES individuals have less clustered networks (Figure S1), whilst the long-tie ratio shows no clear relationship with SES (Figure 1d). We note in Figures S2a and S2b that there is substantial variation across individuals in these measures of network cohesiveness. Clustering is especially high for individuals located on islands away from the UK mainland.

The Geography of Social Capital in the UK

We aggregate a rich set of social capital measures to three different spatial levels across the UK (local authorities, postcode districts, and MSOAs) and make these measures publicly available.

EC is highest in Southern England and lower in South Wales, the North East, Scotland’s Central Belt, and Northern Ireland (Figure 2a). By ONS Area Classifications [36, 37], EC is higher in Rural-Urban Fringe/Affluent Rural areas and lower in Industrial, Mining Legacy, and Multi-ethnic urban areas (Figure S3). EC correlates negatively with Brexit vote share (-0.2) and positively with EU referendum turnout (0.4), conditional on local SES composition [38]. We also construct age and language connectedness: the share of 45–64 year-old friends among 25–44 year-olds, and the share of friends who use Facebook in English among those who use Facebook in other languages, respectively. Figure 2 shows maps of these metrics.

Our two measures of network cohesiveness display distinct spatial patterns. Clustering is higher in rural and peripheral areas, especially in Scotland and Wales, reflecting tighter, more overlapping local networks. The long-tie ratio is higher in large urban labour markets and university towns.

We measure civic engagement through participation in volunteering and activism groups on Facebook. Volunteering and activism rates display clear spatial patterns: participation is

higher in remote and rural areas (e.g., the Scottish Highlands and parts of Wales), with pockets of higher engagement around major urban centres (Figure 2a). By ONS Area Classification, Figure S3 shows that “Prosperous Semi-rural” areas exhibit the highest volunteering rates (about 10%), whilst “Ethnically Diverse Metropolitan Living” and “Northern Ireland Countryside” show the lowest (around 3%).

Social Capital and Economic Mobility

Area-Level Correlations

Recent U.S. evidence shows that greater EC is associated with substantially higher economic mobility for disadvantaged children [24]. We test whether similar patterns exist in England using intergenerational economic mobility estimates we construct from administrative tax data based on methods developed by Carneiro *et al.* [39]. Our primary outcome is the mean national earnings rank at age 28 for pupils eligible for Free School Meals (FSM) at age 16 born between 1986–1992 across English local authority districts.

Figure 3 shows the relationship between social capital and economic mobility at the local-authority level. Figure 3a presents bivariate correlations between economic mobility and each social-capital measure. Economic connectedness (EC) and the long-tie ratio (LTR) exhibit the strongest positive correlations with mobility (0.57 and 0.70 respectively), consistent with theories linking cross-class exposure and structurally diverse networks to better economic outcomes [40]. Figure 3b shows multivariable regressions with all standardised social-capital measures included simultaneously. EC and the LTR remain the strongest predictors. These patterns persist when we replicate this analysis at the more granular postcode district level (Figure S4).

We compare the predictive power of our social capital variables for economic mobility with other factors explored in previous work, using a large set of area-level characteristics obtained from government statistics [41, 42]. Figure S5 shows that the LTR and EC correlate more strongly with economic mobility than most other economic, educational, health and demographic indicators we consider. We find that both the LTR and EC are amongst the earliest selected predictors in a Lasso, with the LTR selected first (Figure 3c). In multivariable regressions including other early Lasso selections, both measures remain strong predictors of economic mobility (Figure 3d).

To illustrate the economic significance of these relationships, consider two FSM-eligible children growing up in local authorities at the 10th versus 90th percentiles of EC (44% versus 57% high-SES friends—a 13-percentage-point difference). This gap is associated with a 6.14-centile difference in adult earnings rank, corresponding to an approximately £2,924 (28% increase) in an-

nual earnings for the average FSM child. A parallel calculation for the long-tie ratio, which ranges from 3.3% to 5.5% across the 10th–90th percentiles of the local authority distribution, links to an earnings difference of approximately £2,690. The effects of economic connectedness and long ties are of similar magnitude, suggesting that both the presence of high-SES friends and the structure of social ties are independently important for the economic mobility of disadvantaged children.

Since ties sharing fewer mutual friends tend to be weaker in intensity and closeness [43, 44], our results lend further support to the theory that weak ties—in the language of Granovetter [16], who relates tie strength to the overlap between two individuals’ friendship networks—play an important role in shaping economic outcomes. We interpret our evidence as most directly pointing to mechanisms based on access to non-redundant information about schools, jobs, and opportunities. In such cases, a single tie to a distant part of the network may transmit information that would otherwise be absent from a local peer group. This interpretation is also consistent with the distinction emphasized by the complex-contagion literature. While weak or long ties may be valuable for simple information transmission, they may be less effective—and may even inhibit—diffusion of behaviours or outcomes that are governed by norms, coordination, or wider social adoption within one’s peer group. In such settings, clustered ties and exposure to multiple distinct components of the network may be more important [27–29].

We also find that the relationship between long ties and economic mobility depends on an area’s affluence. Figure 4a shows that while affluent areas exhibit high mobility regardless of long-tie ratios, poor areas with higher long-tie ratios achieve substantially better mobility than equally deprived areas with fewer long ties.

In Figure S4, we show that our results are similar when running correlations at the more granular postcode district level.

Contrasts with Results from the U.S.: The Importance of Long Ties

While our findings on EC and mobility broadly mirror those of Chetty *et al.* [24] in the U.S., our finding that the LTR among low-SES individuals strongly predicts economic mobility is markedly stronger than theirs: they found the support ratio (equal to 1 minus the LTR) to only weakly predict mobility. This difference does not stem from our focus on low-SES individuals, since we obtain similar correlations between the LTR and economic mobility when averaging the LTR across all individuals in an area (as Chetty *et al.* do). Similarly, while we calculate the LTR over all long-tie relationships, Chetty *et al.* restrict to within-county friendships when calculating their support ratio. However, as shown in Figure S6, imposing similar within-area restrictions when calculating the LTR does not meaningfully affect the correlation between the LTR and

mobility, and in fact strengthens the relationship when restricting to friendships that lie within local authorities (which are the UK geographical areas most analogous to US counties). Instead, our results point to genuine differences between the UK and the U.S. in terms of how predictive the LTR is of economic mobility.

Social Capital and Other Outcomes

Previous research has established links between social capital and life outcomes including educational attainment, mortality, and crime [45–47]. We examine whether our Facebook-derived measures predict these outcomes.

In bivariate analyses, higher EC correlates with better GCSE results (Figure S7a), fewer preventable deaths (Figure S8a), and lower crime rates (Figure S9a). The LTR shows similar associations with educational attainment but not with mortality or crime. Applying the same Lasso approach with area-level covariates, we find distinct patterns across outcomes. For education, the LTR is amongst the earliest selected variables (Figure S7c) and remains a moderate predictor in multivariable regressions (Figure S7d). For mortality, EC emerges as the strongest initial predictor (Figure S8c) and maintains this relationship when controlling for other variables (Figure S8d). Neither social capital measure shows robust associations with crime once compared to other predictors (Figures S9c and S9d).

Determinants of Economic Connectedness

An individual’s high-SES friend share rises steeply with their own SES (Figures 1b and 1c). To understand why, we conduct a similar exercise to Chetty *et al.* [30] and assign friendships, where possible, to the settings in which they were formed. We make use of nine settings: (1) neighborhoods (MSOAs), (2) secondary schools, (3) sixth form colleges, (4) universities, (5) workplaces, (6) faith-based groups, (7) hobby groups, (8) activism groups, and (9) volunteering groups.

Figures S10 and S11 show friending shares by setting for low- versus high-SES individuals. Low-SES individuals form a larger share of their friendships in neighbourhoods compared to high-SES individuals, whilst high-SES individuals form a greater share of their friendships in universities compared to low-SES individuals.

We then decompose economic connectedness into three components: (i) *friending shares* (where ties form across settings), (ii) *exposure* (the SES composition of those settings), and (iii) *friending bias* (the tendency to befriend within SES lines, conditional on exposure).

Figure 5 reveals three patterns. First, exposure is highest in universities, reflecting their predominantly affluent student populations. Second, low-SES users meet socioeconomically mixed peers in hobby and recreation groups, whilst high-SES users encounter mostly other high-SES individuals there, suggesting sorting into different activities within the setting. Third, low-SES individuals show the highest friending bias in neighbourhoods and the lowest in secondary schools and universities. High-SES users show higher absolute friending bias than low-SES users because, while cross-SES friendships are equal in number in each direction, they make up a smaller share of high-SES users' larger networks.

Figure 5d presents a counterfactual decomposition of the EC gap between low- and high-SES individuals. Giving low-SES individuals the same friending shares across settings as high-SES individuals closes 9% of the gap; additionally equalising within-setting exposure closes a further 32%; the remaining 59% is attributable to differences in friending bias.

We provide maps of average exposure and friending bias for postcode districts in the UK in Figures S12 and S13.

Which Friendships are Long Ties?

Since the long-tie ratio strongly predicts economic mobility, we analyse which types of friendships are most likely to be long ties.

Friendships we cannot assign to any specific setting are far more likely to be long ties than those within identifiable settings. Around 5% of unassigned friendships are long ties, compared to less than 2% for friendships within settings like neighbourhoods or schools (Figure 4b). This suggests long ties predominantly form outside people's typical social contexts. However, long ties remain rare even amongst unassigned friendships, indicating they represent a distinctive subset of relationships rather than measurement error in our setting classification.

Friendships that span multiple settings—*multiplexed* friendships—are especially unlikely to be long ties. This is intuitive since relationships that exist across several contexts yield more opportunities for mutual friends to form. We provide further analysis of multiplexing patterns in Appendix B.3.

Finally, long ties occur at similar rates across income groups. We find that 3.0% of low-SES to low-SES friendships are long ties, 2.6% of high-SES to high-SES friendships, and 2.7% of cross-SES friendships. A long tie is similarly likely to connect two people of the same income level as to bridge across income levels. The marginally lower rate amongst high-SES individuals likely reflects that they have more friends overall (Figure 1c), providing more opportunities for mutual connections to form.

Individual-Level Social Capital and Wellbeing

To go beyond area-level analysis and understand the individual-level relationship between social network structure and outcomes, between June and July of 2024 we administered a survey to Facebook users in the UK. This is one of the first direct linkages of individual social capital measures derived from a population-scale social graph to individual subjective wellbeing. The survey was targeted at a random sample of adults with a predicted home country of the United Kingdom. A total of 5,472 individuals completed the survey (51.3% female). Of these, 3,770 are in our analytic sample—that is, they can be linked to our individual-level social capital measures. (Most individuals who responded to the survey but are not in our analytic sample were not included because they do not satisfy our age criteria of being between 25–64. The vast majority of remaining individuals who are not matched are not in our analytic sample because they do not satisfy our 100 friends cutoff.) A further restriction to respondents who reported their household income in the survey yields a subsample of 2,138 for our controlled specifications. On average, participants took 9 minutes to complete the survey.

Bivariate Associations

Figure 6 presents the bivariate correlations between our individual-level social capital measures and the four composite survey indices, estimated from equation (1).

Measures of connectedness to high-SES individuals—both the number and the share of high-SES friends—are positively associated with life satisfaction, trust, and social support, and negatively associated with feelings of disconnection. The magnitudes of these associations are comparable to the bivariate correlations between self-reported income and the same outcomes (Figure S14), suggesting that the composition of one’s social network is at least as strongly associated with reported wellbeing as one’s own income.

Network structure also matters. The long-tie ratio is associated with worse outcomes across all four domains we examine. The clustering coefficient, by contrast, is not strongly associated with responses in any domain. While both a lack of long ties and a high level of clustering are seen as related concepts capturing inwardness and non-expansiveness of networks, our finding that a lack of long ties are associated with wellbeing and trust while clustering is not is consistent with the particular model of favour exchange and cooperation on networks in Jackson *et al.* [21], which emphasizes the distinction between these two concepts. Having more friends is positively associated with all outcomes.

Associations Controlling for Demographics

Figure 7 presents the partial correlations from equation (2), which add controls for age, gender, and self-reported household income. The results are qualitatively unchanged relative to the bivariate estimates. This stability reflects the fact that respondents' own income accounts for only a modest share of the individual variation in our social capital measures (the correlation between self-reported income and the share of high-SES friends is 0.26 in the survey sample): networks are stratified by class, as documented above, but two people with the same income can nonetheless have very different networks, and this residual variation carries a substantial part of the wellbeing associations.

After controlling for demographics, respondents with more friends, more close friends, a greater proportion of high-SES friends, and higher support ratios report higher life satisfaction, lower feelings of disconnection, greater trust, and stronger social support.

To provide a sense of magnitudes, we compare individuals in the top and bottom deciles of the share of very high-SES friends (those in the top decile of the SES distribution). The most economically connected individuals report happiness scores of 6.89 compared to 5.90 on a 10-point scale (a 16.8% difference) and trust scores of 3.33 compared to 2.34 on a 5-point scale (a 42.3% difference). Controlling for household income narrows these gaps to 4.6% for happiness and 23% for trust, but substantial associations remain.

In absolute terms, however, the effect sizes are small. An additional 100 friends is associated with only a 0.2-point increase in life satisfaction (on a 10-point scale), a 0.1-point increase in trust, a 0.1-point decrease in feelings of disconnection, and a 0.1-point increase in social support (on a 5-point scale). Individual social capital metrics are statistically significant predictors of wellbeing, but they do not explain a large share of the between-individual variance. This finding corroborates similar studies that find positive but modest associations between social connections and subjective wellbeing [48].

Heterogeneity by Respondent SES

We next examine whether the social-capital–wellbeing associations differ by the respondent's own socioeconomic background. We split the sample using predicted SES (Section A.1), ranked within birth cohorts, rather than self-reported income, because splitting on survey income and birth cohort simultaneously would yield subsamples too small for precise estimation.

Figures S15 and S16 present the bivariate correlations for low- and high-SES respondents (predicted SES below and above the national cohort median). The patterns are qualitatively similar

across the two groups: the direction and approximate magnitude of the associations do not differ markedly by socioeconomic background.

Discussion

This paper introduces UK-wide, fine-grained measures of social capital constructed from Facebook friendship networks covering roughly 20.5 million adults. We document that EC and the LTR are two of the strongest predictors of economic mobility in the UK, and characterise the determinants of each. We also link individual-level social capital measures to a survey of subjective wellbeing, trust, social support, and social disconnection, finding that individuals with more high-SES connections, more close friends, and more mutually supported friendships report higher wellbeing across all four domains. These findings are robust to controlling for age, gender, and self-reported income, and similar for low- and high-SES respondents.

One contribution of the paper is to show that the EC–mobility relationship extends beyond the United States. The UK differs from the U.S. along several institutional dimensions that could plausibly shape how friendships form and how much they matter for opportunity—residential income segregation, health care, schooling, and university admissions. The persistence of the relationship suggests that cross-class friendships capture a dimension of social networks relevant to economic opportunity across institutional contexts, rather than being specific to the U.S.

Our area-level results also speak to possible mechanisms. Two patterns are consistent with interpreting the LTR–mobility relationship as reflecting access to non-redundant information. First, the LTR is related to mobility and educational attainment but not preventable mortality or crime—an outcome-specific pattern that is more naturally aligned with information about jobs, education, or opportunities than with mechanisms based primarily on social support or norms. Second, the relationship is strongest in more deprived areas, where information frictions are likely especially binding. Both patterns are consistent with classic arguments on the value of weak or bridging ties in allowing information to percolate through a network [16–18, 49]. This interpretation is also consistent with the distinction emphasized by the complex-contagion literature: long ties may help transmit simple information, but they need not facilitate the spread of norm-based behaviours or actions that require social reinforcement [27–29]. We therefore view the LTR–mobility relationship as more suggestive of information and opportunity transmission than of mechanisms based primarily on the diffusion of norms or behaviours.

The relationships between social capital and outcomes we document in our survey may be driven by several mechanisms. First, social capital may indeed causally improve wellbeing: hav-

ing more high-SES friends may provide access to information, resources, and social norms that raise life satisfaction and trust. Second, the relationship may reflect reverse causality. Happier, more trusting individuals may be more successful at forming and maintaining friendships, particularly across socioeconomic lines. A large psychology literature documents that positive affect facilitates social engagement [50], and longitudinal evidence suggests that while social connections predict subsequent wellbeing, the reverse pathway also operates [51]. Third, the correlation may be driven by omitted variables. Personality traits such as extraversion and agreeableness are associated with both larger social networks and higher life satisfaction [52]. Local area characteristics—the quality of public services, the built environment, labour market conditions—could independently shape both network structure and wellbeing. While controlling for self-reported income addresses one important confound, it does not account for wealth, personality, health, or geography. Distinguishing among these explanations is an important direction for future work on the social-capital–wellbeing link, which remains relatively unexplored compared to the voluminous literature on the similarly strong association between income and wellbeing.

We make all the area-level social capital and mobility metrics we construct publicly available at the [Humanitarian Data Exchange](#). While this paper provides no causal evidence, the statistics we make publicly available can facilitate future causal work. Analyses of the causal impact of social networks have largely leveraged quasi-random variation in the *pool of peers* from which individuals can make friends [5, 6, 53, 54]; our friending-bias estimates will help such designs establish whether shifts in peer composition translate into actual changes in friendship networks. Future work could similarly exploit residential moves, school cohort shocks, or randomised interventions, and link network data to longitudinal wellbeing measures.

Overall, our findings are consistent with classic theories in economics and sociology that emphasize the value of connections spanning distinct social groups [15, 16, 18], particularly for the transmission of information and access to economic opportunity. At the same time, our individual-level survey results are consistent with theories emphasizing the role of mutually supported relationships in sustaining trust, cooperation, and social wellbeing [19–23]. An exciting direction for future work, motivated by our results, is understanding when there are tradeoffs between expansive networks that span social groups and tightly-knit networks that provide support and facilitate trust; whether particular network structures allow these two dimensions of social capital to complement rather than substitute for one another; and which institutions and settings foster networks with one, both, or neither of these features.

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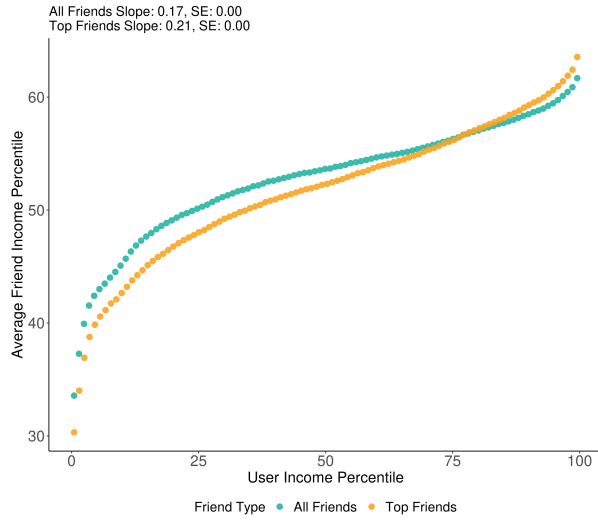
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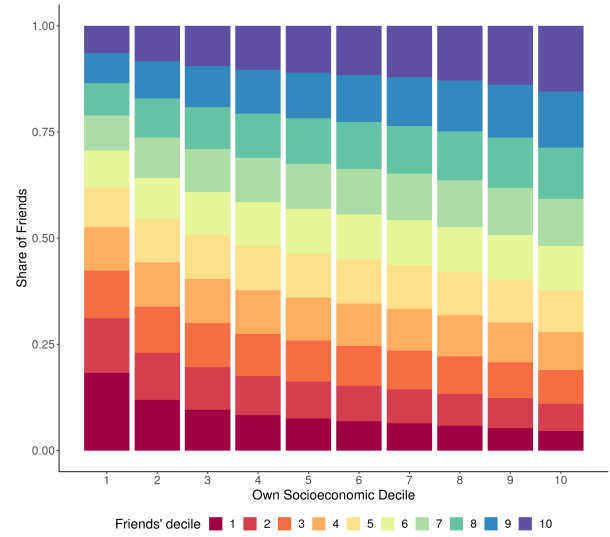
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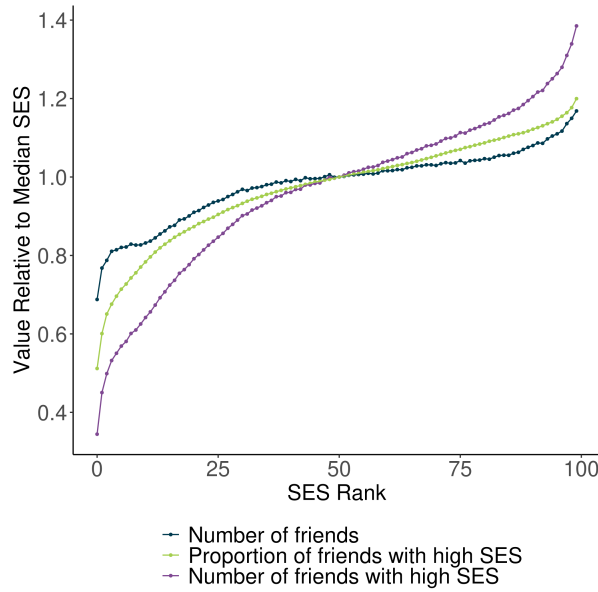
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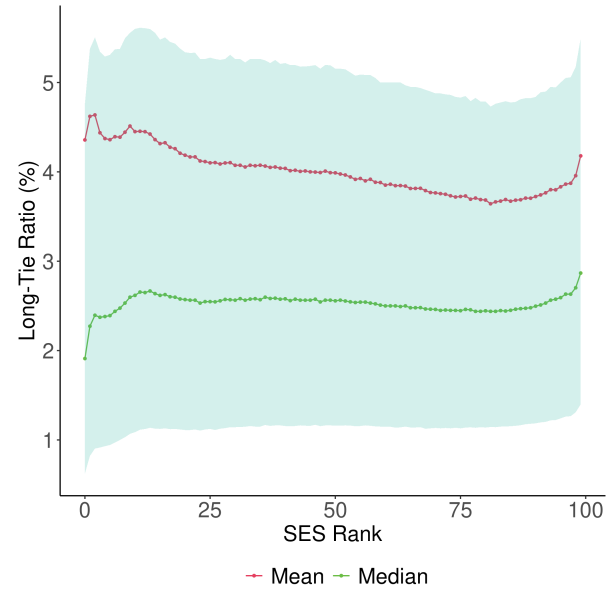
(A) Own SES rank vs. mean friend SES rank.



(B) SES decile to SES decile friendship shares.



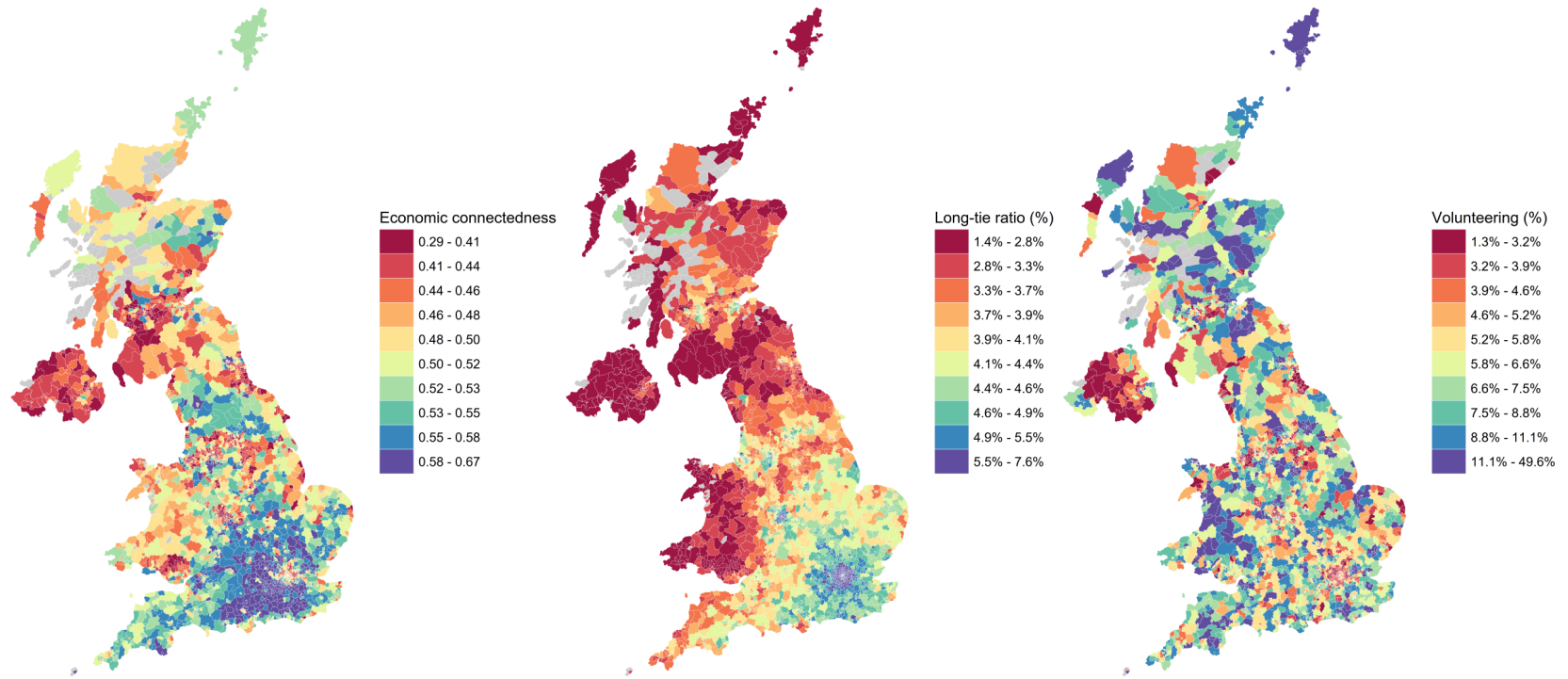
(c) Number of friends by own SES.



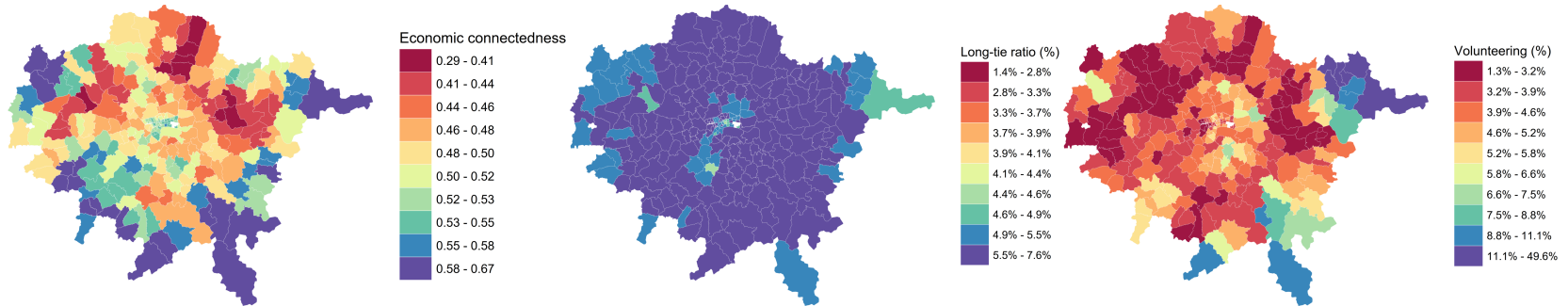
(D) Long-tie ratio, by SES.

FIGURE 1: Friendship patterns by SES.

Notes for Figure 1: The shaded area in panel (D) represents the 25th and 75th percentile of the user-level distribution of the long-tie ratio at each SES centile.



(A) Geographic distribution of social capital measures by postcode district across the UK.



(B) Geographic distribution of social capital measures by postcode district in London.

FIGURE 2: Geographic distribution of social capital measures by postcode district. Panel (a) reports values for all UK postcode districts, while panel (b) zooms in on postcode districts within Greater London. Darker shading corresponds to higher levels of social capital.

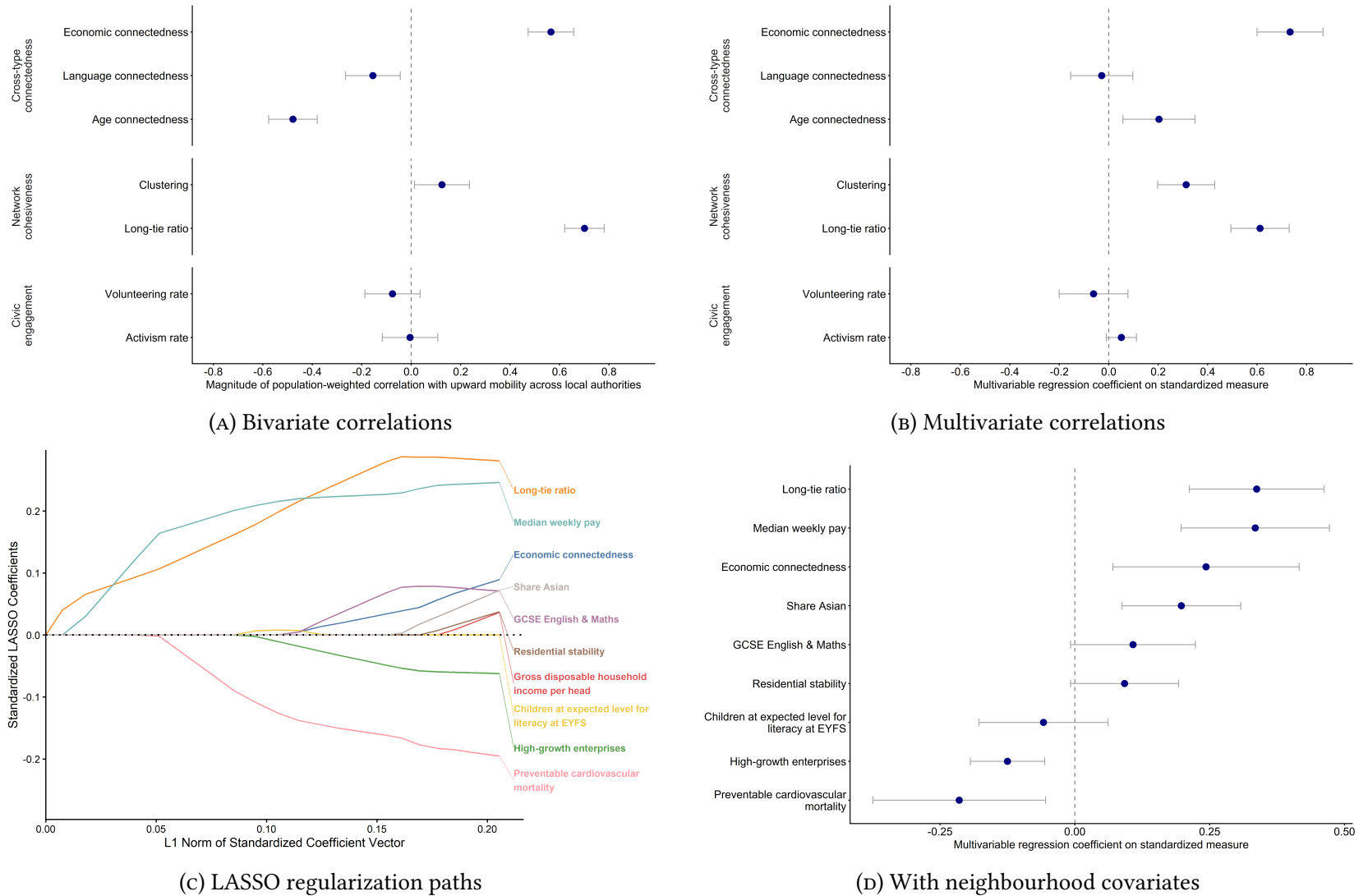
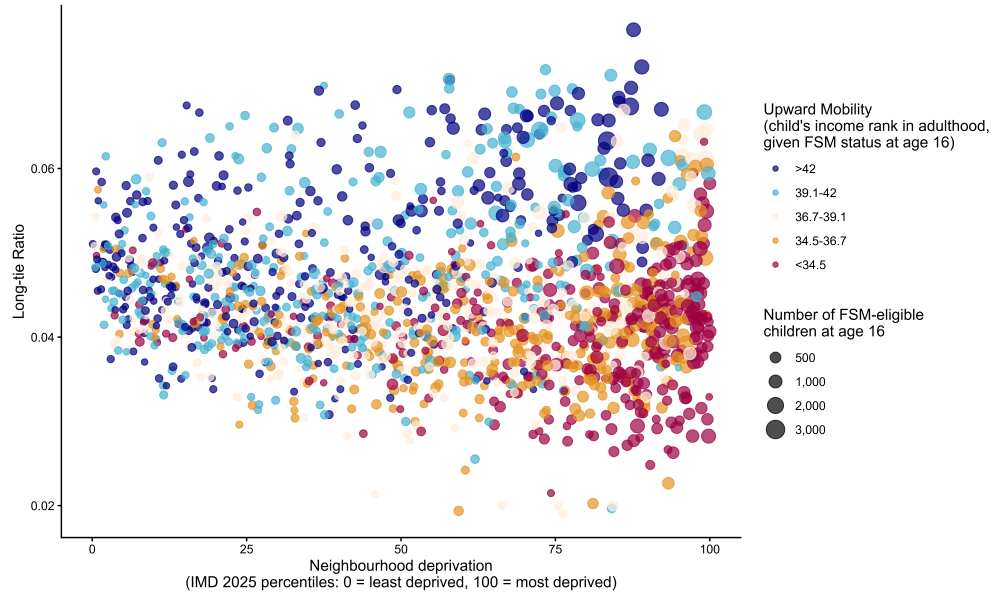
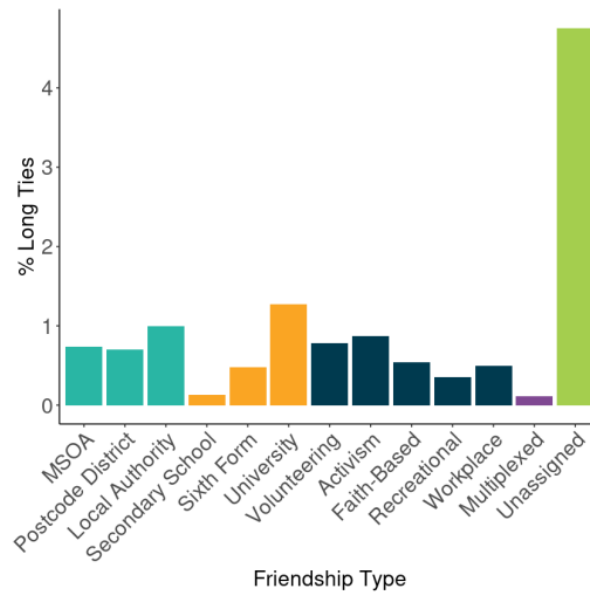


FIGURE 3: Local authority-level relationships between economic mobility and measures of social capital.

Notes for Figure 3: All the correlations reported are at the local-authority level and are weighted by the number of FSM-eligible pupils in the local authority. Error bars represent 95% confidence intervals constructed from heteroskedasticity-robust standard errors. Panel (C) shows the L1-penalized LASSO regularization paths from a model of economic mobility on the full set of social-capital measures and other neighbourhood characteristics drawn from government statistics [41, 42] (All variables used are specified in A.8). Panel (D) uses the leading variables selected by the LASSO.



(A) Long-tie ratio, neighbourhood deprivation, and economic mobility (postcode-district level).



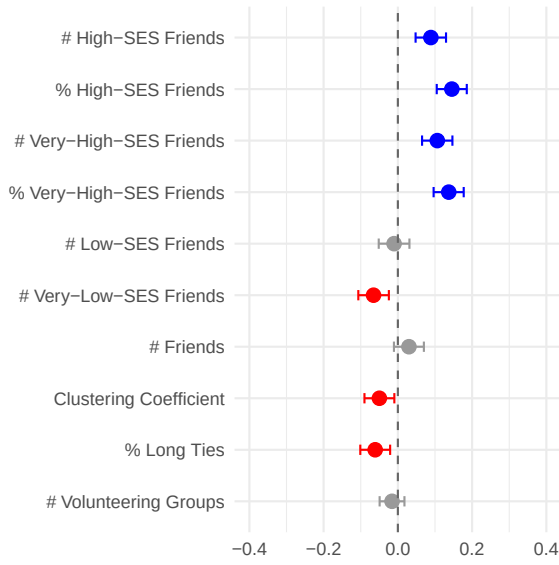
(B) Proportion of friendships that are long ties, within each setting.

FIGURE 4: Long-tie ratios

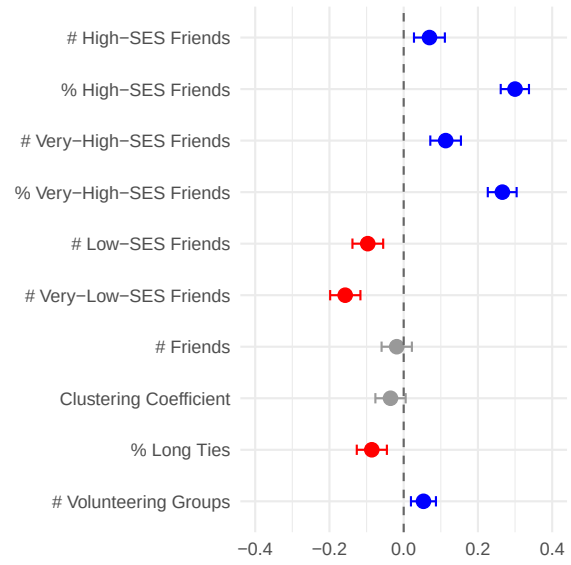
Notes for Figure 4b: Each bar represents the proportion of friendships we assign to the relevant setting that are long ties. (That is, where the two individuals at each end of the friendship do not have any mutual friends, even in other settings.) “Multiplexed” friendships are friendships we are able to assign to 2 or more settings, and “unassigned” friendships are friendships we are not able to assign to any setting.



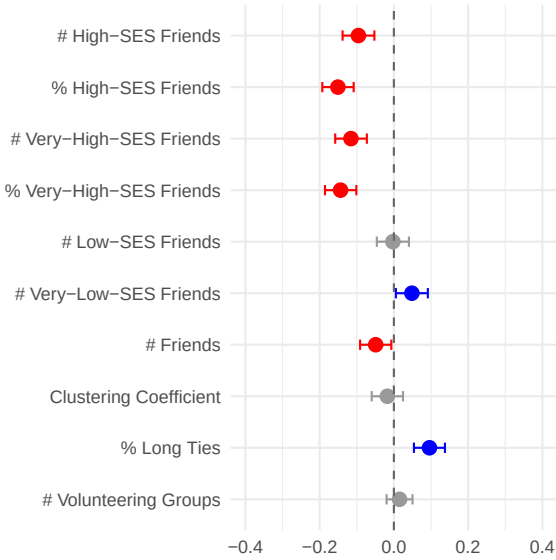
FIGURE 5: EC, exposure, and friending bias by setting and SES, and a decomposition of the differences in EC by SES.



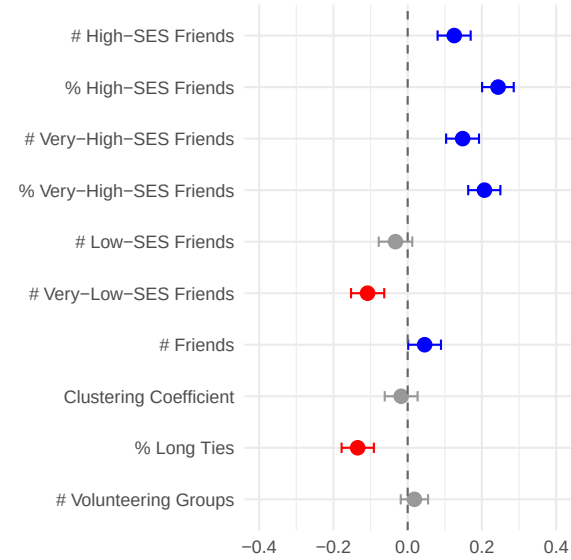
(A) Composite Wellbeing



(B) Composite Trust



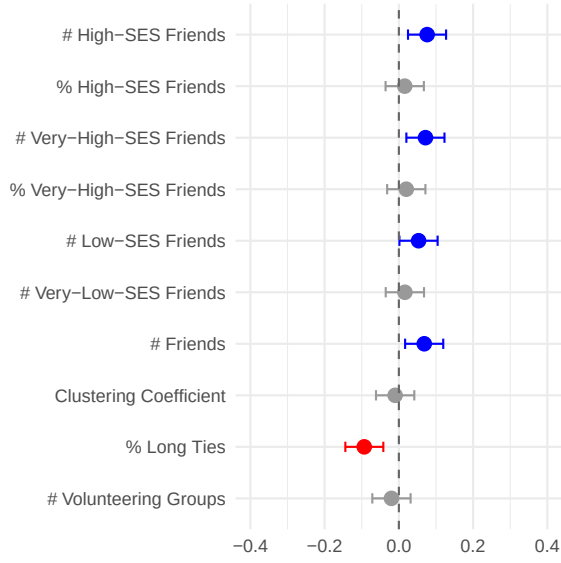
(C) Composite Connectedness



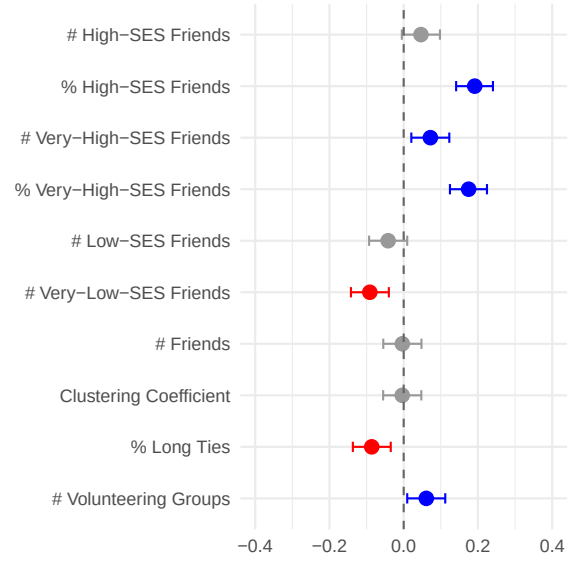
(D) Composite Social Support

FIGURE 6: Bivariate correlations between individual-level social capital measures and composite survey measures.

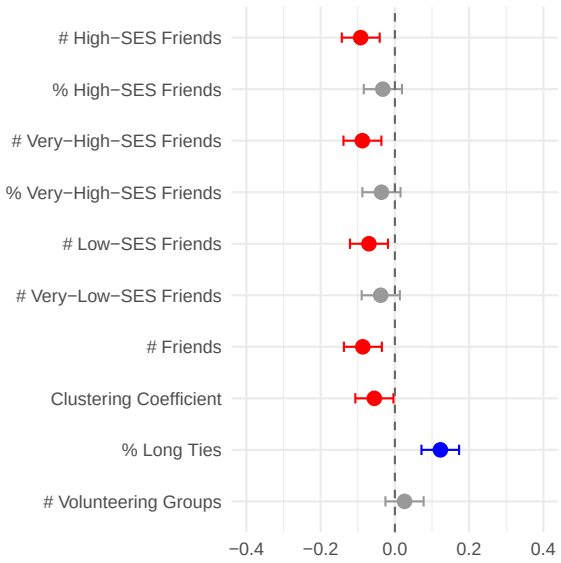
Notes: Each dot represents the coefficient from a bivariate regression of the standardised survey composite on a standardised social capital measure (equation 1). Bars denote 95% confidence intervals. A high-SES friend is defined as a friend with above-median SES within their birth cohort; a very high-SES friend has SES in the top decile. $N = 3,770$.



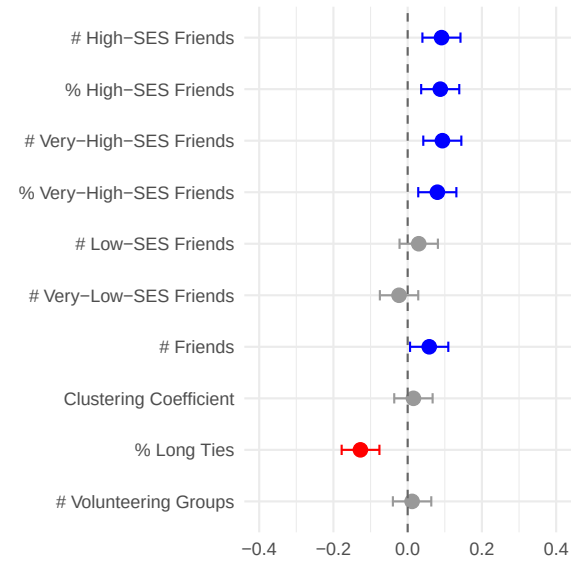
(A) Composite Wellbeing



(B) Composite Trust



(C) Composite Connectedness



(D) Composite Social Support

FIGURE 7: Partial correlations between individual-level social capital measures and composite survey measures, after partialling out age, income, and gender.

Notes: Each dot represents the coefficient on the standardised social capital measure from a regression that also includes standardised age, gender, and self-reported income (equation 2). Bars denote 95% confidence intervals. $N = 2,138$ (respondents with non-missing income).

A Methods

A.1 Data

Our sample consists of 20.5 million Facebook users who, as of October 20th 2025, reside in the UK, have at least 100 Facebook friends, are aged between 25 to 64, have engaged with the platform in the last 30 days, and have not been flagged by Meta as potentially operating a fake account. These users represent about 58% of the UK population between the ages of 25 to 64 [55]. We refer to this group as the *analytic sample*. Figure S17 shows that our analytic sample slightly over-represents females and younger adults, consistent with known social-media usage patterns [56, 57].

We infer a predicted home location for each user from a combination of signals, including the city reported on Facebook profiles and device/connection information (e.g., IP addresses used to connect to Facebook). Figure S18 shows that user counts by area in our analytic sample closely track administrative population counts for individuals aged 25 to 64, with a correlation of 0.93.

We assign each user a socioeconomic status (SES) using a gradient-boosted model that predicts an SES index from features observed for all users on the platform—including device price bands, characteristics of the user’s residential area (e.g., average income), and activity such as Marketplace usage. The model is trained to predict a composite index derived from an on-platform survey of the finances, income, and wealth of 206,539 users in 64 countries and is part of a broader effort to map social capital around the world [58]. To assess the validity of the UK implementation, we fielded a separate survey to 5,472 UK Facebook users; 2,138 of these respondents are in our analytic sample and reported their household income. Ranked within this survey sample, predicted SES correlates with self-reported income at 0.39 (Figure S19). We note that we wouldn’t expect these series to line up perfectly even in the absence of any measurement error since SES and income are distinct concepts, with wealth, household size, and the cost of living also being important contributors to SES that are not captured by our income survey. Our final SES measure ranks users within birth cohorts based on this model score.

To understand the contexts in which social connections are formed and maintained, we assign users to a set of social and institutional groups: secondary schools, universities, further education providers, workplaces, neighbourhoods, faith-based communities, hobby and recreation groups, activism groups, and volunteering groups. (See Appendix A.4 for further details.) We are able to assign 22% of all friendships (over one billion ties) to at least one setting. These assigned friendships closely resemble the full friendship network in their SES composition (Figure S20).

In order to construct SES measures for individuals while they were growing up we link individuals, where possible, to their parents (see Appendix A.5). In total, we are able to link 30% of

the sample to at least one parent. For users whom we are able to link to parents, we assign them a childhood SES on the basis of the parent’s SES score, which we rescale to a percentile rank within the child’s birth cohort.

A.2 Definitions of Our Social Capital Metrics

We operationalise social capital through three distinct yet interconnected categories: cross-type connectedness (bridging social capital), social cohesion (forms of bonding capital), and civic engagement. These measures parallel those developed for the United States in Chetty *et al.* [24].

A.2.1 Cross-Type Connectedness

Cross-type connectedness captures the extent to which people of different “types” form friendships with each other. These types of connections are related to the notion of a “weak tie”, explored by Granovetter [16], which refers to bonds between acquaintances with less frequent social interaction, often connecting people who are not in the same immediate social circle. Putnam [59] builds on this concept and defines “bridging social capital” as relationships across diverse social groups based on ethnicity, religion, SES, or other differences arguing that serves as a “sociological WD-40” to help lubricate social interactions and facilitate cooperation across diverse groups. We measure three types of cross-type connectedness: economic connectedness, age connectedness, and language connectedness.

Economic Connectedness For individual i with friend set F_i , let SES_j denote friend j ’s socioeconomic rank within j ’s birth cohort and $p_{50}(b_j)$ the cohort median. Individual economic connectedness (IEC) is

$$IEC_i = \frac{|\{j \in F_i : SES_j > p_{50}(b_j)\}|}{|F_i|}.$$

For a community c , economic connectedness (EC) averages IEC over below-median (low-SES) individuals L_c :

$$EC_c = \frac{1}{|L_c|} \sum_{i \in L_c} IEC_i.$$

Age Connectedness Other cross-type connectedness measures are calculated similarly. For age connectedness, we first calculate the individual-level fraction of person i ’s friends F_i who are

between the ages of 35 and 44:

$$\text{IAC}_i = \frac{|\{j \in F_i : 35 \leq A_j < 45\}|}{|F_i|}$$

Then, we average this quantity over the set of people Y_c in the community who are aged 18 – 34:

$$\text{AC}_c = \frac{1}{|Y_c|} \sum_{i \in Y_c} \text{IAC}_i$$

Language Connectedness Finally, for language connectedness, the individual-level measure is the fraction of a person i 's friends who are English speakers, as proxied by the language setting on the friend's Facebook account. If E_j is a Boolean variable that is True if person j uses Facebook in English and False otherwise, this individual-level language connectedness can be computed as follows:

$$\text{ILC}_i = \frac{|\{j \in F_i : E_j\}|}{|F_i|}$$

Then, the language connectedness for the community is the average over the set of people NE_c who use Facebook in other languages (i.e., E_i is False for $i \in NE_c$):

$$\text{LC}_c = \frac{1}{|NE_c|} \sum_{i \in NE_c} \text{ILC}_i$$

A.2.2 Social Cohesion

Social cohesion reflects the structural characteristics of social networks. Bourdieu [60] discusses how the structure of a network gives differential access to power and resources and defines social capital as the “aggregate of the actual or potential resources which are linked to possession of a durable network of more or less institutionalized relationships of mutual acquaintance and recognition.” Granovetter [16] argues that these “strong ties” are essential for providing emotional support, fostering a sense of belonging, and reinforcing social cohesion within close-knit groups which Putnam [59] refers to as “bonding social capital”.

Let $\mathbf{A} \in \{0, 1\}^{n \times n}$ denote the undirected adjacency matrix on the analytic-sample friendship network, where $A_{ij} = 1$ if i and j are Facebook friends and $A_{ij} = 0$ otherwise. For a community c with resident set N_c , let $\mathbf{A}^c$ be the adjacency matrix of the induced subgraph on N_c (i.e., friendships among residents of c). For individual i , let $F_i = \{j : A_{ij} = 1\}$ and $F_i^c = F_i \cap N_c$.

The Clustering Coefficient Clustering captures the tendency of an individual’s friends to also be friends with one another. The individual clustering coefficient lies in $[0, 1]$ and is defined as

$$\text{Clustering}_i = \frac{\sum_{j,k \in F_i, j < k} A_{jk}}{\binom{|F_i|}{2}},$$

defined when $|F_i| \geq 2$. Community-level clustering averages this quantity over residents of c [61]:

$$\text{Clustering}_c = \frac{1}{|N_c|} \sum_{i \in N_c} \text{Clustering}_i.$$

The Long-Tie Ratio The *long-tie ratio* assesses the share of an individual’s friendships (within c) that are not reinforced by any mutual friends *in that community*. Let $m_{ij}^c \equiv [(A^c)^2]_{ij}$ be the number of common neighbours of i and j inside c (the count of length-2 paths in the induced subgraph). A friendship (i, j) with $j \in F_i^c$ is an unsupported (“long”) tie if $m_{ij}^c = 0$. The individual measure is

$$\text{LongTieRatio}_i^c = \frac{1}{|F_i^c|} \sum_{j \in F_i^c} \mathbf{1}\{m_{ij}^c = 0\},$$

and for the community-level measure we average over low-SES individuals:

$$\text{LongTieRatio}_c = \frac{1}{|L_c|} \sum_{i \in L_c} \text{LongTieRatio}_i^c.$$

The complement, $1 - \text{LongTieRatio}$, is the *support ratio*—the average fraction of a person’s friends with whom they share at least one other friend [21]. We use the term “long-tie ratio” throughout the paper for consistency.

A.2.3 Civic Engagement

Putnam [59] argues that civic engagement — participation in voluntary associations, community organizations, and other forms of collective activity — is a source of social capital for a community and helps generate norms of reciprocity, trust, and networks of social connection.

Volunteering and Activism Rates Our measures of civic engagement are based on participation in public volunteering and activism groups on Facebook. We consider Facebook groups that are classified into these categories based on their titles and which do not have the privacy setting “secret” enabled. Then, the volunteering rate VR_c for community c is just the fraction of

people in community c who participate in at least one volunteering group, and the activism rate AR_c is the fraction of people who participate in at least one activism group.

A.3 Friending Shares, Exposure, and Friending Bias

Let i index individuals and s index settings. Write F_i for i 's set of friends and F_{is} for the subset assigned to s . Define the *friending share* of i in s as

$$w_{is} \equiv \frac{|F_{is}|}{|F_i|}, \quad \sum_s w_{is} = 1.$$

Individual economic connectedness in s is the high-SES share among those friends:

$$EC_{is} \equiv \frac{1}{|F_{is}|} \sum_{j \in F_{is}} \mathbf{1}\{j \text{ is high-SES}\},$$

and overall EC for i averages across settings:

$$EC_i = \sum_s w_{is} EC_{is}.$$

Exposure in s is the share of potential alters in s who are high-SES (computed within cohort bands and the relevant assignment window for s):

$$p_{is} \in [0, 1].$$

Friending bias compares realised cross-SES ties to what exposure would predict. For any population (e.g., low-SES residents of area c), we define

$$FB_{\cdot s} = 1 - \frac{EC_{\cdot s}}{p_{\cdot s}},$$

so $FB_{\cdot s} = 0$ indicates random mixing within s . Aggregating for low-SES residents of area c (denote that set by L_c), with $w_{cs} = \frac{1}{|L_c|} \sum_{i \in L_c} w_{is}$ and $EC_{cs} = \frac{1}{|L_c|} \sum_{i \in L_c} EC_{is}$,

$$EC_c = \sum_s w_{cs} (1 - FB_{cs}) p_{cs}.$$

This identity makes explicit the three determinants of EC.

A.4 Assigning Users to Groups and Friendships to Settings

To study the contexts in which social connections form and persist, we assign users to social and institutional groups: secondary schools, sixth-form colleges, universities, further education providers, workplaces, neighbourhoods, faith-based communities, hobby and recreation groups, activism groups, and volunteering groups.

Secondary schools. We use a two-step procedure. First, we match users to the secondary school self-reported on their Facebook profiles. If a user lists multiple schools, we assign the school at which they have the most friends. We exclude virtual schools and schools with fewer than 25 students. We then merge duplicate school names referring to the same institution (e.g., punctuation or suffix differences), requiring agreement on location and using string-distance checks to avoid erroneous merges. Second, for users without a valid self-report, we impute a school based on friendship networks: for each unassigned user, we count friends at each candidate school and rank schools by that count. If the user has at least five friends at the top-ranked school *and* at least twice as many friends at the top-ranked school as at the second-ranked school, we assign the top-ranked school.

Sixth forms and universities. We assign sixth-form colleges and universities using self-reported information on profiles. We do not impute these affiliations from networks because many users do not attend sixth form or university, which would risk false positives.

Workplaces. Workplace assignments are based on self-reported employment entries on profiles.

Neighbourhoods. Neighbourhood assignment follows the predicted home location procedure described in the main text, enabling fine-grained geographic analyses.

Faith-based and hobby & recreation groups. We link users to locally relevant Facebook groups and pages. For hobby & recreation, assignment is based on membership in groups/pages classified to this category. For faith-based communities, assignment is based on likes/follows of relevant pages. These page- and group-based links yield local participation measures and allow us to assign a subset of friendships to settings when both endpoints are members of the same group (see main text for setting-level friending shares).

Assigning Friendships to Settings We then assign a friendship to a setting if both users involved in the friendship are members of the same group within that setting. For secondary schools and sixth forms, we additionally impose that the two users must be within three birth cohorts of each other. Overall, we assign 22% of all friendships (over one billion ties) to at least one setting, and the friendships we assign closely resemble the full friendship network in their SES composition (Figure S20).

A.5 Linking Users in the Analytic Sample to Their Parents

We link a subset of users to parents using a hierarchical procedure that prioritises higher-reliability signals and uses family structure for consistency checks.

Partners. We first link partners using (i) self-reported relationships and (ii) public tags in life-event posts. (Life events include marriage, engagement, having a child, expecting a baby, and pregnancy. Only public posts are used.) We restrict to opposite-gender pairs and exclude tags involving other family members.

Siblings. We link siblings and step-siblings via self-reports, requiring ages within 14 years of each other.

Parents. We then link to parents using three sources:

1. *Self-reports.* Users who list parents on their profiles are linked directly, imposing plausible age gaps (parent 18–45 years older than child).
2. *Name-based matches.* Excluding the 100 most common surnames in our analytic sample, we match based on shared last name and age gaps (18–45 years). We also allow a mother’s spouse’s surname to accommodate cases where the child is connected to the mother but not the father on the platform. We do not perform name-based matching for women who have taken a spouse’s surname to avoid in-law matches.
3. *Public wall posts.* We search for public wall posts on Mother’s Day and Father’s Day containing kinship terms (e.g., “mum”, “mother”, “dad”, “father”) and link the tagged profiles accordingly.

We propagate confirmed parent links across sibling sets (if sibling *A* is linked to a parent, siblings of *A* inherit that link).

Prioritisation. When multiple candidates exist, we resolve conflicts using the following order: (1) self-reports; (2) public wall-post evidence; (3) name-based father match; (4) name-based mother match via spouse’s surname; (5) name-based mother match. This ordering balances coverage and precision.

A.6 Constructing Intergenerational Economic Mobility Estimates for the UK

A.6.1 Constructing Mobility Estimates using Eligibility for Free School Meals

We use the Department for Education’s Longitudinal Education Outcomes (LEO) dataset—linking school records to HMRC data (equivalent to IRS) earnings—to estimate economic mobility across England at two spatial scales: 309 local authority districts and 1,670 postcode districts.

Following Carneiro *et al.* [39], we proxy childhood disadvantage with Free School Meals (FSM) eligibility at age 16, which requires receipt of means-tested benefits and thus credibly indicates low household income. Roughly 15% of pupils in our cohorts are FSM-eligible. FSM is not observed for private-school pupils (about 7% of pupils), who typically come from the top decile of the parental income distribution [62], so we are unlikely to omit many disadvantaged pupils.

Adult earnings outcomes come from PAYE (employee earnings) and self-assessment (self-employment and other income). For each birth cohort, we rank individuals nationally by income at age 28. For a geographic area a , economic mobility is defined as the mean age-28 earnings rank among those who were FSM-eligible and resident in a at age 16:

$$\mu_a^{\text{FSM}} = \frac{1}{|\mathcal{F}_a|} \sum_{i \in \mathcal{F}_a} \text{rank}_{28}(y_i),$$

where $\mathcal{F}_a$ is the set of FSM pupils linked to area a .

We extend Carneiro *et al.* [39] from the 1986–1988 birth cohorts to 1986–1992. Our updated local-authority estimates correlate strongly with Carneiro *et al.* [39] (weighted $r = 0.89$). Furthermore, when comparing LA estimates using the three-year versus seven-year cohorts, the average fall or increase in FSM children’s income positions relative to their non-FSM peers is only 1.3 rank points across local authorities.

To assess whether the expanded cohorts improved the precision of mobility estimates, we calculated signal-to-noise ratios for both cohort specifications. The observed variation in mobility estimates across areas reflects both genuine geographic differences (signal) and sampling error (noise). Using a variance decomposition, we isolated the signal component.

Let σ_{obs} denote the standard deviation of μ_a^{FSM} across all areas and $\overline{\text{SE}}$ denote the average standard error across areas. The signal standard deviation is:

$$\sigma_{\text{signal}} = \sqrt{\sigma_{\text{obs}}^2 - \overline{\text{SE}}^2},$$

and the signal-to-noise ratio is:

$$\text{SNR} = \frac{\sigma_{\text{signal}}}{\sigma_{\text{obs}}}$$

Estimating economic mobility using the 1986-1988 birth cohorts produced an SNR of 0.63, whilst the extended cohort dataset yielded an SNR of 0.72. The higher SNR confirms that the larger sample sizes substantially reduced measurement error as a proportion of total variation.

The extended birth cohorts in LEO's latest release enable us to publish economic mobility estimates at geographical areas more granular than local authority. Given the limited number of FSM pupils, postcode district is the most granular level at which we can compute robust estimates with coverage across most of England. Postcode districts are identified by the first part of a UK postcode (e.g., "N1" in N1 6RD) and represent specific neighbourhoods within cities or towns. We apply the same methodology used at the local authority level.

A.6.2 National PCA-Based Mobility Measures

Following the general approach of previous research [63], we construct a continuous childhood SES index using Principal Component Analysis (PCA) applied to multiple area-level indicators from the 2001 Census [64] and the 2004 Index of Multiple Deprivation [65], linked to individuals in the LEO data. This approach allows us to summarise multiple correlated indicators of socioeconomic status into a single composite measure.

Our index draws on small-area measures at the Output Area (OA) and Lower Super Output Area (LSOA) levels. From the 2001 Census [64], we include at the OA level:

- Percentage of individuals who own their home
- Percentage of individuals who are council tenants
- Percentage of those in work in higher professional and managerial occupations
- Percentage of those in work in lower professional and managerial occupations
- Percentage working in routine occupations
- Percentage long-term unemployed

- Percentage with at least Level 4 qualifications
- Percentage with at least Level 3 qualifications
- Percentage with no formal qualifications

Additionally, we include two measures from administrative education data: the percentage of pupils eligible for Free School Meals at the OA level, and the Index of Multiple Deprivation score [65] for the child’s LSOA.

To ensure all variables are oriented consistently, we first rank each input variable from 1 to 100, where higher ranks uniformly indicate less deprivation (e.g., higher rank for home-ownership means greater prevalence, whilst higher rank for FSM eligibility means lower prevalence). We then standardise these ranks before applying PCA. The first principal component serves as our composite childhood SES measure. Finally, we re-rank children nationally within cohort based on this first principal component to obtain a childhood SES percentile rank ranging from 0 to 100. Adult SES is measured as the national earnings rank at age 28, consistent with our main FSM-based measure of intergenerational economic mobility.

At the national level, the rank–rank slope (adult rank regressed on childhood SES rank) aligns closely with Van Der Erve *et al.* [63] for adjacent cohorts, indicating that our index successfully recovers familiar intergenerational economic mobility gradients.

A.6.3 Estimating Economic Mobility in the UK using Facebook Data

To extend coverage to Scotland, Wales, and Northern Ireland and to reach finer geographies, we estimate intergenerational economic mobility using data from Facebook and the parent–child links described in Appendix A.5.

We mirror the LEO time window by focusing on the 1986–1992 birth cohorts. Children’s SES ranks are computed within birth cohort among linked children; parents’ SES ranks are computed among linked parents. We estimate the standard rank–rank model

$$R_i^{\text{child}} = \alpha + \beta R_i^{\text{parent}} + \varepsilon_i,$$

where higher β indicates stronger intergenerational persistence (lower relative mobility). Prior U.S. validation found highly similar slopes using Facebook and IRS tax data (0.32 vs. 0.34) [24].

In the UK, rank–rank slopes are likewise close across sources: 0.19 (SE = 0.005) in the Facebook data versus 0.21 (SE = 0.004) in LEO (Figure S21). At the area level, Facebook-based economic mobility correlates strongly with FSM-based mobility across English local authorities (Figure S22).

Finally, Facebook allows UK-wide coverage and finer spatial resolution. We estimate postcode-district-specific rank-rank models and report predicted adult ranks for children with parents at the 25th percentile of the national parental SES distribution, enabling the first UK-wide mobility map at this granularity (Figure S23).

The extended LEO cohorts allow us to compute FSM-based mobility at postcode-district granularity for much of England (Figure S23).

A.7 Other Outcome Data

A.7.1 Educational Attainment

We measure educational attainment using the Department for Education’s school-level Key Stage 4 performance data for 2023/24 [66]. Our measure is Attainment 8, the headline indicator that averages pupils’ GCSE results across eight qualifications (with English and mathematics double-weighted). We select this measure because GCSE attainment strongly predicts later educational outcomes, including degree completion [67]. To ensure like-for-like comparability, we include only mainstream state-funded secondary schools. We aggregate school-level Attainment 8 scores to Local Authority Districts using pupil-weighted means, where each school’s contribution is proportional to its KS4 pupil count.

A.7.2 Preventable Mortality

We measure mortality using the Office for Health Improvement and Disparities’ (OHID) data on under-75 mortality from preventable causes, averaged over 2019–2023 [68]. We aggregate MSOA-level data to Local Authority Districts using population weighting. "Preventable" deaths include those avoidable through public health and primary prevention: cardiovascular disease, smoking- and alcohol-related cancers, chronic respiratory disease, vaccine-preventable infections (including COVID-19), injuries (transport, falls, poisonings), and substance-related harms. We prioritise preventable mortality over other measures of physical health such as life expectancy because it responds more directly to community conditions than social capital influences such as health norms, information flow, and mutual support [46].

A.7.3 Crime

We measure crime using police-recorded incidents per 1,000 residents for calendar year 2024. We use crime data published by individual police forces across England and Wales, aggregated

to Local Authority Districts to match our social capital measures [69]. We use total recorded crime rates following evidence that social capital reduces crime through mechanisms including collective efficacy, informal social control, and strengthened social interactions [70].

A.8 External Covariates

We use the following area characteristics from government statistics [41, 42]. Unless otherwise stated, non-census indicators are drawn from the March 2024 release of the ONS Subnational Indicators Explorer and refer to the latest available pre-2024 period; for each series we report the reference year or period used. Demographic measures are constructed from the 2021 Census of England and Wales via Nomis and refer to usual residents on Census Day (21 March 2021).

Economic and labour market statistics (ONS Subnational Indicators Explorer):

- Employment rate: percentage of usual residents aged 16 to 64 in employment in the local authority area in 2022/23 (October 2022 to September 2023).
- Unemployment rate: modelled percentage of residents aged 16 and over who are unemployed and actively seeking work in 2022/23 (October 2022 to September 2023).
- Median weekly pay: gross median weekly earnings in pounds for full-time employee jobs located in the area in 2023.
- Household income: gross disposable household income per head of population in pounds in 2021, after taxes and social contributions and including cash benefits and other transfers.
- Labour productivity: gross value added per hour worked in pounds for economic activity in the area in 2021.
- High-growth enterprises: number of enterprises in the area classified as “high-growth” in 2022 (typically defined by rapid expansion in employment or turnover), scaled by population or business stock where indicated.
- 4G coverage: percentage of premises in the local authority with outdoor 4G mobile coverage from at least one provider as at September 2023.
- Gigabit broadband: percentage of premises in the local authority with access to gigabit-capable fixed broadband as at September 2023.

Education and skills statistics (ONS Subnational Indicators Explorer):

- Qualifications: percentage of residents aged 16 to 64 whose highest qualification is NVQ Level 3 (A-level equivalent) or above in 2021.
- Apprenticeship starts: rate of individuals starting government-funded apprenticeships in 2022/23, typically expressed per 100,000 residents.
- Apprenticeship completions: rate of apprenticeship achievements (successful completions) in 2022/23, typically expressed per 100,000 residents.
- GCSEs by age 19: percentage of young people who have achieved GCSE (or equivalent) qualifications in both English and maths by age 19 in 2021/22.
- Early years communication: percentage of children at the end of the Early Years Foundation Stage meeting the expected level in communication and language in 2022/23.
- Early years literacy: percentage of children at the end of the Early Years Foundation Stage meeting the expected level in literacy in 2022/23.
- Early years maths: percentage of children at the end of the Early Years Foundation Stage meeting the expected level in mathematics in 2022/23.

Health and wellbeing statistics (ONS Subnational Indicators Explorer):

- Adult obesity: percentage of adults aged 18 and over classified as obese (body mass index of 30 or above) between November 2021 and November 2022 (16 November 2021 to 15 November 2022).
- Child obesity (Reception): percentage of children aged 4–5 years (Reception year) classified as obese in 2022/23.
- Child obesity (Year 6): percentage of children aged 10–11 years (Year 6) classified as obese in 2022/23.
- Smoking prevalence: percentage of adults who report being cigarette smokers in 2022.
- Preventable circulatory mortality: age-standardised rate of deaths from circulatory diseases considered preventable among persons aged under 75, per 100,000 population, averaged over 2020–2022.
- Early cancer diagnosis: percentage of new cancer diagnoses that occur at stage 1 or stage 2 in 2021.

- Life satisfaction: average self-reported life satisfaction score on a 0–10 scale for residents of the area over the period April 2022 to March 2023.
- Happiness: average self-reported happiness-yesterday score on a 0–10 scale over April 2022 to March 2023.
- Anxiety: average self-reported anxiety-yesterday score on a 0–10 scale, where higher scores indicate greater anxiety, over April 2022 to March 2023.
- Life worthwhile: average self-reported score on a 0–10 scale for the extent to which residents feel that the things they do in life are worthwhile, over April 2022 to March 2023.

Demographics (2021 Census via Nomis):

- Urban population: share of the local authority’s usual resident population living in MSOAs classified as “Urban” in the official rural–urban classification. We compute this as the population-weighted proportion of MSA-level population flagged as urban, using 2021 Census usual resident counts and aggregating to local authorities via an MSA–LAD cross-walk.
- Residential stability: share of usual residents aged one and over whose address one year before Census Day (21 March 2021) was the same as their current address.
- Single parent households: share of households that are single-parent families with one adult and one or more dependent children.
- White population: share of usual residents whose ethnic group is recorded in any “White” category.
- Black population: share of usual residents whose ethnic group is recorded in any “Black, Black British, Caribbean or African” category.
- Asian population: share of usual residents whose ethnic group is recorded in any “Asian, Asian British or Asian Welsh” category.
- Professional occupations: share of employed residents aged 16 and over in NS-SEC categories L1–L6, covering higher managerial, administrative and professional occupations (L1–L3) and lower managerial, administrative and professional occupations (L4–L6).

Geography and infrastructure statistics (ONS Subnational Indicators Explorer):

- Drive time to employment: average travel time in minutes by car to the nearest employment centre with 500–4,999 jobs, for 2019 (revised estimates).
- Public transport/walk time: average travel time in minutes by public transport and walking to the nearest employment centre with 500–4,999 jobs, for 2019 (revised estimates).
- Cycle time to employment: average travel time in minutes by bicycle to the nearest employment centre with 500–4,999 jobs, for 2019 (revised estimates).

Housing statistics (ONS Subnational Indicators Explorer):

- Housing supply: net additions to the local housing stock per 1,000 existing dwellings in the financial year ending 2023, including new builds, conversions, and demolitions.

A.9 Survey Design and Outcomes

Between June and July 2024, we administered a survey to Facebook users in the UK to better understand the relationship between individual-level social capital and subjective wellbeing.¹ The survey was targeted at a random sample of adults aged 18–64 on Facebook with a predicted home country of the United Kingdom. Participants saw the survey translated into their local language. The survey was voluntary, participants could quit at any point, and participants were not compensated.

Participants were recruited via an invitation to take a survey that was shown as a story in Facebook News Feeds on web and mobile interfaces with the text: “Today we’re interested in your opinions about people’s feelings on social connection. Your responses, together with information we have about you and how you use Meta Products, may be used for purposes such as to personalize and improve our Products, support research and innovation for social good, and for other purposes described in our Privacy Policy. To learn more, see our Privacy Policy.” Once participants clicked “Continue” they were taken to the survey with a header containing the following text: “The following questions are about your overall well-being. There are no right or wrong answers. You can choose to skip any question that you’d prefer not to answer or exit the survey at any time.” No additional consent text was included.

A total of 5,472 individuals completed the survey (51.3% female), from an initial pool of approximately 272,000 who saw the recruitment invitation in their News Feed (~10,000 clicked

¹The survey went through two rounds of review at Facebook. The research plan was reviewed by a five-person panel of experts in the research area, research ethics, law, and policy. This panel reviewed the proposal for potential benefits, such as improvements for people on Facebook or contributions to general knowledge, as well as participant risks and required regulation adherence. More about this research review is available online [here](#).

through), yielding a response rate of approximately 3.5%. Of these, 3,770 are in our analytic sample—that is, they can be linked to our individual-level social capital measures. Most individuals who responded to the survey but are not in our analytic sample were not included because they do not satisfy our age criteria of being between 25–64. The vast majority of the remaining unmatched individuals are not in our analytic sample because they do not satisfy our 100 friends cutoff. A further restriction to respondents who reported their household income in the survey yields a subsample of 2,138 for our controlled specifications. On average, participants took 9 minutes to complete the survey. We provide a breakdown of survey responses in Figures [S24–S27](#), and screenshots of our survey in Figures [S28–S35](#).

Survey Content. The survey consisted of 16 questions covering subjective wellbeing, trust, feelings of social disconnection, social support, and household income.

Subjective wellbeing (4 questions): The survey contained four questions about subjective wellbeing adapted from the four ONS personal wellbeing questions [\[71\]](#):

1. Overall, how happy did you feel yesterday?
2. Overall, how satisfied are you with your life nowadays?
3. Overall, to what extent do you feel the things you do in your life are worthwhile?
4. Overall, how worried are you about the current state of the world?

Participants were asked to give an answer on a scale of 1–10 where 1 is “Not at All” and 10 is “Extremely”. The four questions were shown in a random order.

Trust (3 questions): The survey contained three trust questions adapted from the OECD trust surveys [\[72\]](#), the World Values Survey [\[73\]](#), and the European Social Survey [\[74\]](#). This section started with the prompt: “The next questions are about your feelings of social connection. There are no right or wrong answers. For the following groups, would you say that most people can be trusted?”

1. People in general
2. People in your country
3. People in your neighbourhood

Participants were asked to select one of five options: (1) No one can be trusted, (2) A few can be trusted, (3) About half can be trusted, (4) Many can be trusted, (5) Most can be trusted. Questions were shown in a random order.

Feelings of social disconnection (3 questions): The survey included three questions on feelings of social connection, adapted from the UCLA loneliness scale [75]. This section began: “The following statements describe how people sometimes feel. For each statement, please indicate how often you feel the way described.”

1. How often do you feel that you lack companionship?
2. How often do you feel left out?
3. How often do you feel isolated from others?

Participants chose from five options: (1) None of the time, (2) A little of the time, (3) Some of the time, (4) Most of the time, (5) All of the time. Questions were shown in a random order.

Social support (5 questions): The survey included five questions on social support. One question was taken from each of the subscales in the MOS Social Support Survey [76], and we used an additional question on financial support. The text prompt for this section was: “People sometimes look to others for companionship, assistance, or other types of support. How often is each of the following kinds of support available to you if you need it?”

1. Someone to turn to for suggestions about how to deal with a personal problem.
2. Someone to have a good time with.
3. Someone to help with daily chores or take care of you if you were sick.
4. Someone who shows you love and affection.
5. Someone who would lend you money if you fell on hard times.

Response options were the same as for the feelings-of-disconnection questions. Questions were shown in a random order.

Household income (1 question): Finally, the survey asked participants about their annual household income: “What is the total annual income of everyone in your household (before tax but including any benefits)?” Respondents could select from 11 options: “Below £10,000”, “£10,001 to £20,000”, ..., “£90,001 to £100,000”, and “Over £100,000”, or they could select “Prefer not to answer”.

The survey concluded with the text: “Thank you for taking the time to complete this survey. Some of the questions or topics may have been challenging to think about or reflect on. If you or anyone you know would like additional support or to talk to someone about any of these issues please visit Facebook’s online well-being resources: <https://www.facebook.com/safety/wellbeing>. If you are experiencing an emergency or emotional crisis, contact 911, emergency services or a helpline immediately.”

Responses within each domain are highly correlated (Figure S36). We construct composite indices by averaging responses within each category. When we construct our composite wellbeing index, we average the three positively-worded items (happiness, satisfaction, and worthwhile-ness) and omit the “worried about the state of the world” item, which is only weakly correlated with the other three (pairwise r between 0.03 and 0.06). While happiness and life satisfaction are conceptually distinct—with life satisfaction reflecting a more evaluative, cognitive assessment and happiness capturing experienced affect [77]—we combine them given their high empirical correlation in our sample ($r = 0.73$). We show the correlations with the raw survey responses in Figures S37–S52.

Empirical Strategy

Our goal is to characterise the cross-sectional relationship between individual-level social capital and subjective wellbeing. We estimate two specifications.

First, for each social capital measure X_i and each survey outcome Y_i , we estimate the bivariate regression:

$$\tilde{Y}_i = \alpha + \beta \tilde{X}_i + \varepsilon_i \quad (1)$$

where tildes denote that both variables have been standardised to mean zero and unit variance. The coefficient β is therefore a standardised bivariate correlation.

Second, we estimate a controlled specification that includes basic demographics:

$$\tilde{Y}_i = \alpha + \beta \tilde{X}_i + \gamma_1 \widetilde{\text{Income}_i} + \gamma_2 \widetilde{\text{Age}_i} + \gamma_3 \widetilde{\text{Female}_i} + \varepsilon_i \quad (2)$$

where income is the self-reported household income bracket, and all variables are standardised. Since many respondents declined to report income, the controlled specifications use the subsample of 2,138 respondents with non-missing income data. Formally, we present partial correlation coefficients by first projecting $\tilde{Y}_i$ and $\tilde{X}_i$ onto our control variables, and then correlating the residuals.

Each social capital measure enters individually rather than jointly, because many of the mea-

tures are highly correlated (Figure S53). We report 95% confidence intervals based on transformed Fisher- z statistics.

B Supplementary Text

B.1 Social Capital in Specific Settings

We examine three settings in which a large share of friendships are formed and where the components of economic connectedness (EC), exposure, and friending bias differ markedly: universities and hobby & recreation groups (both low-bias contexts), and neighbourhoods (a high-bias context). These settings matter for two reasons. First, they account for sizable shares of within-setting friendships (Figure S10). Second, their EC–exposure–bias profiles (Figure 5) help clarify where cross-class interaction is “available” (exposure) and where it is actually realised (low friending bias).

Universities

Figure 5 shows that universities are distinctive in offering high exposure to high-SES peers for both below- and above-median students. To characterise cross-class interaction in this context—where most people are young and not yet in the labour market—we construct EC, exposure, and friending bias using the *parental* SES of university attendees. (We describe our method of linking kids to parents in Appendix A.5.) We refer to the share of peers with above-median parental SES as *parental exposure*. EC for a university is then the share of above-median (by parental SES) friends among below-median (by parental SES) students’ within-university friendships, and friending bias is $1 - \text{EC}/\text{Exposure}$ within the institution.

There is large heterogeneity across institutions. Table S1 lists the top and bottom universities by EC, exposure, and friending bias. Highly selective institutions combine high parental exposure with high EC (e.g., Cambridge, Imperial, UCL), while post-1992 institutions tend to exhibit lower exposure and, correspondingly, lower EC.

We validate our university-level measures against administrative data from Britton *et al.* [78]. Figure S54 compares parental exposure in our data to the share of students who received FSM before university (“access rate”). Despite differences in definitions (FSM is a strict poverty proxy; parental exposure is a median split on an SES index), the two measures align closely (correlation ≈ -0.5): institutions with higher parental exposure in our data tend to have lower FSM access rates in the admin data, as expected.

We then relate economic connectedness within universities to earnings outcomes. Figure S55 plots our university-level EC (based on parental SES) against Britton *et al.* [78]’s “success rate” (the share of FSM students who reach the top income quintile at age 30). The relationship is strong

(correlation ≈ 0.82): universities where disadvantaged students form more cross-class friendships tend to be those where disadvantaged students subsequently do better in the labour market. This pattern is descriptive, but it is robust to alternative normalisations of EC and consistent with the idea that cross-class social integration during university coincides with stronger economic mobility among disadvantaged students.

Interpretation. Universities appear to be fertile ground for cross-class ties *conditional on attendance* (high exposure, relatively low friending bias). But attendance itself is socioeconomically selective (Figure S10). Policies that widen access while sustaining cross-class social integration—through residential mixing in halls, course- and society-level integration, and support for structured peer programmes—may therefore be especially consequential.

Hobby and Recreation Groups

Hobby and recreation groups are the other low-bias setting highlighted in Figure 5. Figure S56 maps friending bias for these groups by local authority district. In the vast majority of areas, friending bias within hobby and recreation groups is lower than the overall friending bias across all friendships, indicating that—conditional on participation—these groups facilitate cross-class connections at rates closer to random mixing than other settings.

Participation and coverage. Participation in these groups is widespread, even under conservative matching rules. We match users to a hobby/recreation group if: (i) the group exists on Facebook and is not “secret”; (ii) it is classified as hobby/recreation; (iii) it is locally relevant to the user (modal LAD or city matches); and (iv) the user has at least one local friend in the group. Despite these requirements, 39% of users in the analytic sample match to at least one hobby/recreation group. In postcode districts with adequate sample, at least 20% of high-SES users match in 97% of districts, and at least 20% of low-SES users match in 94% of districts.

Interpretation. Although hobby/recreation groups account for a modest share of total friendships (Figure S10), their combination of broad participation and low friending bias makes them promising levers for increasing cross-class interaction. Programme design that reduces cost and time barriers, promotes open membership, and mixes ability levels (e.g., in community sports, music, or maker clubs) may further lower friending bias.

Neighbourhoods

Neighbourhoods account for the largest fraction of assignable friendships for both low- and high-SES individuals (Figure S10), yet they exhibit the highest friending bias (Figure 5). Table S2 lists local authority districts (LADs) at the extremes of EC, exposure, and friending bias. Areas in the South East (e.g., Hart, Surrey Heath, Wokingham) combine high exposure with high EC; several London boroughs and large city LADs appear at the bottom for EC and exposure, while very sparsely populated, remote LADs have unusual friending-bias values (likely reflecting small-network structure).

Scale and segregation. Friending bias in neighbourhoods is sensitive to geographic granularity. As neighbourhood units become coarser (e.g., aggregating to wider districts), measured exposure converges to the broader area composition and friending bias tends to shrink mechanically; at finer scales (e.g., postcode districts), residential sorting and hyper-local interaction yield higher friending bias. The postcode district level used in our decomposition therefore provides a meaningful balance: small enough to capture lived neighbourhoods, yet broad enough to maintain coverage and precision.

Interpretation. Because neighbourhoods generate a large volume of friendships, even modest reductions in friending bias—via mixed-tenure developments, improved transport connectivity that expands feasible friend sets, or co-locating amenities that draw diverse users—could meaningfully increase cross-class ties. The contrast with hobby/recreation groups also suggests that structured, purpose-driven settings may mitigate the tendency toward within-class sorting seen in residential contexts.

B.2 Further Details on the Determinants of Economic Connectedness

In this section, we provide further details on the decomposition we conduct in Figure 5d.

As in Chetty *et al.* [30], we decompose differences in EC by SES into three components: differences in friending shares across settings, differences in exposure within settings, and differences in friending bias. We provide formal definitions of each in Appendix A.3.

Since friending bias and exposure can only be calculated in reference to a particular community, we focus on friendships we can assign to one of nine settings: (1) geographic neighbourhoods, (2) secondary schools, (3) sixth-form colleges, (4) universities, (5) workplaces, (6) faith-based communities, (7) hobby and recreation groups, (8) activism groups, and (9) volunteering

groups. Appendix A.4 outlines how we assign users to particular groups within settings.

We construct economic connectedness for a representative low-SES individual by taking the weighted average of economic connectedness within each of our nine settings, with weights corresponding to the average share of assigned friendships assigned to that particular setting over all low-SES individuals. This yields a value of economic connectedness for our representative low-SES individual of 0.494. A similar procedure for a representative high-SES individual yields a value of economic connectedness of 0.603. These values closely match the values of economic connectedness for low- and high-SES individuals calculated using all friendships. We now break down this difference in connectedness between our representative low-SES and high-SES individuals.

Suppose that we reassigned the share of friends our representative low-SES individual makes in each setting to be equal to the share of friends made in each setting by our representative high-SES individual. Then this would only close a small portion of the gap in EC between our representative individuals. Specifically, it would shift EC for our representative low-SES individual from 0.494 to 0.504. As a result, even though the share of friendships made in each setting varies dramatically by SES, as shown in Figure S10, equating these shares would do little to close the gap in connectedness between low- and high-SES individuals.

Now, we equate both the friending shares and exposure of the representative low-SES individual to those of the representative high-SES individual, while keeping the friending bias in each setting of the representative low-SES individual constant. This closes about 33% of the gap in connectedness between our two representative individuals, moving EC for the representative low-SES individual from 0.504 to 0.539.

On the other hand, equating both the friending shares and friending bias of the representative low-SES individual to those of the representative high-SES individual, while keeping the exposure in each setting of the representative low-SES individual constant, closes about two thirds of the gap by moving the EC of the representative low-SES agent to 0.570, with about 60% of the gap being closed by friending bias alone.

B.3 Multiplexing

Using our assignments of friendships to settings, we are able to analyse the degree to which friendships overlap across several settings. For example, are you likely to also interact with your connections from work in faith-based settings? When a connection spans several settings, such as occurring in the workplace and a hobby and recreation group, that relationship is *multiplexed* [79, 80]. Understanding multiplexity is important because multiplexed relationships, by virtue

of their value in multiple settings, may enable greater levels of cooperation in relationships [81] and experimental evidence shows that the degree of multiplexity in relationships affects the speed with which new information spreads through a society [82].

Figure S57 shows the probability of friendships in each setting also being assigned to another setting relative to the probability of any friendship being assigned to that setting. For example, a friendship we assign to the religious setting is 3.82 times more likely to also be assigned to a hobby and recreation setting than a random friendship. Similarly, neighbourhood friendships are also around three times as likely to also exist within religious groups and hobby and recreation than a random friendship. University friendships, on the other hand, are about five times *less* likely to be within-neighbourhood friendships than a random friendship, partly reflecting the fact that UK universities draw in students from across the country, many of whom they do not remain in the same area upon graduating.

We follow Chandrasekhar *et al.* [82] in constructing a multiplexing index for each individual. This multiplexing index represents, for each user, the fraction of friendships assigned to at least one setting that are assigned to two or more settings. Formally, letting $\mathbf{A}^s$ denote the adjacency matrix including only friendships in setting s (with entries a_{ij}^s), and $\mathcal{S}$ denote the set of settings to which we assign friendships (neighbourhoods, secondary schools, universities, workplaces, hobby and recreation groups, and faith-based communities) our multiplexing index m_i for individual i is:

$$m_i = \frac{\sum_j \frac{\sum_{s \in \mathcal{S}} a_{ij}^s}{S}}{\sum_j \mathbf{1} \left(\sum_{s \in \mathcal{S}} a_{ij}^s > 0 \right)}$$

where $\mathbf{1}$ denotes the indicator function. (We exclude sixth form as a setting in this section, since in many cases secondary schools have sixth-forms built in to them.)

In Figure S58, we plot the average multiplexing index over individuals by SES and gender. We see that multiplexity is a more common feature of friendships for women than men. This was also found in the social networks of villages in Karnataka, India [82], although in that study the notion of multiplexing is across different types of support as opposed to friendships and connections that span multiple settings. We also see an n-shape pattern in multiplexity for both men and women by SES rank, with this pattern being more noticeable for men. Individuals in the middle of the SES distribution tend to have more multiplexed friendships than those at the far tails.

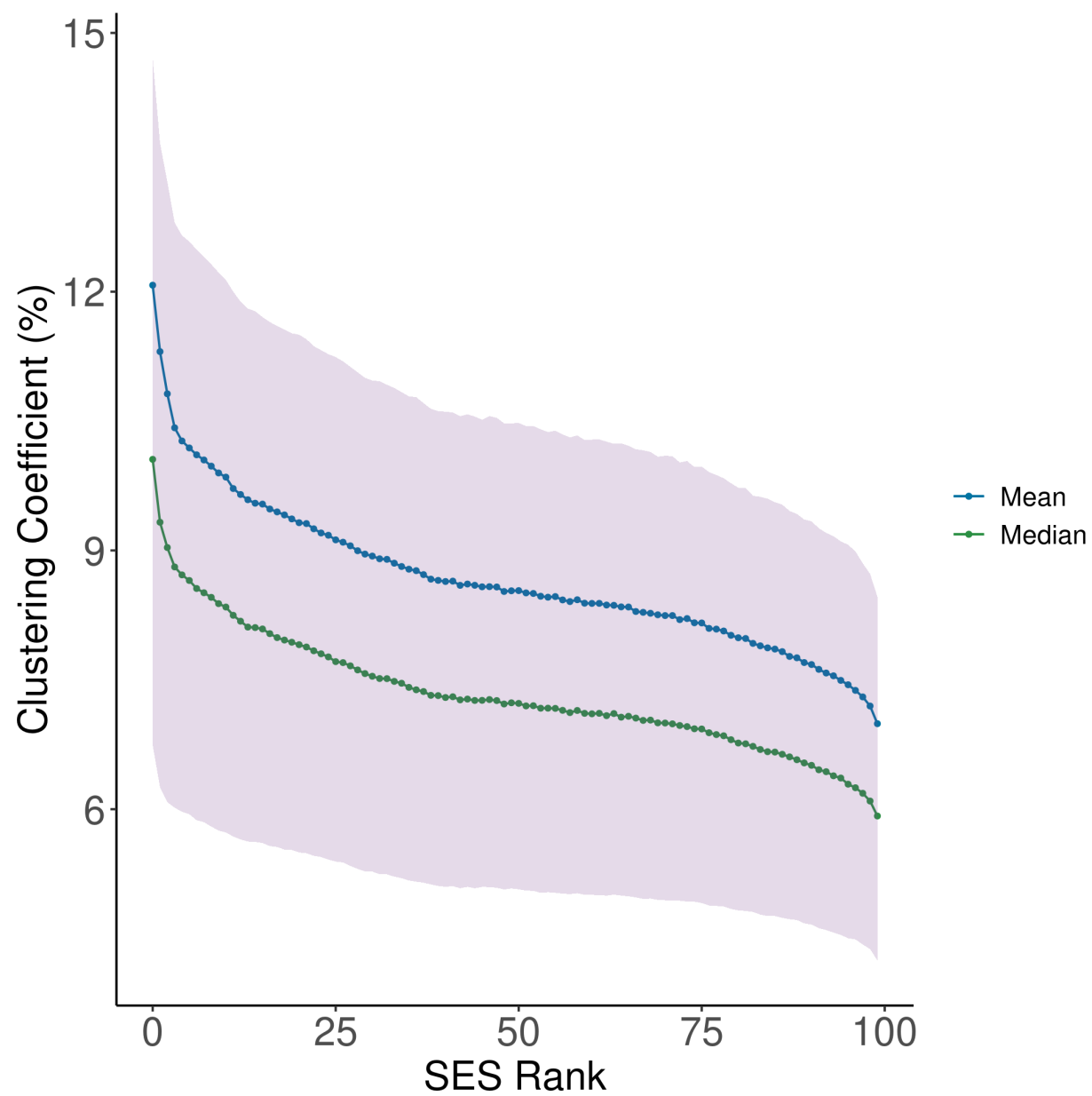
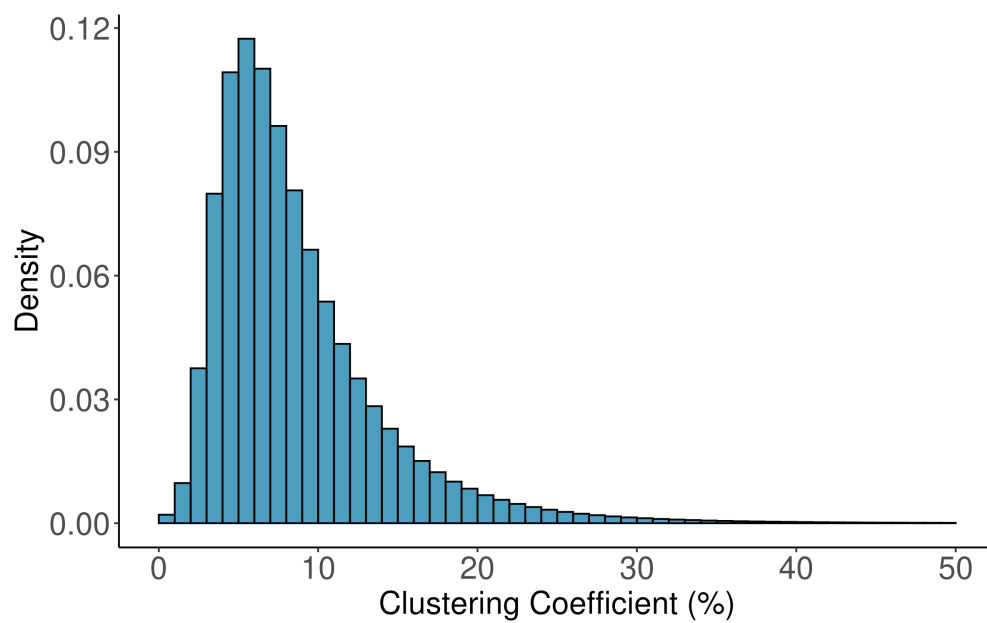
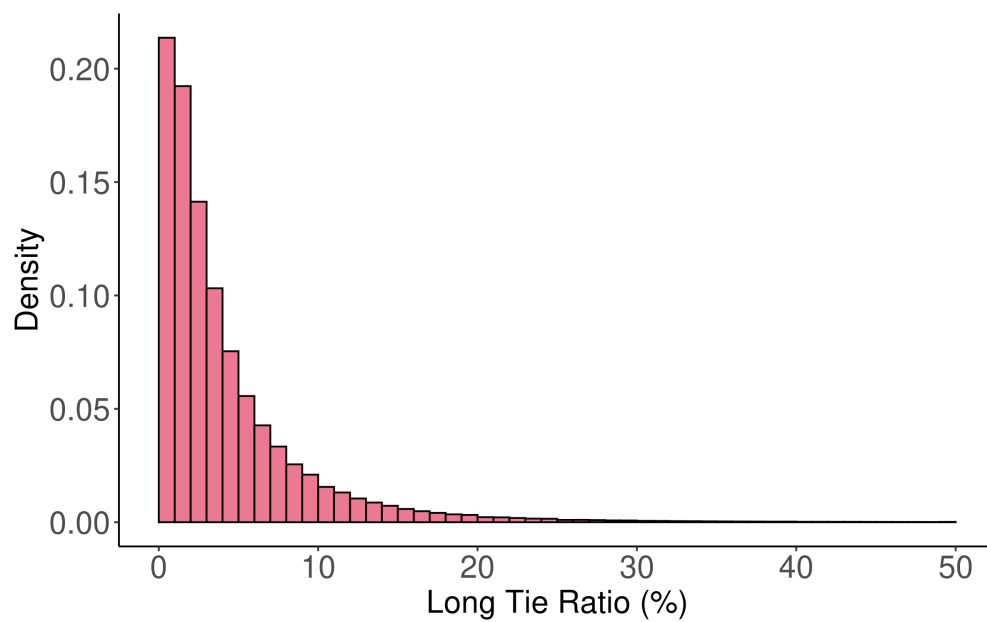


FIGURE S1: Local clustering coefficient, by SES.

Notes for Figure S1: The shaded area in this figure represents the 25th and 75th percentile of the user-level distribution of the local clustering coefficient at each SES centile.



(A) Clustering Coefficient



(B) Long-Tie Ratio

FIGURE S2: User-level histograms for the local clustering coefficient and long-tie ratio.

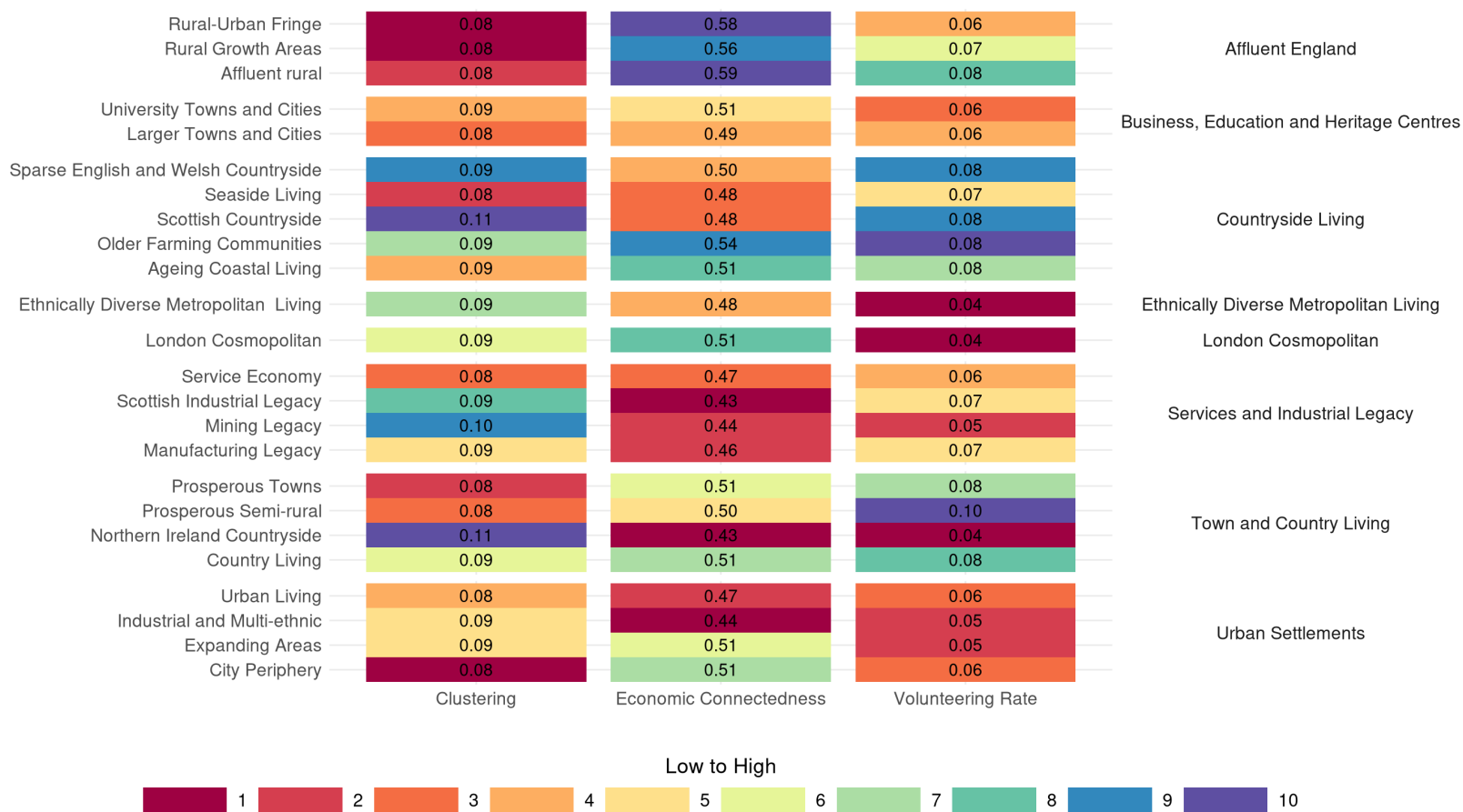
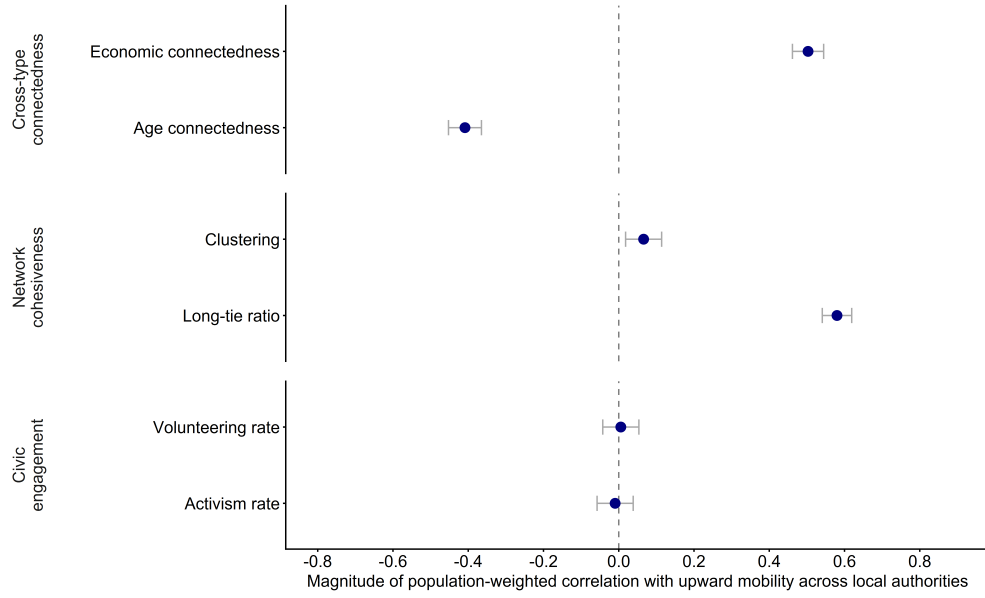
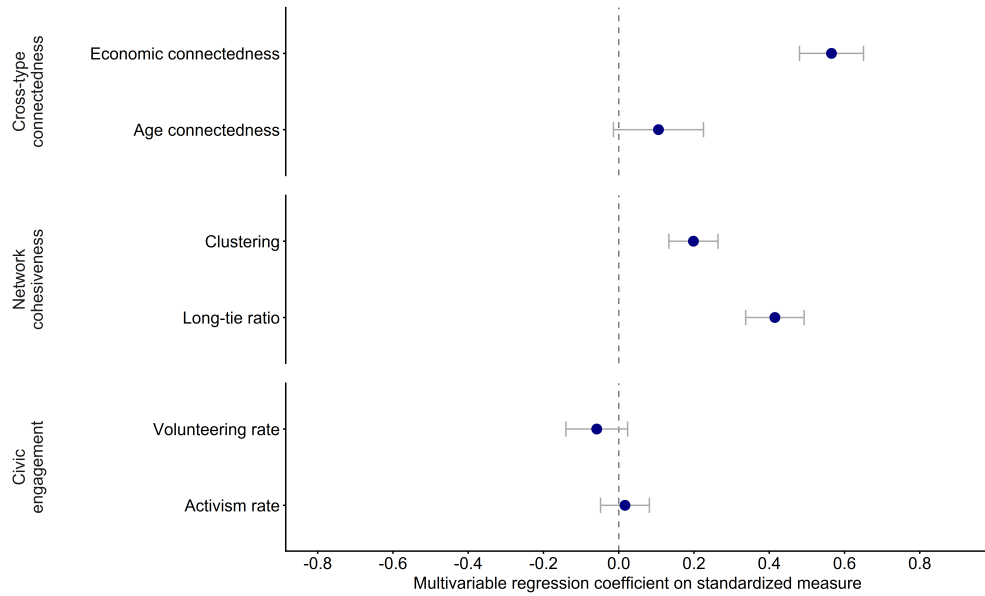


FIGURE S3: Social capital by ONS Area Classifications.



(A)



(B)

FIGURE S4: Postcode–district–level relationships between economic mobility and social capital measures. **A**, Bivariate correlations between economic mobility and individual social capital metrics. **B**, Coefficients from multivariable regressions of economic mobility on all social capital measures. Both the outcome and dependent variables standardized to have a mean of zero and a standard deviation of one. Intervals represent 95% confidence intervals calculated using heteroskedasticity-robust standard errors clustered by postcode area. All correlations and regressions are weighted by the number of FSM–eligible pupils in each postcode district. Owing to incomplete geographical coverage, Language connectedness is excluded from the postcode district–level analysis.

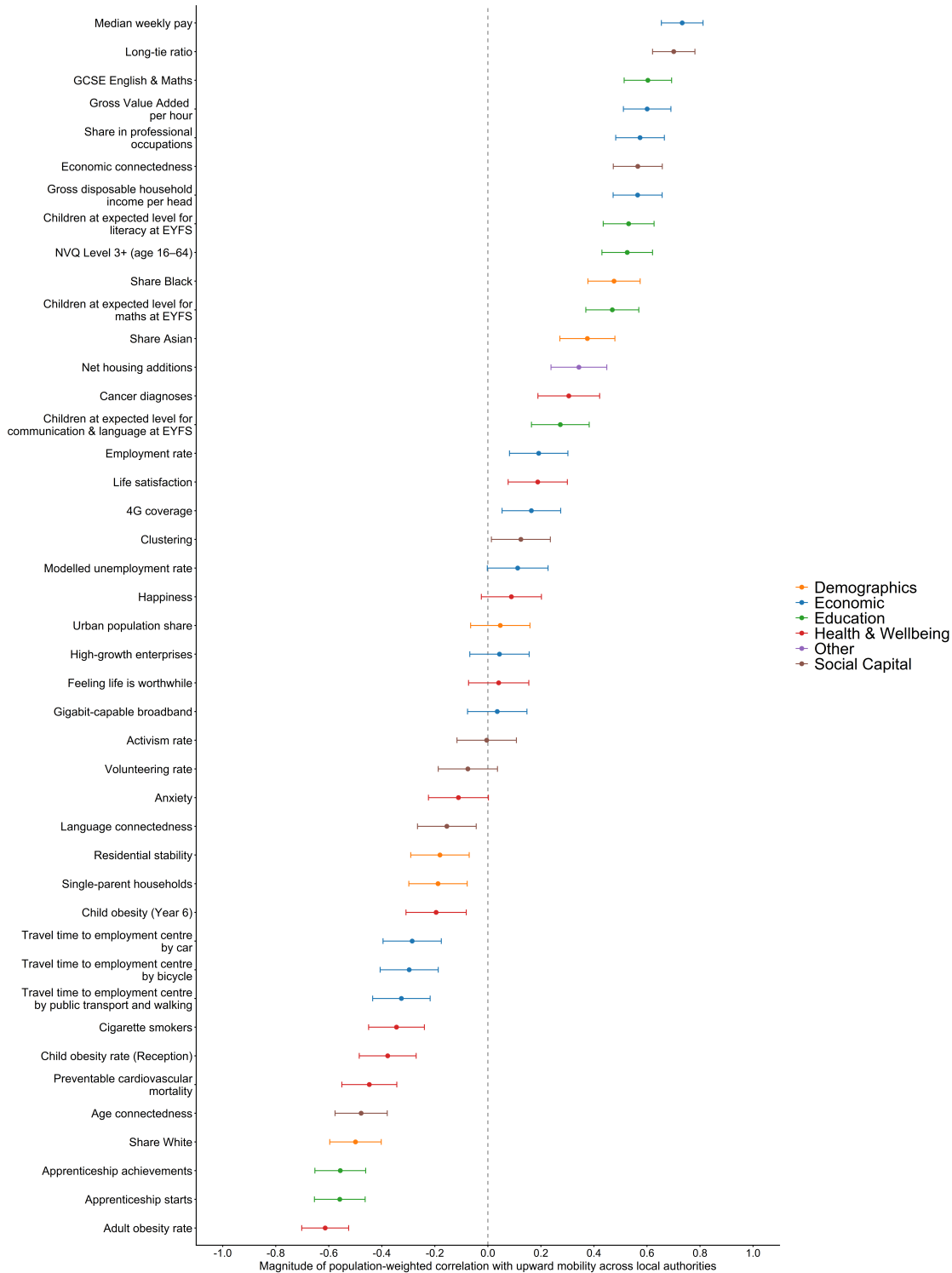


FIGURE S5: Local authority-level bivariate correlations between economic mobility and area characteristics. *Notes:* Demographic variables are sourced from [42]. All other area statistics are sourced from [41]. Details on all variables appear in A.8. All correlations are weighted by the number of FSM-eligible pupils in each local authority. Intervals represent coefficient standard errors.

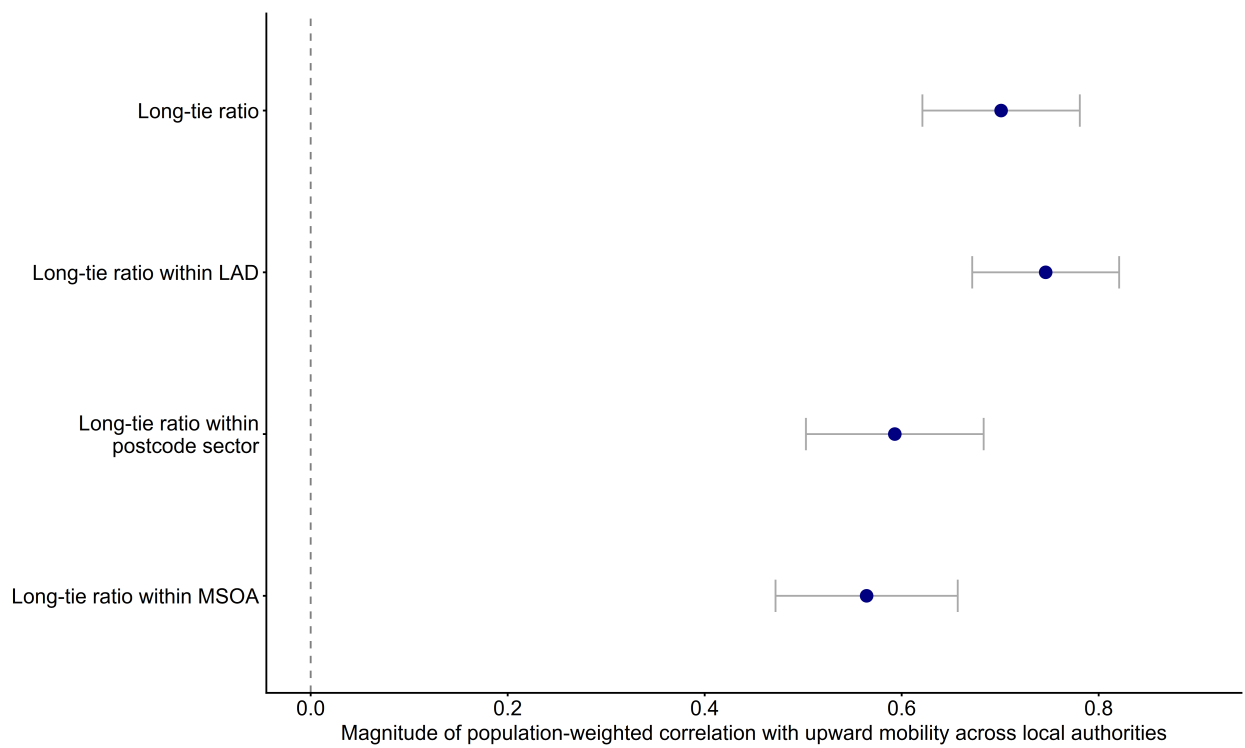


FIGURE S6: Long-tie ratio relationship with economic mobility by geographic friendship restrictions.

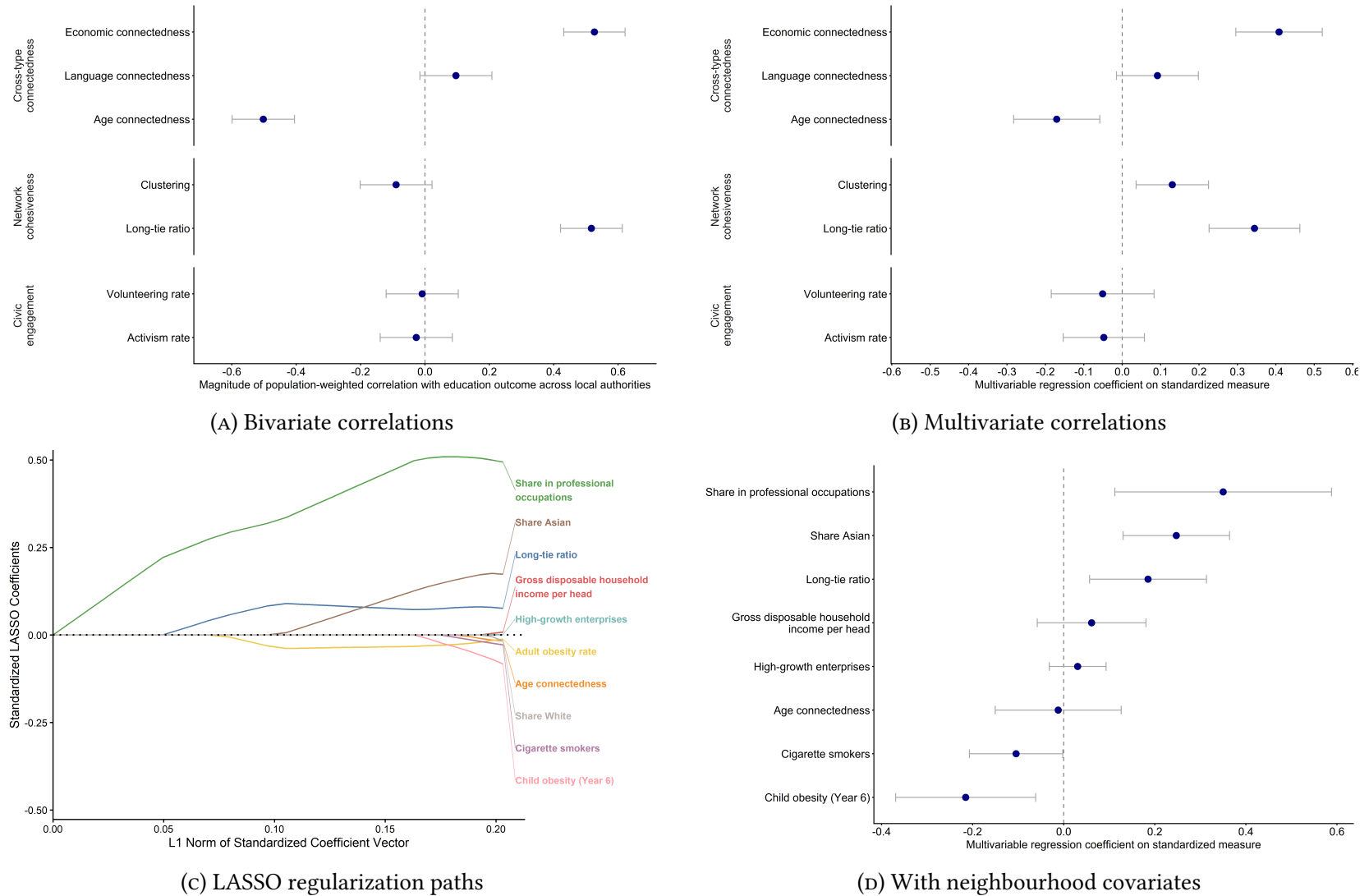


FIGURE S7: Local authority-level relationships between educational attainment and measures of social capital.

Notes for Figure S7: All correlations and regressions reported are at the local-authority level and are weighted by the number of pupils in the local authority. Error bars represent 95% confidence intervals constructed from heteroskedasticity-robust standard errors. Panel (C) shows the L1-penalized LASSO regularization paths from a model of educational attainment on the full set of social-capital measures and other neighbourhood characteristics drawn from government statistics [41, 42] (All variables used are specified in A.8). Panel (D) uses the leading variables selected by the LASSO.

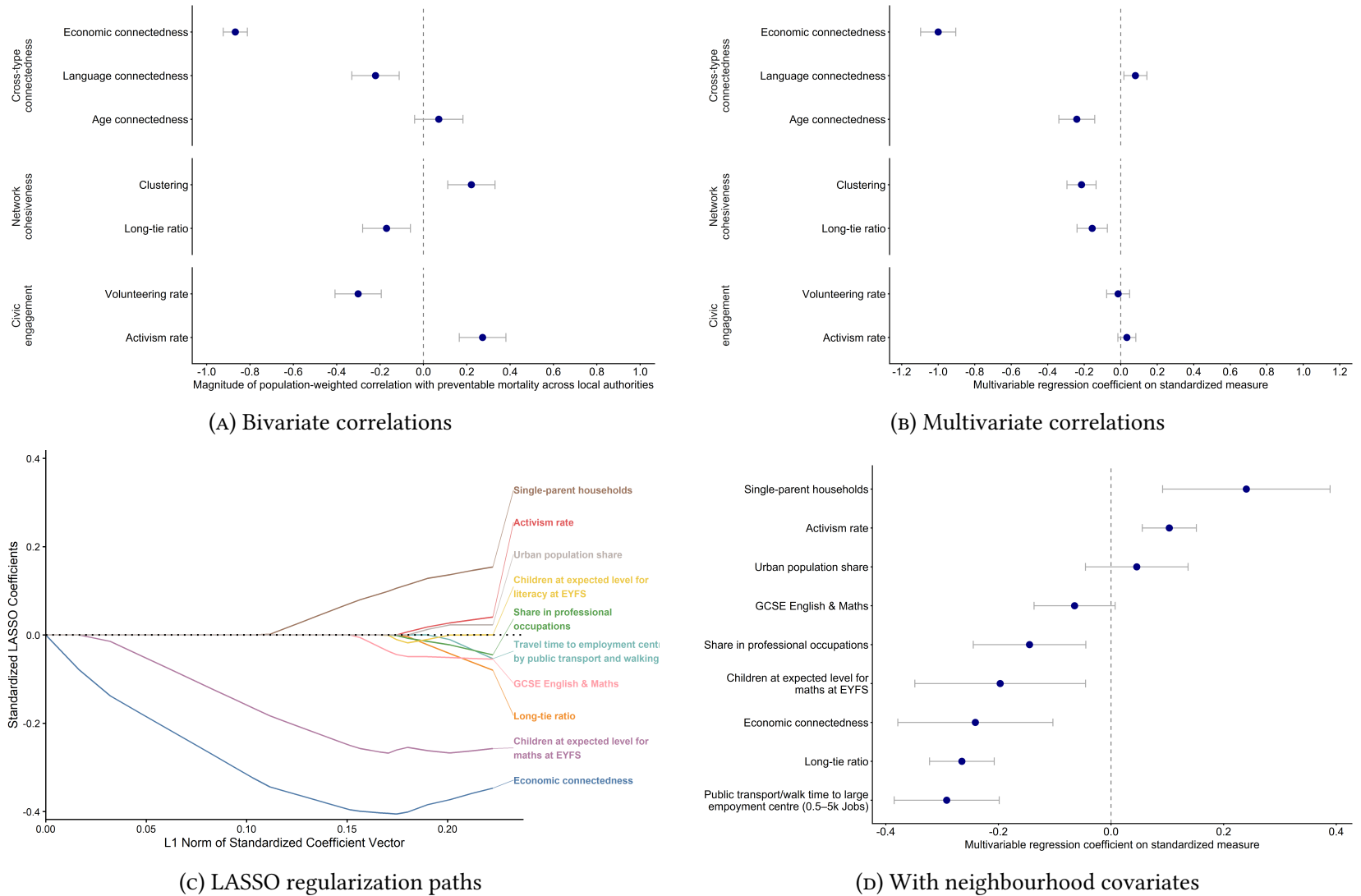


FIGURE S8: Local authority-level relationships between preventable mortality and measures of social capital.

Notes for Figure S8: All correlations and regressions reported are at the local-authority level and are weighted by the local authority population. Error bars represent 95% confidence intervals constructed from heteroskedasticity-robust standard errors. Panel (C) shows the L1-penalized LASSO regularization paths from a model of preventable mortality on the full set of social-capital measures and other neighbourhood characteristics drawn from government statistics [41, 42] (All variables used are specified in A.8). Panel (D) uses the leading variables selected by the LASSO.

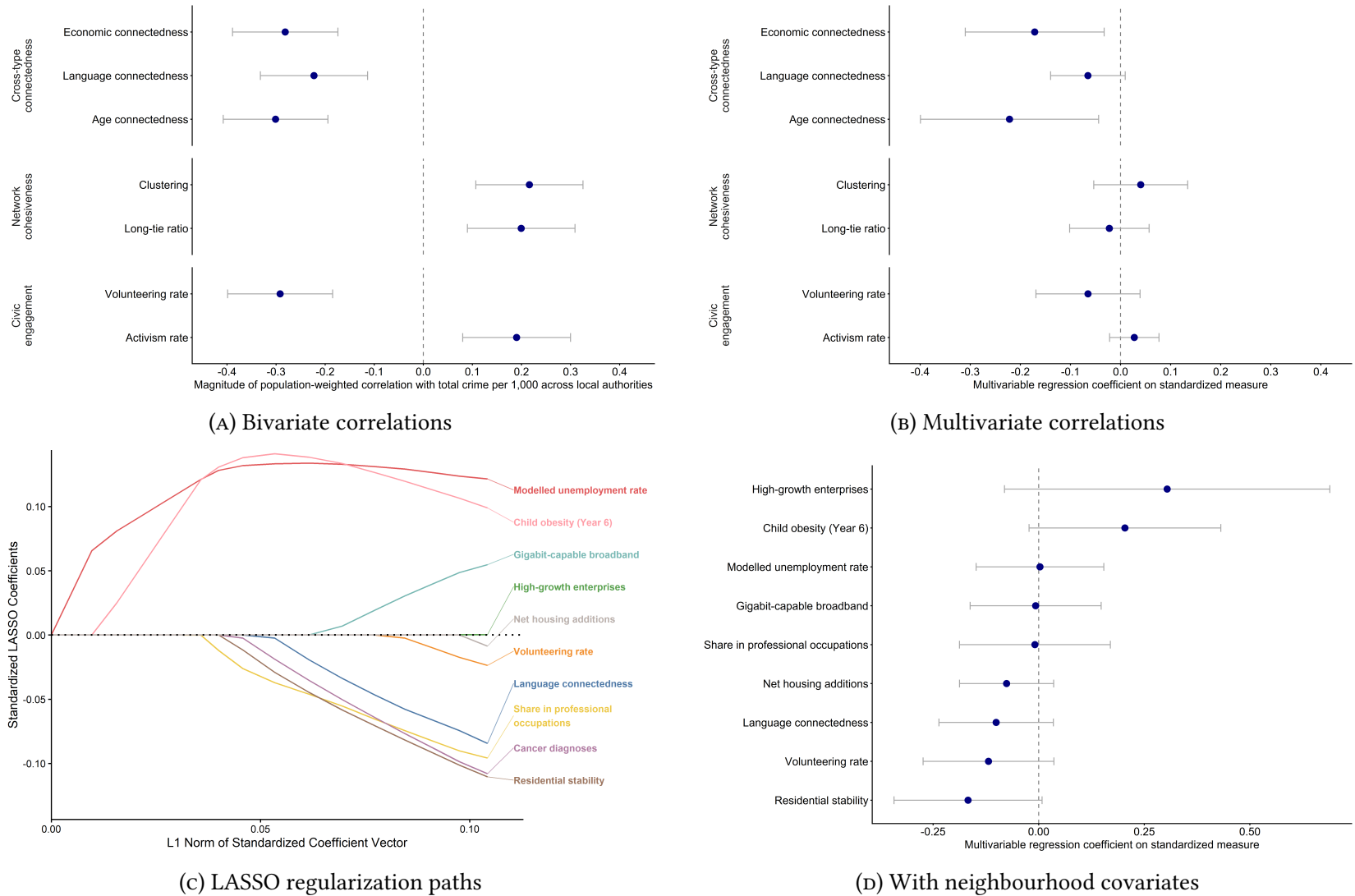


FIGURE S9: Local authority-level relationships between crime and measures of social capital.

Notes for Figure S9: All correlations and regressions reported are at the local-authority level and are weighted by the local authority population. Error bars represent 95% confidence intervals constructed from heteroskedasticity-robust standard errors. Panel (C) shows the L1-penalized LASSO regularization paths from a model of crime on the full set of social-capital measures and other neighbourhood characteristics drawn from government statistics [41, 42] (All variables used are specified in A.8). Panel (D) uses the leading variables selected by the LASSO.

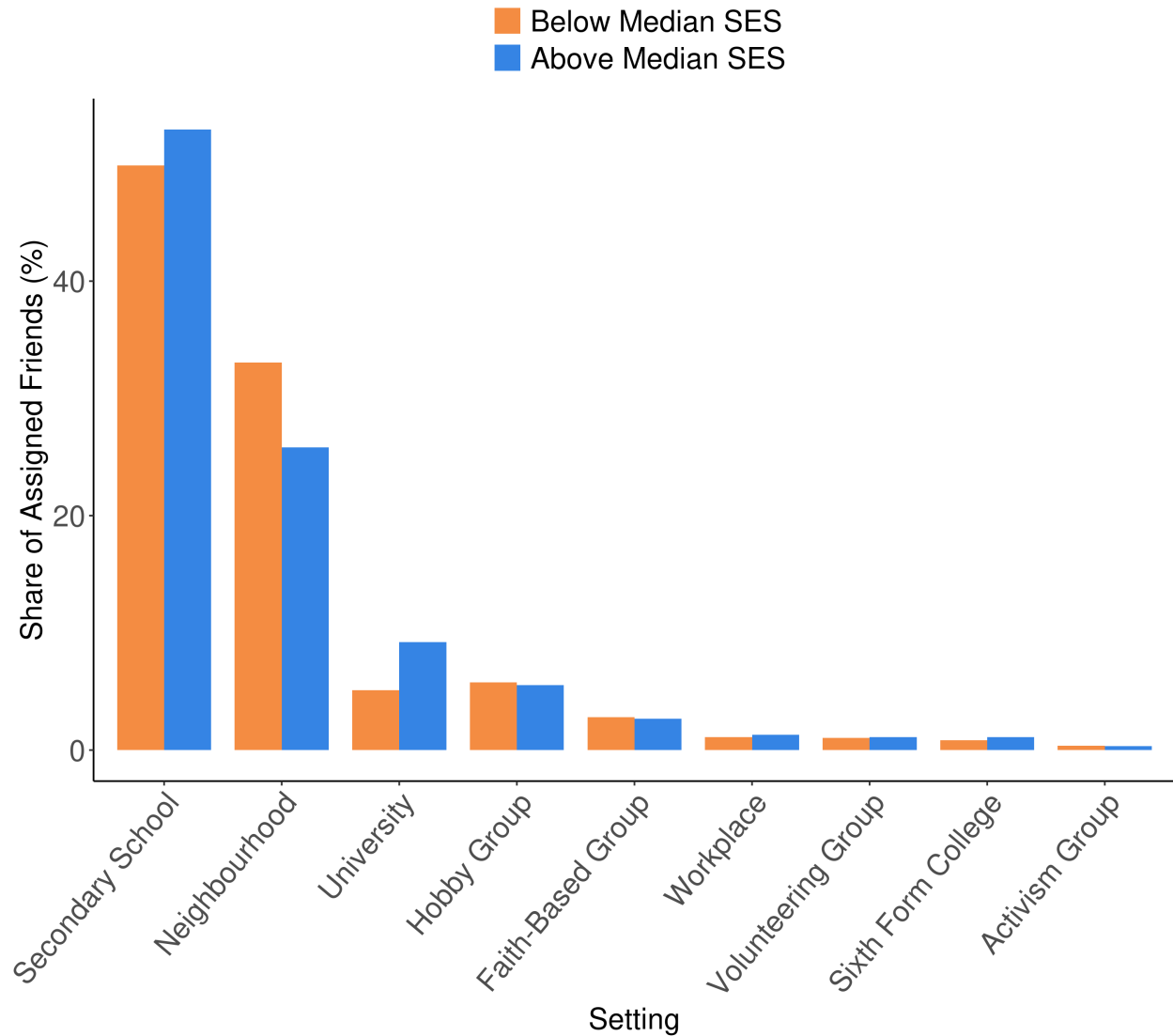


FIGURE S10: Friending shares by setting, for below- vs. above-median SES users.

Notes for Figure S10: This figure captures the average share of users' total friendships assigned to any setting made in each setting, separately for above- and below-median SES users in our sample.

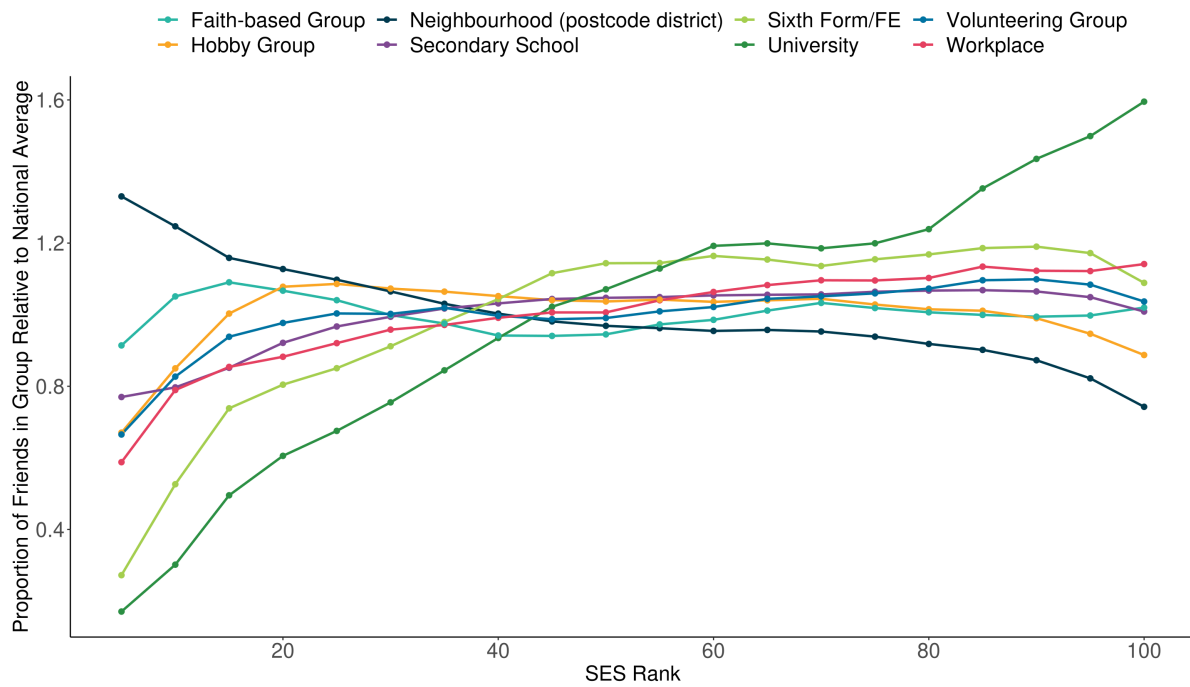


FIGURE S11: Relative friending shares by setting and SES ventile.

Notes: Dots plot the ventile-specific average share in each setting divided by the overall average share in that setting (see text).

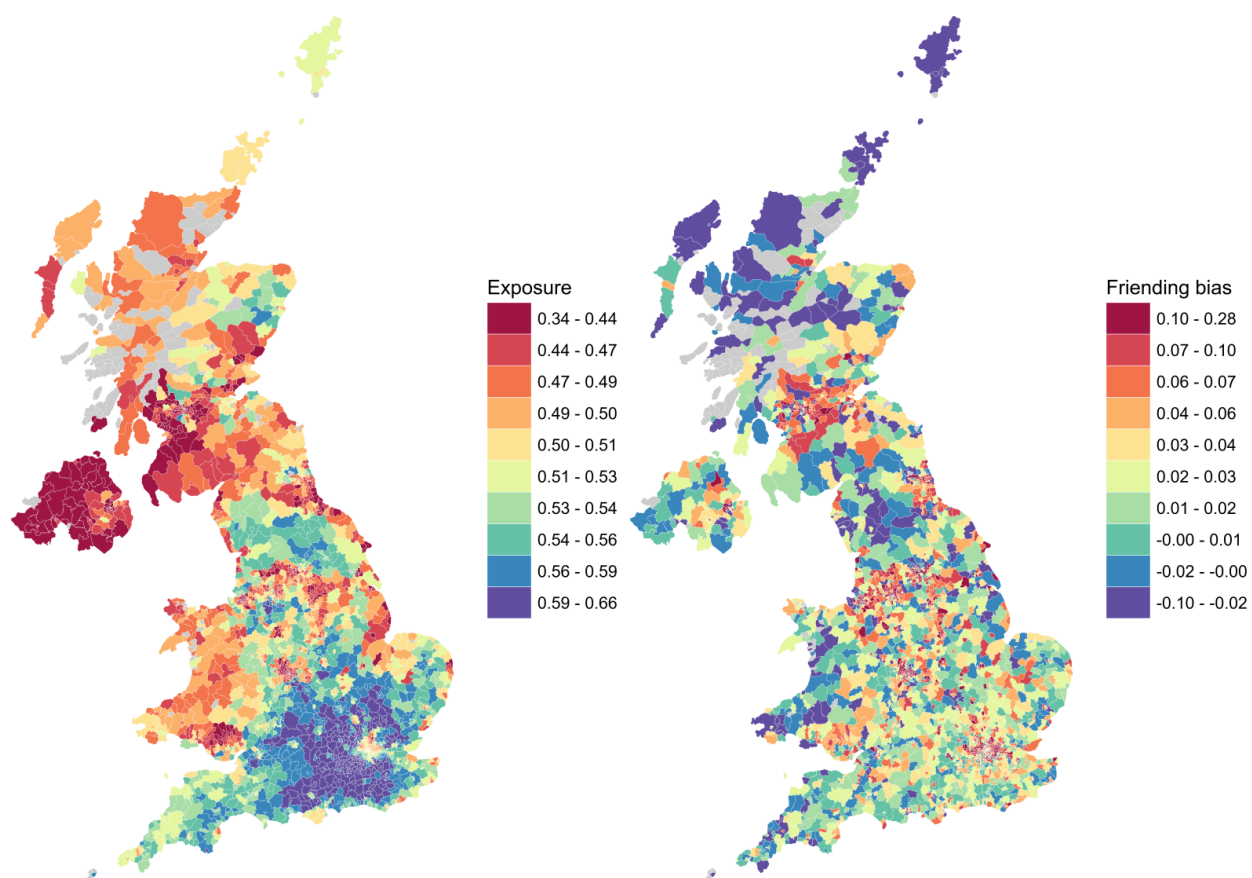


FIGURE S12: Exposure and friending bias by postcode district across the UK.

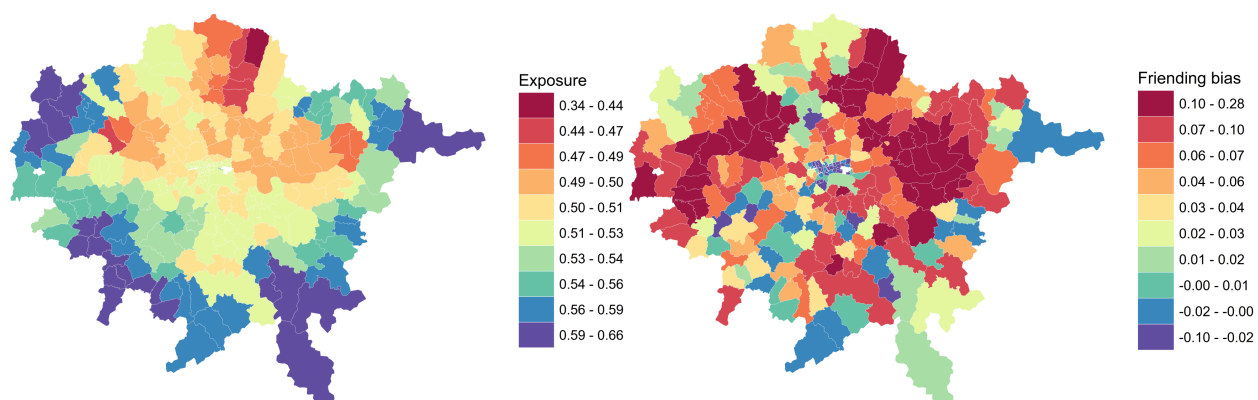


FIGURE S13: Exposure and friending bias by postcode district in Greater London.

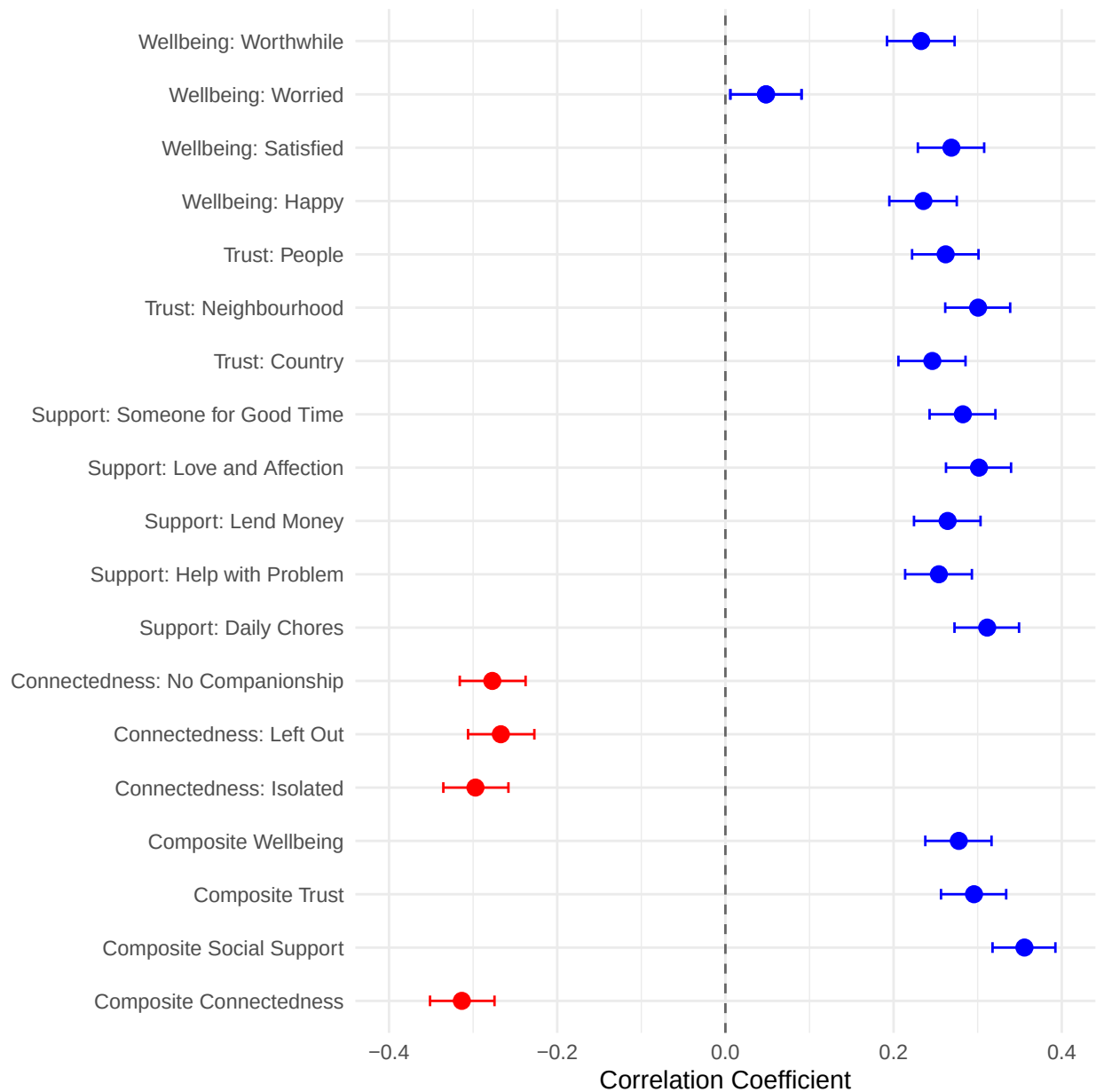
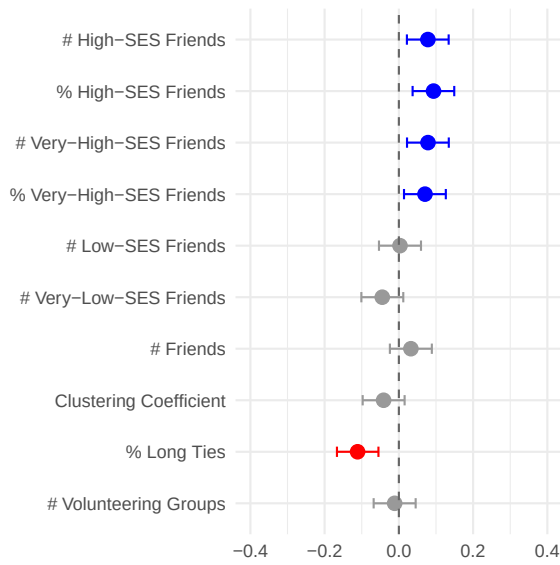
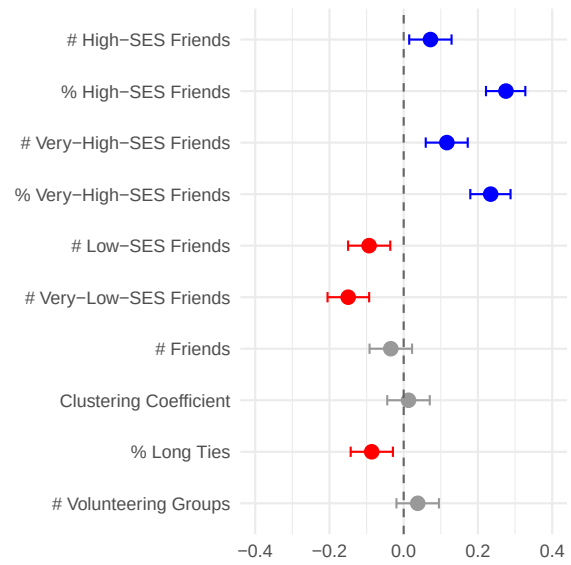


FIGURE S14: Bivariate correlations between self-reported household income and survey responses.

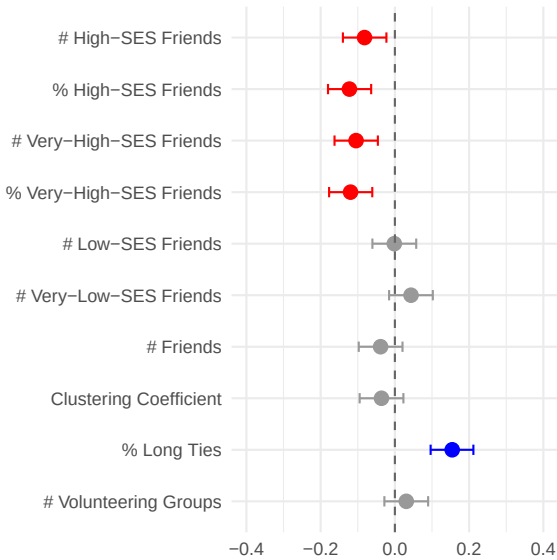
Notes: Each dot represents the bivariate correlation between standardised self-reported income and a standardised survey response. Bars denote 95% confidence intervals. $N = 2,138$ (respondents with non-missing income).



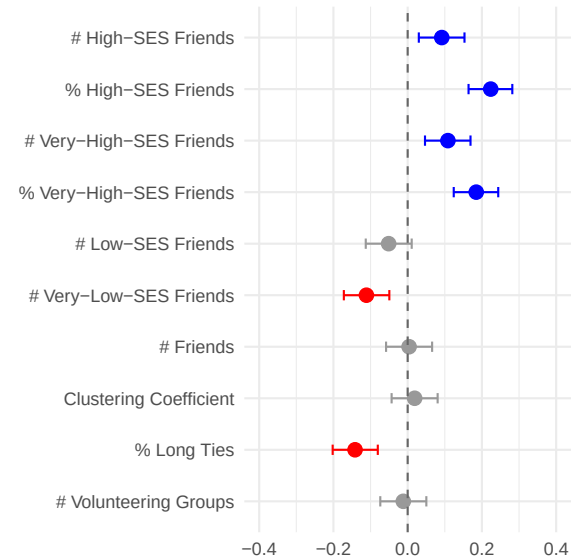
(A) Composite Wellbeing



(B) Composite Trust



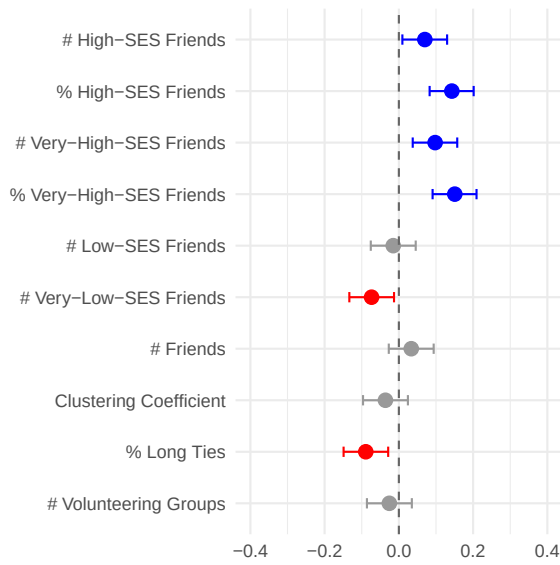
(C) Composite Connectedness



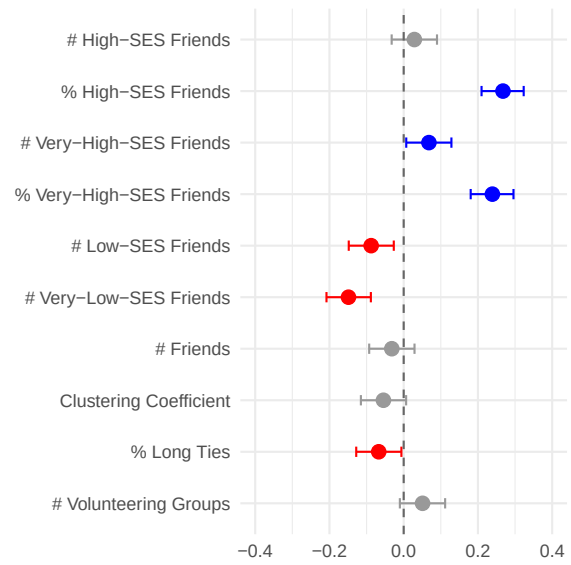
(D) Composite Social Support

FIGURE S15: Bivariate correlations between individual-level social capital measures and composite survey measures for low-SES individuals.

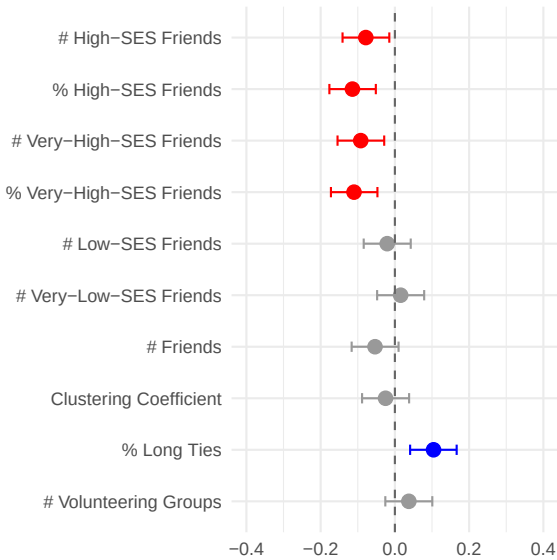
Notes: Each dot represents the coefficient from a bivariate regression of the standardised survey composite on a standardised social capital measure (equation 1). Bars denote 95% confidence intervals. A high-SES friend is defined as a friend with above-median SES within their birth cohort; a very high-SES friend has SES in the top decile.



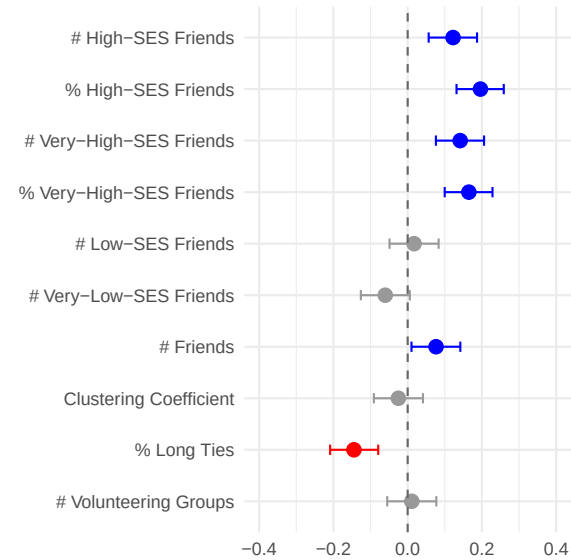
(A) Composite Wellbeing



(B) Composite Trust



(C) Composite Connectedness



(D) Composite Social Support

FIGURE S16: Bivariate correlations between individual-level social capital measures and composite survey measures for high-SES individuals.

Notes: Each dot represents the coefficient from a bivariate regression of the standardised survey composite on a standardised social capital measure (equation 1). Bars denote 95% confidence intervals. A high-SES friend is defined as a friend with above-median SES within their birth cohort; a very high-SES friend has SES in the top decile.

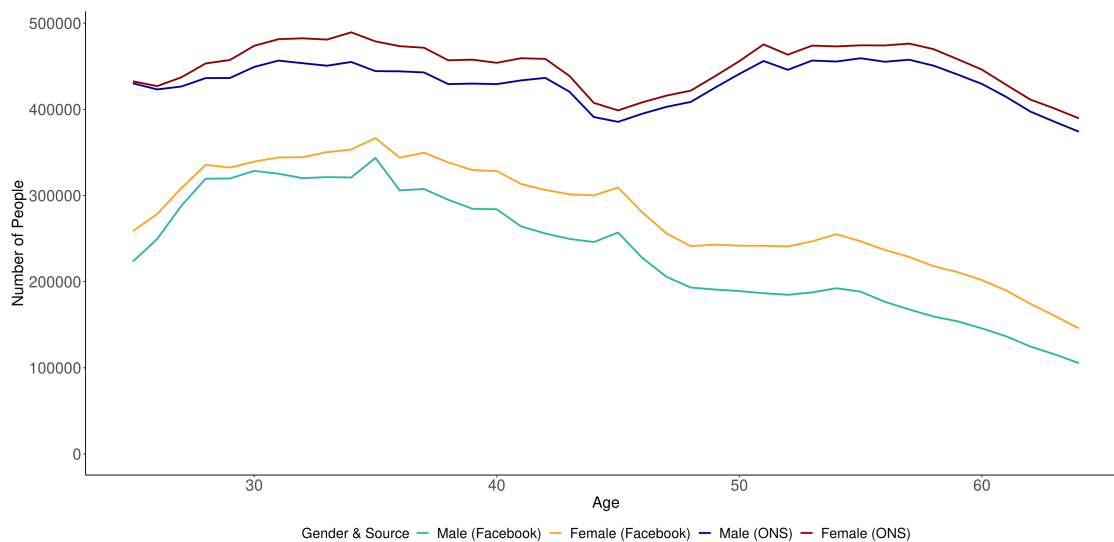


FIGURE S17: Age Distribution by Gender in the Analytic Sample.

Notes for Figure S17: The ONS series uses data from [55] on national mid-year population estimates for the UK and its constituent countries, by age and sex. We compare these counts to the Facebook analytic sample (ages 25–64).

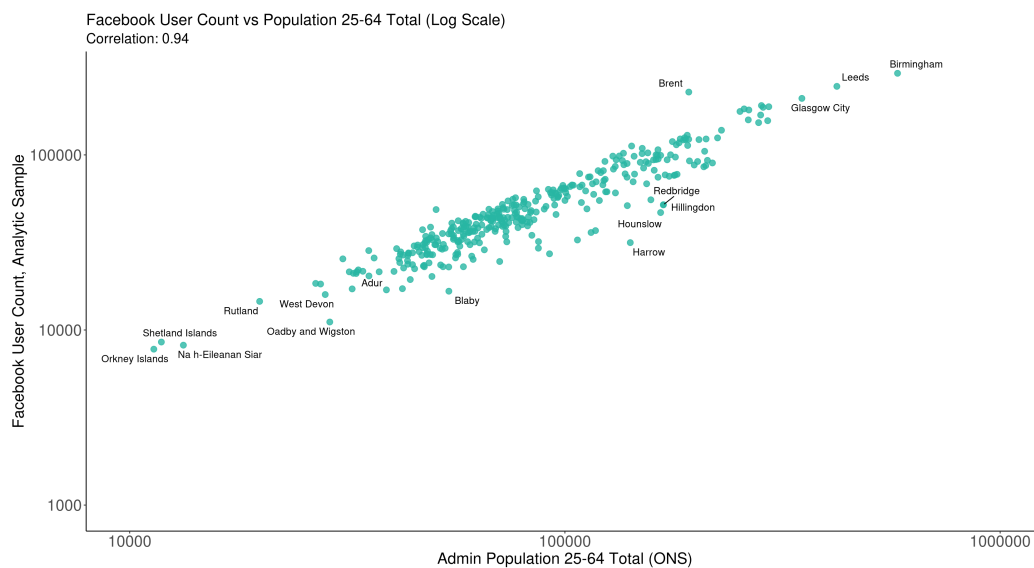


FIGURE S18: Correlation between analytic-sample user counts and administrative population counts for 25–64 year-olds by administrative area.

Notes for Figure S18: The ONS series uses data from [55] on national mid-year population estimates for the UK and its constituent countries, by age and sex. We compare these to Facebook analytic-sample counts for ages 25–64.

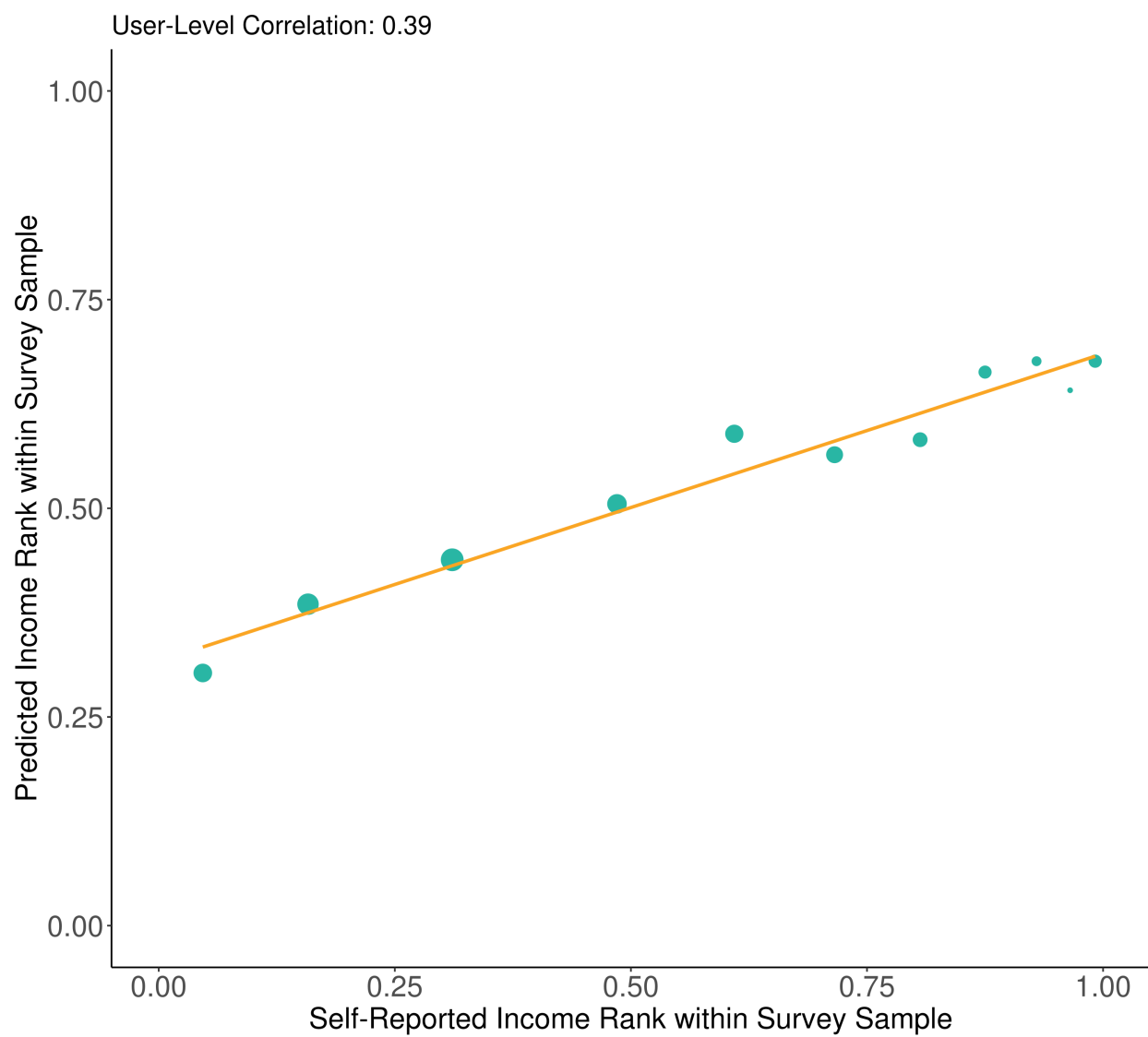


FIGURE S19: Binned scatter plot of self-reported income vs. predicted SES for 2,138 respondents to our well-being survey.

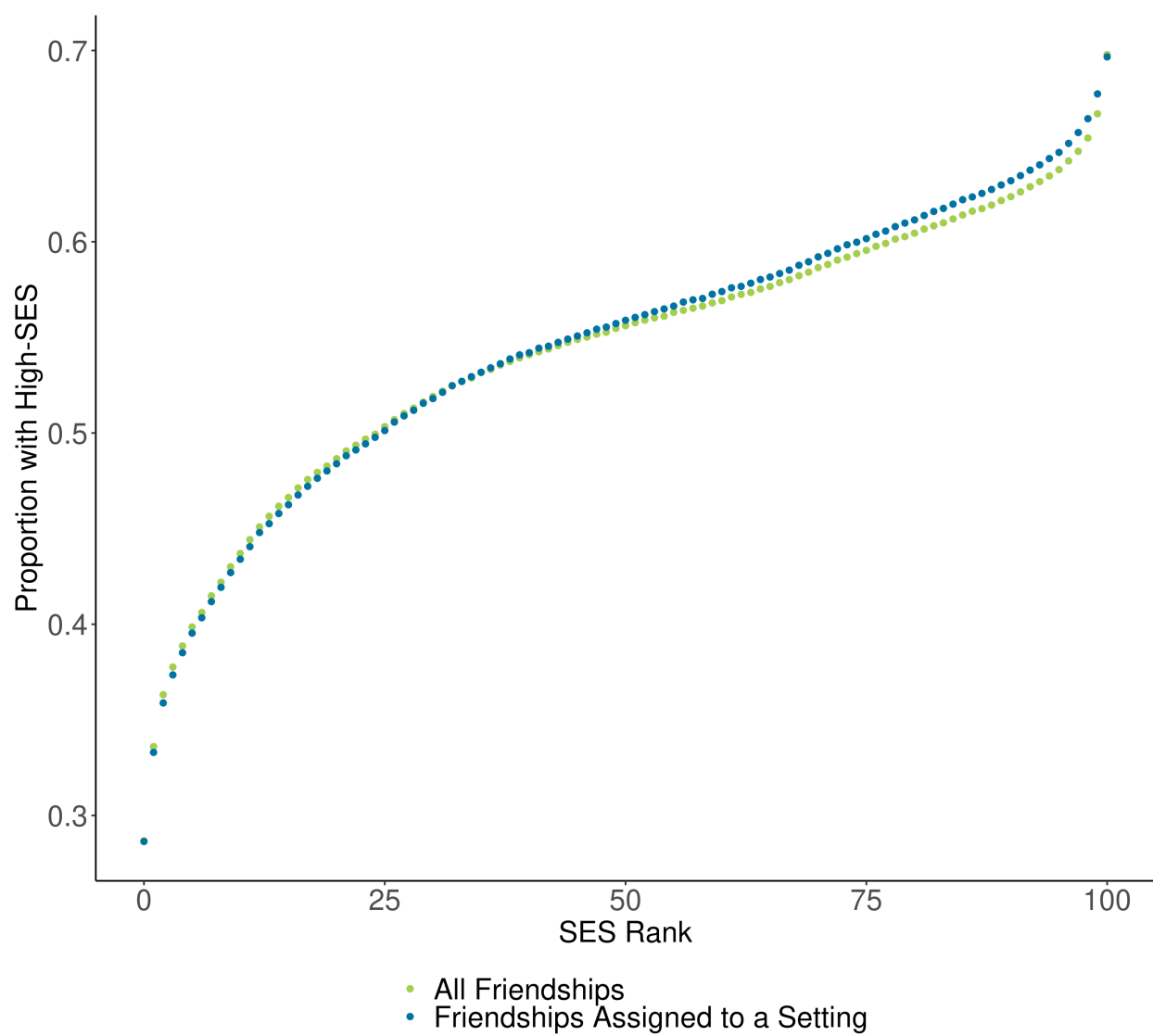


FIGURE S20: High-SES share among all friendships vs. among friendships assigned to a setting, by ego SES.

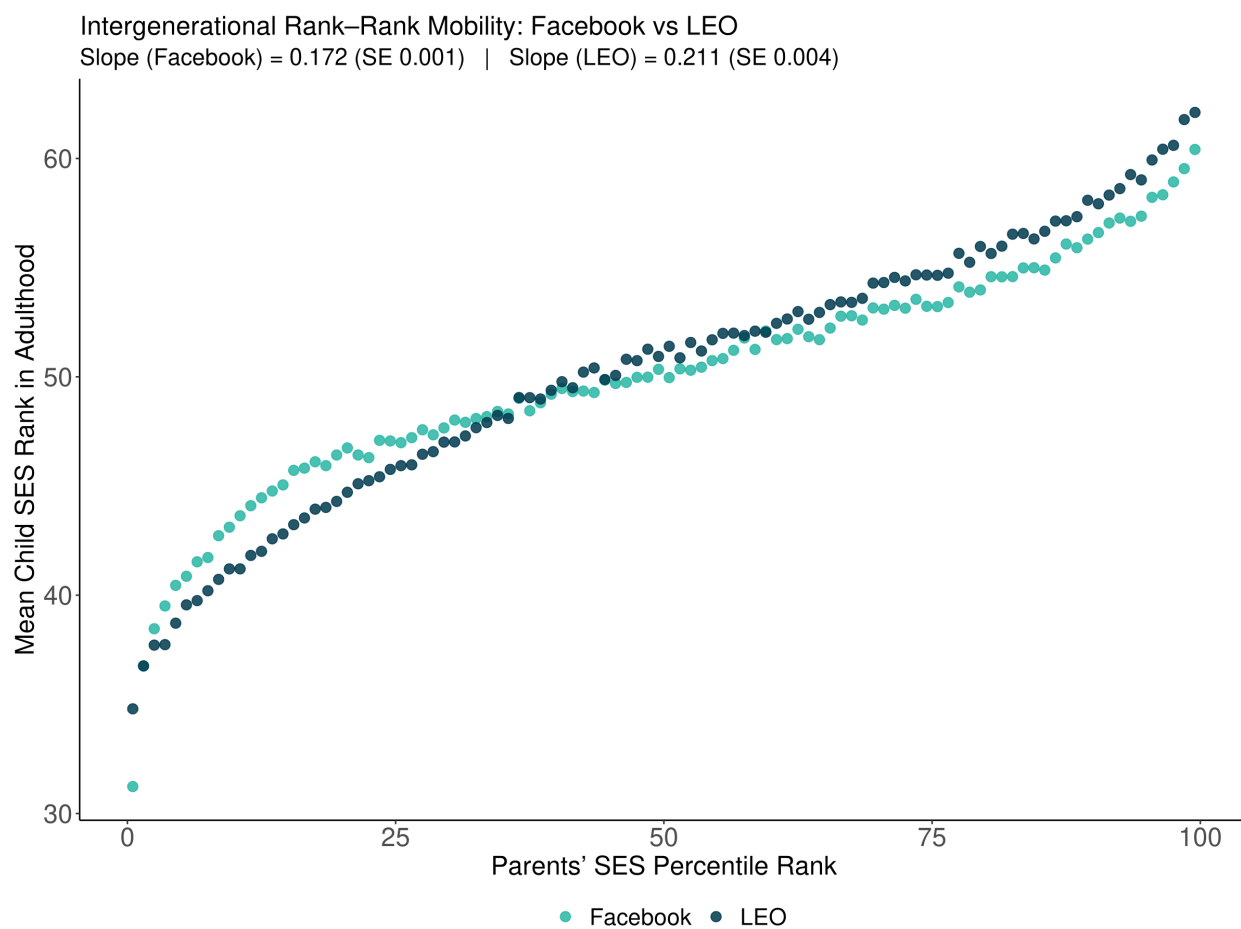


FIGURE S21: Intergenerational persistence of socioeconomic status in Facebook and LEO data.

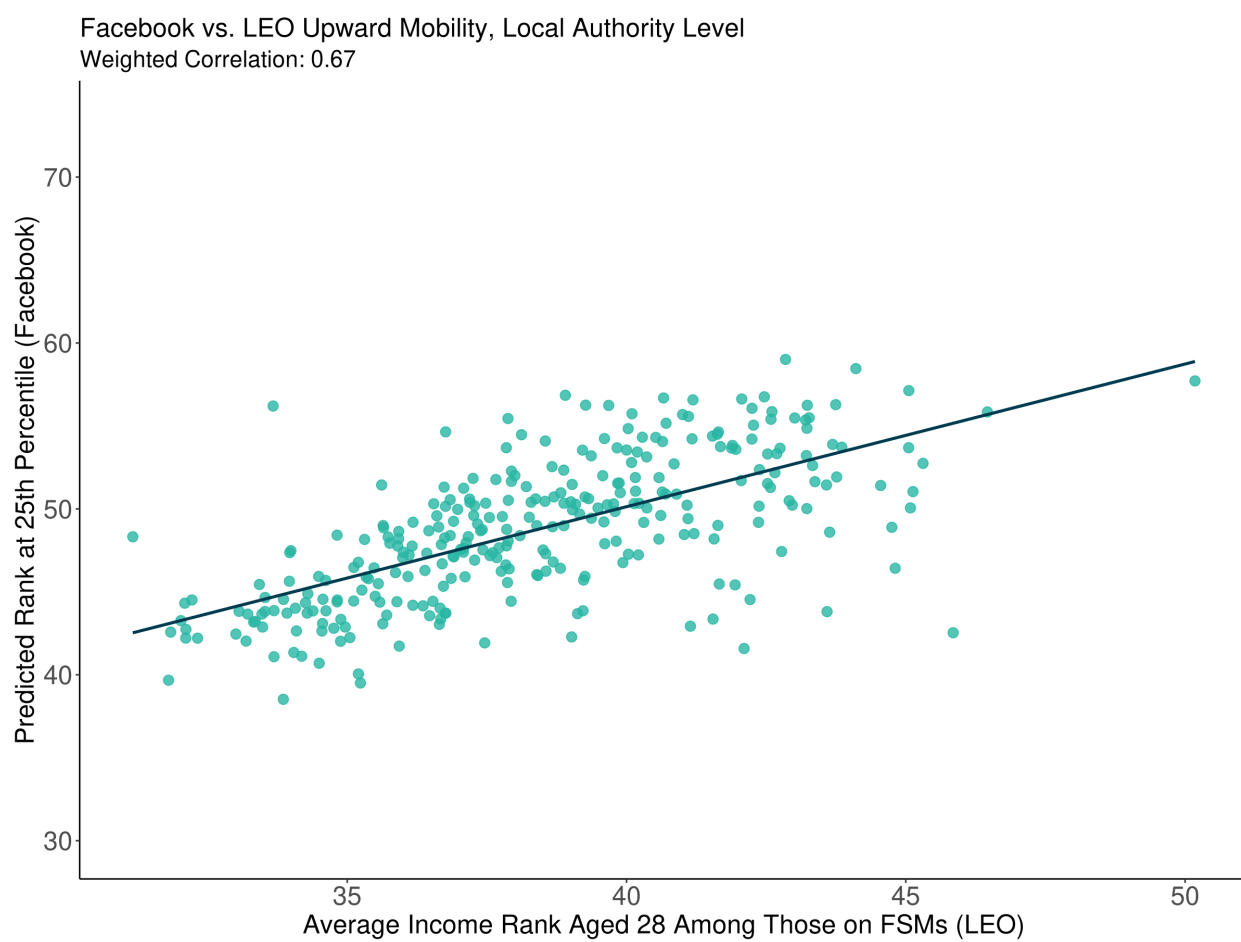


FIGURE S22: Correlation between Facebook and LEO economic mobility estimates at local-authority level (England).

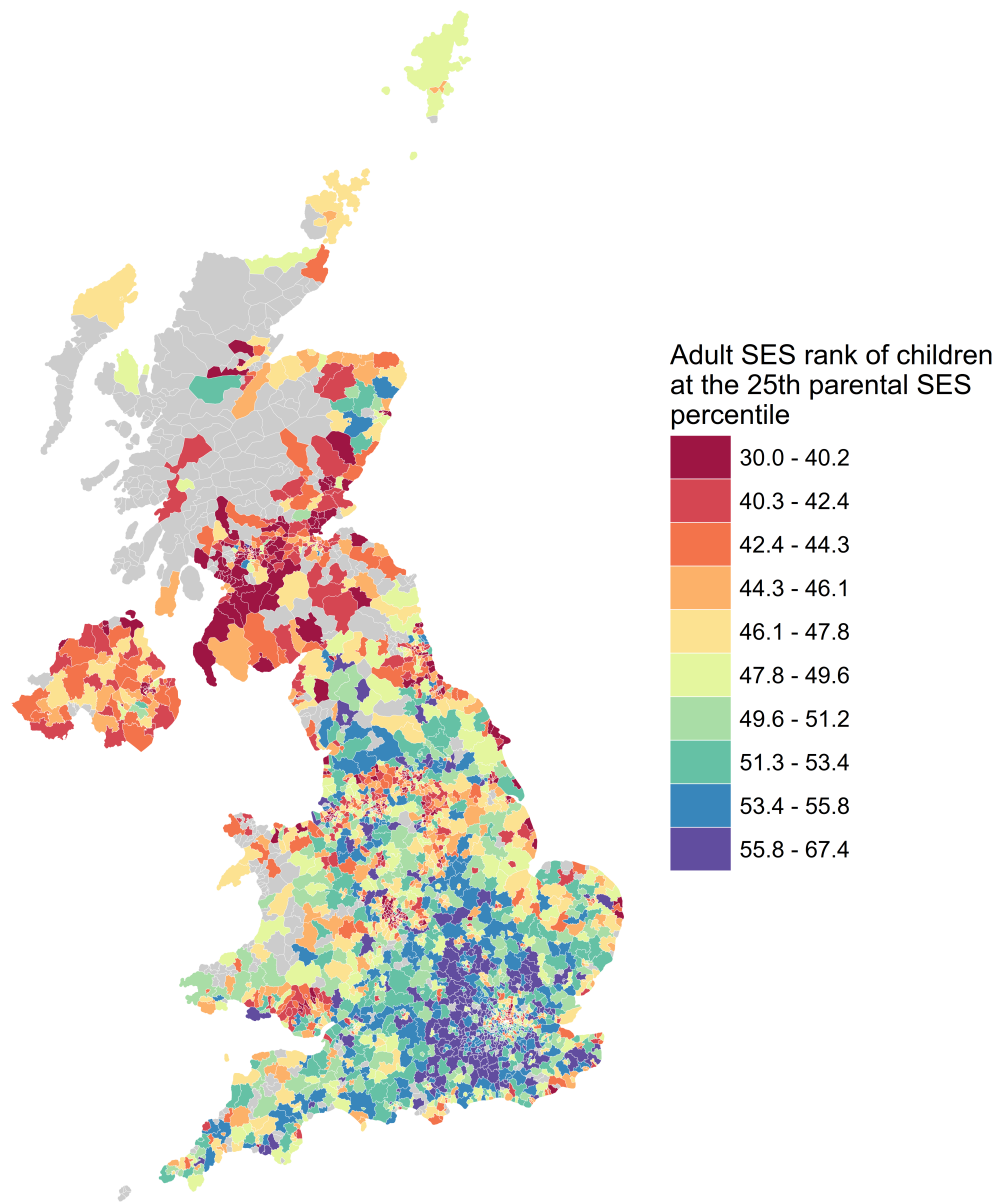
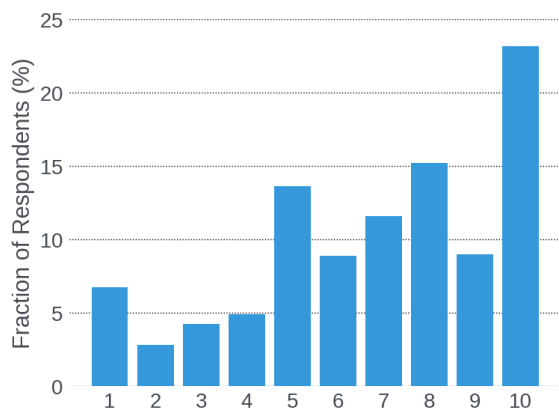
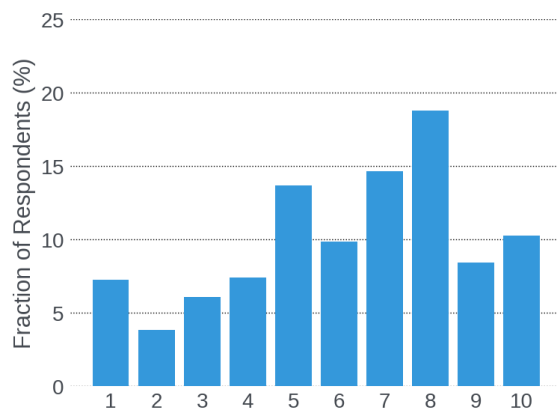


FIGURE S23: Geographic distribution of economic mobility in the UK by postcode district (Facebook-based).

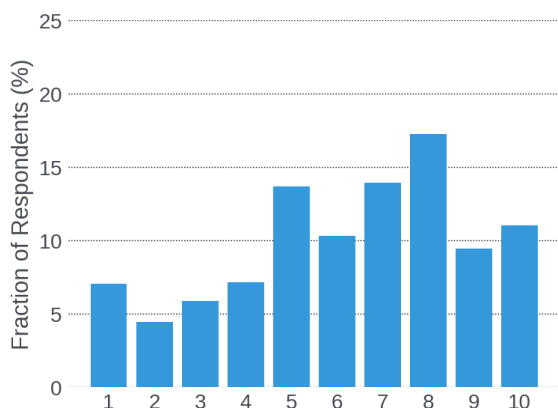
Notes: Predictions are adult SES ranks for children at the 25th percentile of the national parental SES distribution. Child ranks are measured within birth cohort (1986–1992); parent ranks are measured among linked parents.



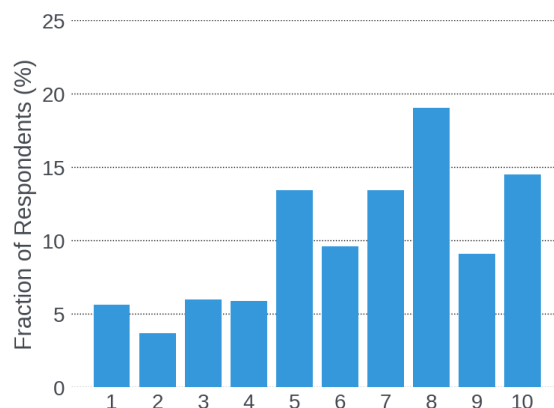
(A) Overall, how worried are you about the state of the world?



(B) Overall, how satisfied are you with your life nowadays?



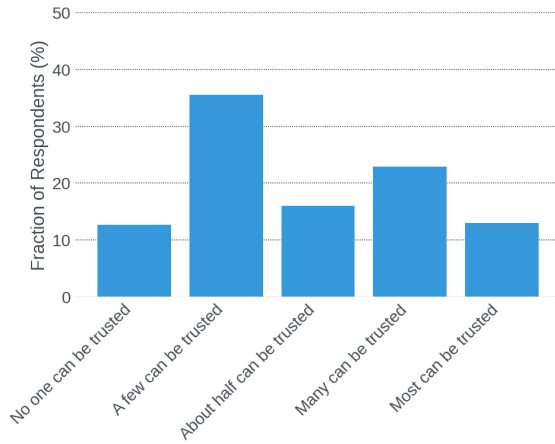
(C) Overall, how happy did you feel yesterday?



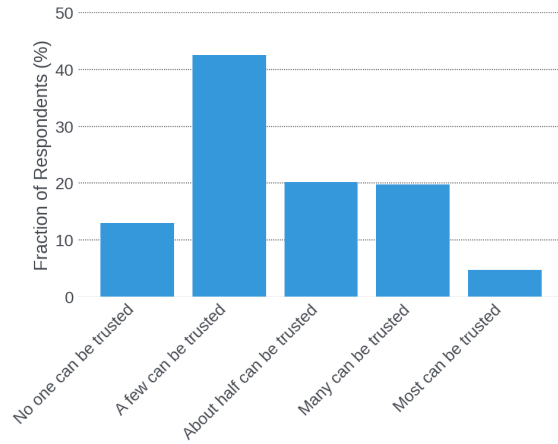
(D) Overall, to what extent do you feel the things you do in your life are worthwhile?

FIGURE S24: Frequency of each survey response for our wellbeing questions.

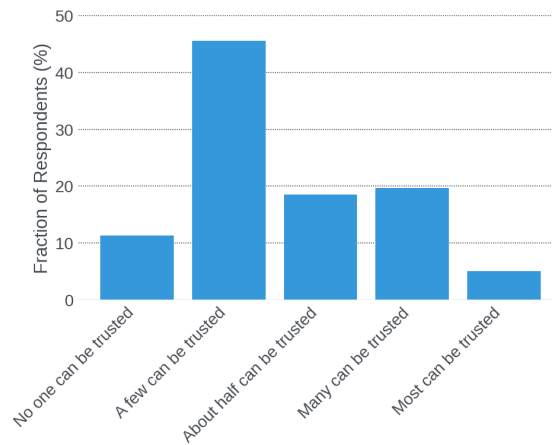
Notes: For each question, participants were asked to give a response on a scale of 1–10 where 1 is “Not at All” and 10 is “Extremely”.



(A) People in your neighbourhood.



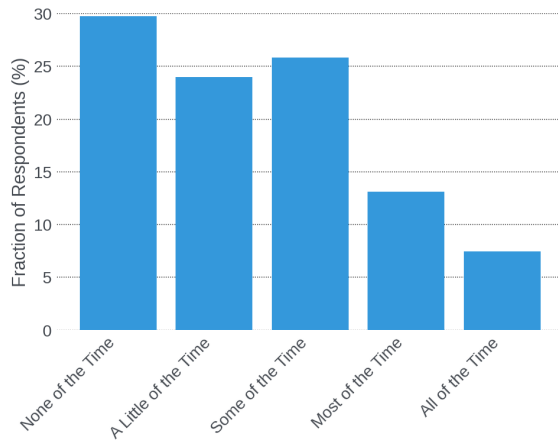
(B) People in your country.



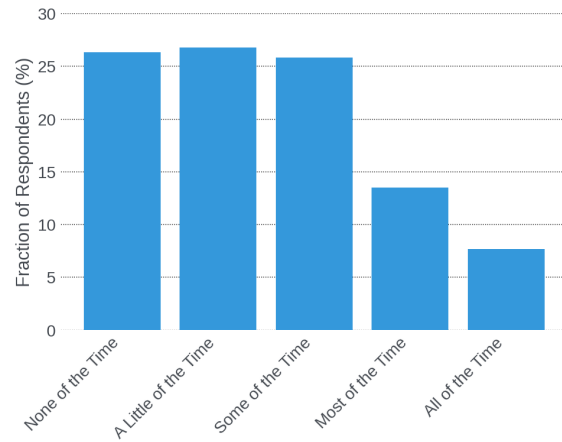
(C) People in general.

FIGURE S25: Frequency of each survey response for our trust questions.

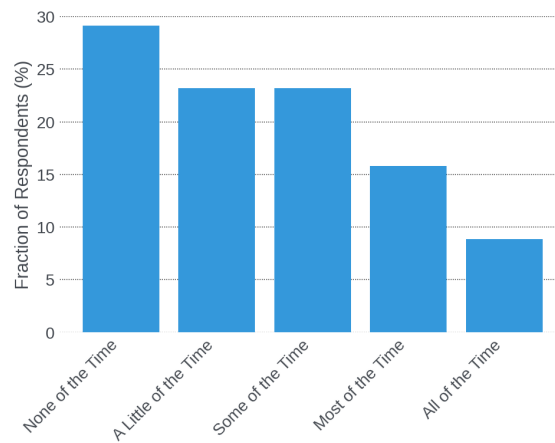
Notes: Participants were asked “For the following groups, would you say that most people can be trusted?”



(A) How often do you feel that you lack companionship?



(B) How often do you feel left out?



(C) How often do you feel isolated from others?

FIGURE S26: Frequency of each survey response for our connectedness questions.

Notes: Participants were asked “For each statement, please indicate how often you feel the way described.”

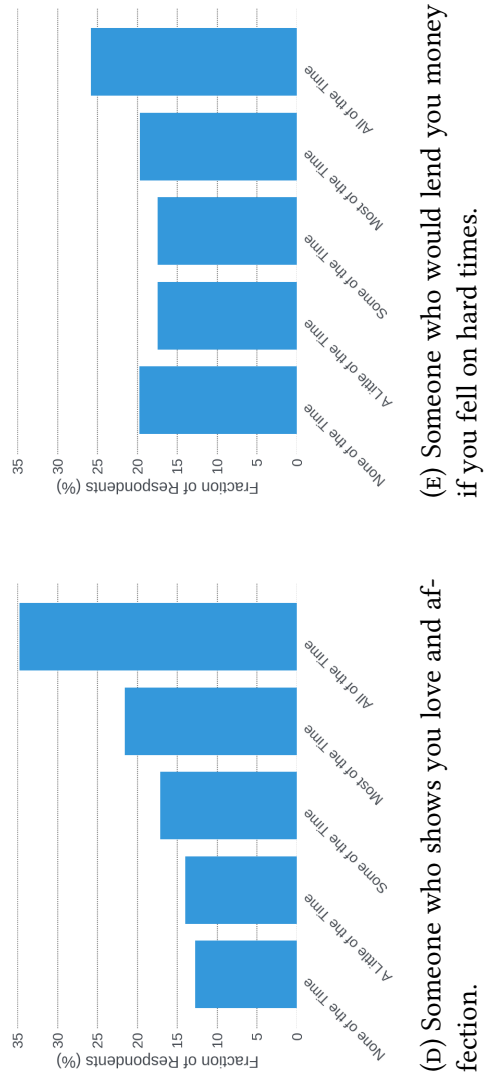
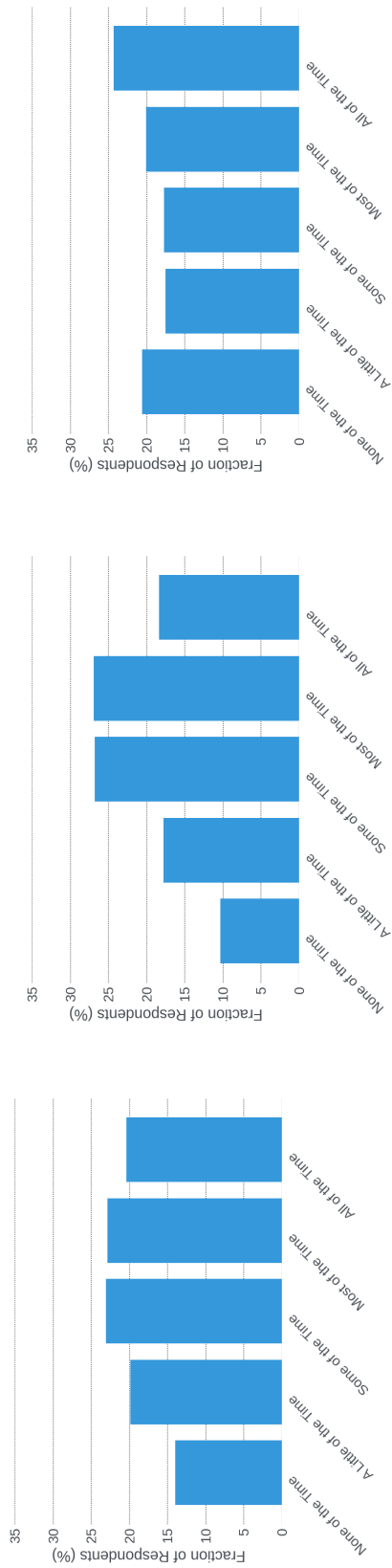


FIGURE S27: Frequency of each survey response for our social support questions.

Notes: Participants were asked “How often is each of the following kinds of support available to you if you need it?”

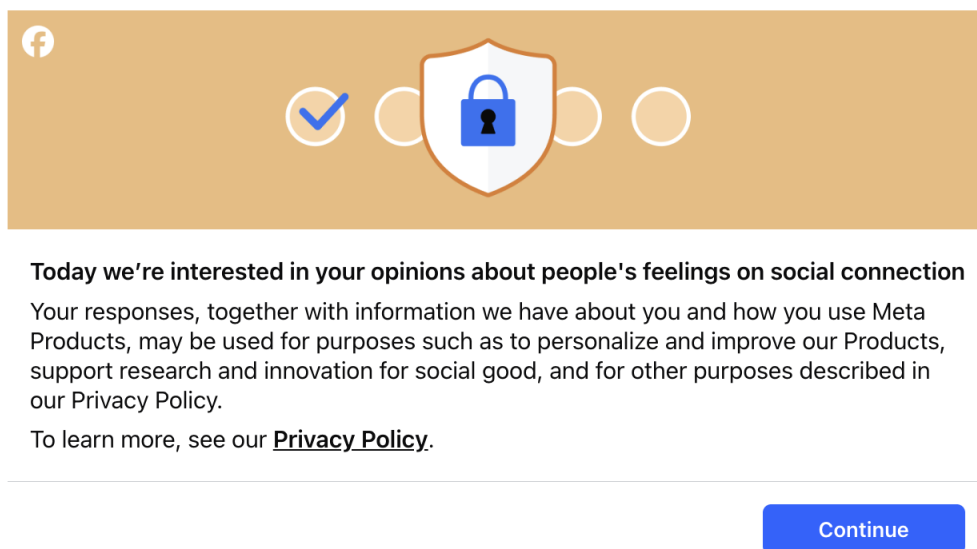


FIGURE S28: Page 1 of our survey.
Meta's privacy policy is available [here](#).

The following questions are about your overall wellbeing. There are no right or wrong answers. you can choose to skip any question that you'd prefer not to answer or exit the survey at any time.

For each of the following questions on how you are feeling, please give an answer on a scale of 1 to 10, where 1 is "Not at all" and 10 is "Extremely"

Overall, how satisfied are you with your life nowadays?

Select option ▼

Overall, how happy did you feel yesterday?

Select option ▼

Overall, to what extent do you feel that the things you do in your life are worthwhile?

Select option ▼

Overall, how worried are you about the current state of the world?

Select option ▼

Continue

FIGURE S29: Page 2

**The following questions are about your feelings of social connection.
There are no right or wrong answers.**

For the following groups, would you say that most people can be trusted?

	No one can be trusted	A few can be trusted	About half can be trusted	Many can be trusted	Most can be trusted
People in general	☐	☐	☐	☐	☐
People in your country	☐	☐	☐	☐	☐
People in your neighbourhood	☐	☐	☐	☐	☐

Continue

FIGURE S30: Page 3

The next question is about your involvement in groups, clubs and organisations in your local area. These could be formally organised groups or just groups of people who get together to do an activity or talk about things. Please exclude involvement that was just related to giving money.

**In the last 12 months have you been involved with any of these groups?
(tick all that apply)**

- ☐ Sport or exercise groups (e.g. five-a-side, hiking groups)
 - ☐ Religious groups (e.g. faith-based groups, religious school)
 - ☐ Hobby or social clubs (e.g. groups for the arts, Rotary Club, book reading clubs)
 - ☐ Neighbourhood groups (e.g. neighbourhood watch, tenants association, active member of a neighbourhood WhatsApp group)
 - ☐ Youth groups (e.g. parents groups, youth clubs, mentoring)
 - ☐ Other local groups (e.g. local food bank, adult education, older people support groups, local political parties, scouts)
-

Continue

FIGURE S31: Page 4

The following statements describe how people sometimes feel. For each statement, please indicate how often you feel the way described.

	None of the Time	A Little of the Time	Some of the Time	Most of the Time	All of the Time
How often do you feel that you lack companionship?	☐	☐	☐	☐	☐
How often do you feel left out?	☐	☐	☐	☐	☐
How often do you feel isolated from others?	☐	☐	☐	☐	☐

Continue

FIGURE S32: Page 5

People sometimes look to others for companionship, assistance, or other types of support. How often is each of the following kinds of support available to you if you need it?

	None of the Time	A Little of the Time	Some of the Time	Most of the Time	All of the Time
Someone to turn to for suggestions about how to deal with a personal problem	☐	☐	☐	☐	☐
Someone to have a good time with	☐	☐	☐	☐	☐
Someone to help with daily chores or take care of you if you were sick	☐	☐	☐	☐	☐
Someone who shows you love and affection	☐	☐	☐	☐	☐
Someone who would lend you money if you fell on hard times	☐	☐	☐	☐	☐

Continue

FIGURE S33: Page 6

What is the total annual income of everyone in your household (before tax but including any benefits)

- ☐ Below £10,000
- ☐ £10,001 to £20,000
- ☐ £20,001 to £30,000
- ☐ £30,001 to £40,000
- ☐ £40,001 to £50,000
- ☐ £50,001 to £60,000
- ☐ £60,001 to £70,000
- ☐ £70,001 to £80,000
- ☐ £80,001 to £90,000
- ☐ £90,001 to £100,000
- ☐ Over £100,000
- ☐ Prefer not to say

Continue

FIGURE S34: Page 7

Thank you for taking the time to complete this survey.

Some of the questions or topics may have been challenging to think about or reflect on. If you or anyone you know would like additional support or to talk to someone about any of these issues please visit Facebook's online well-being resources: <https://www.facebook.com/safety/wellbeing>. If you are experiencing an emergency or emotional crisis, contact 911, emergency services or a helpline immediately.

Submit

FIGURE S35: Page 8

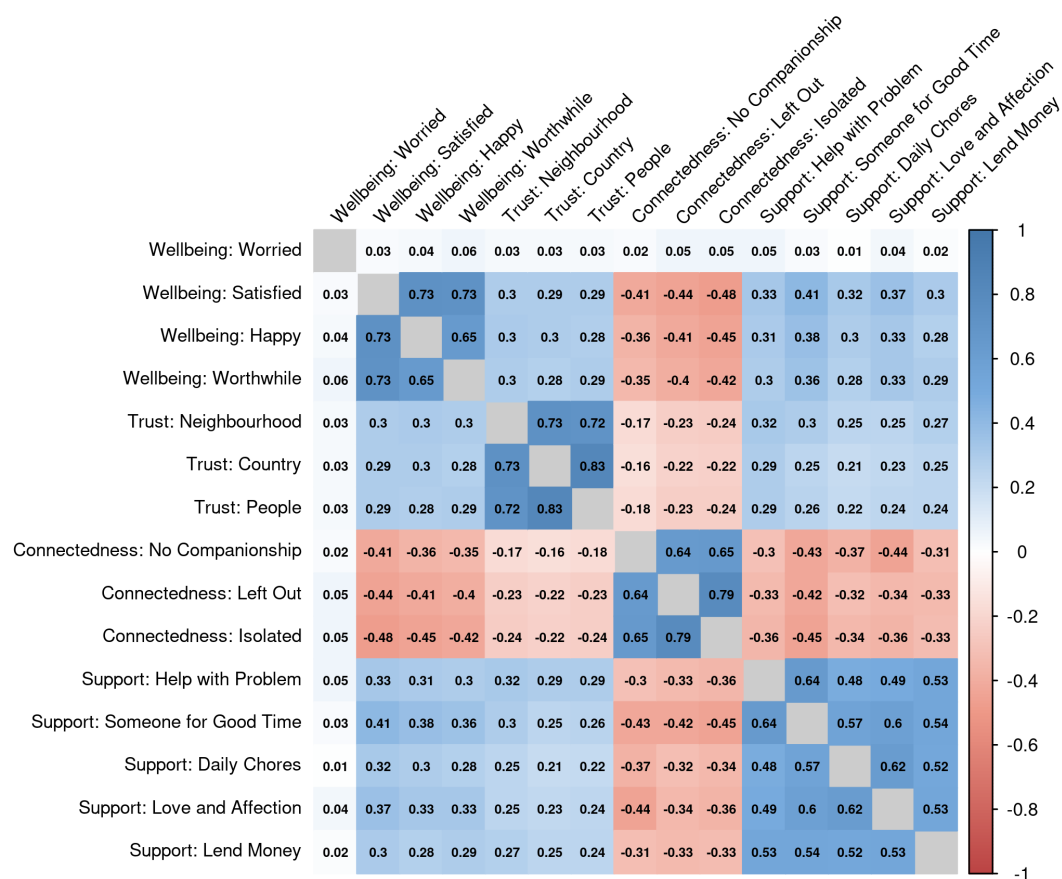
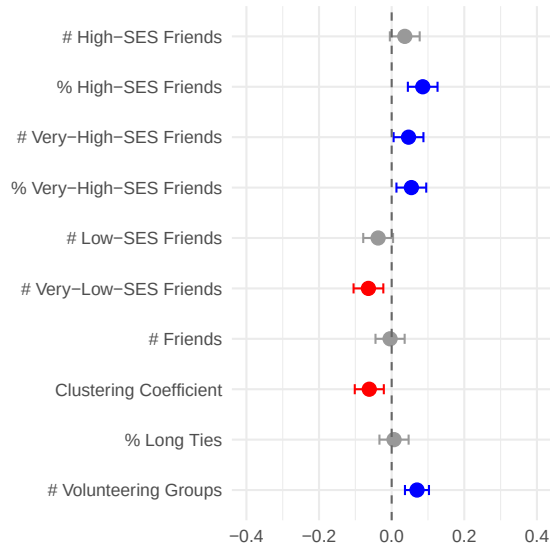
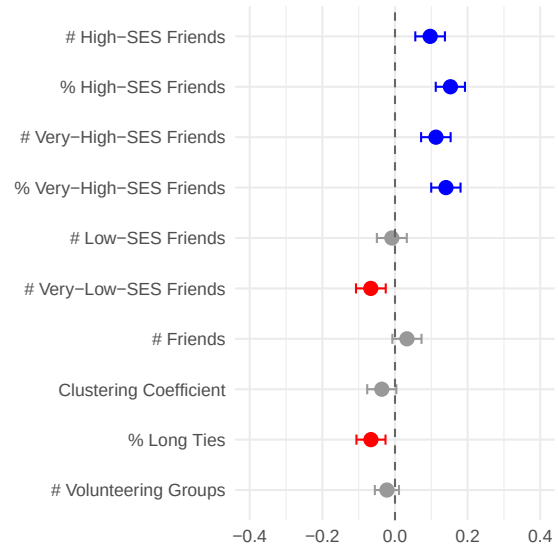


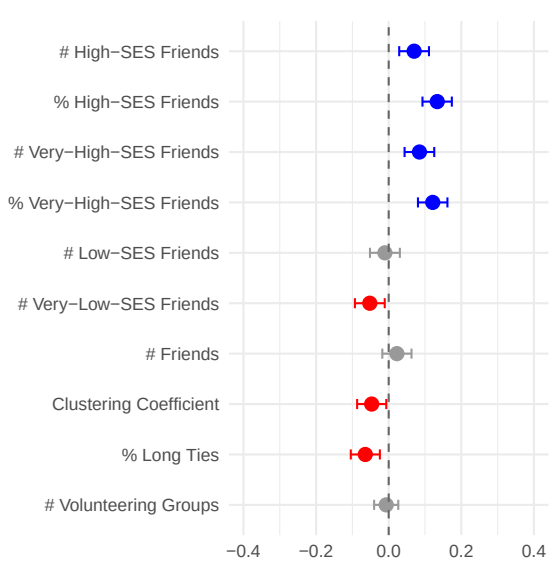
FIGURE S36: Respondent-level correlations between survey responses.



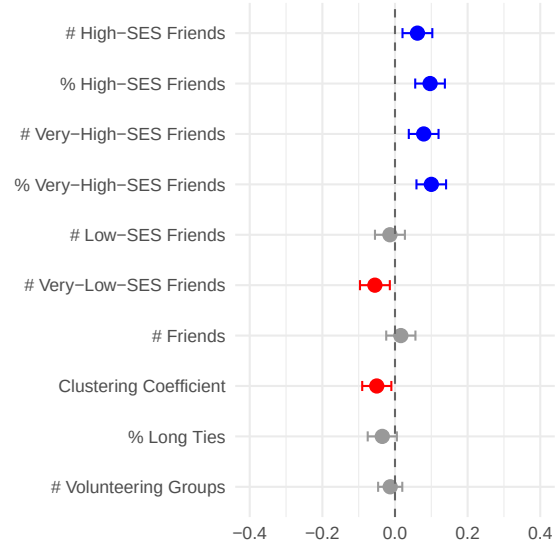
(A) Overall, how worried are you about the state of the world?



(B) Overall, how satisfied are you with your life nowadays?

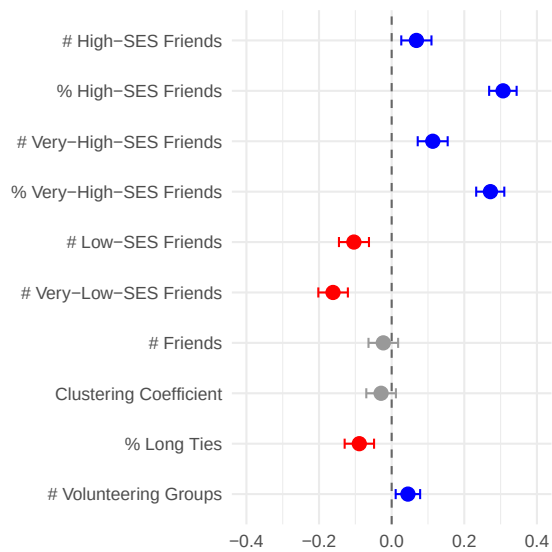


(C) Overall, how happy did you feel yesterday?

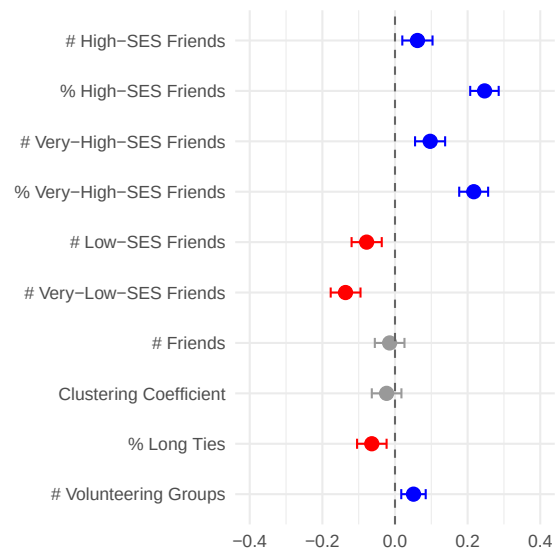


(D) Overall, to what extent do you feel the things you do in your life are worthwhile?

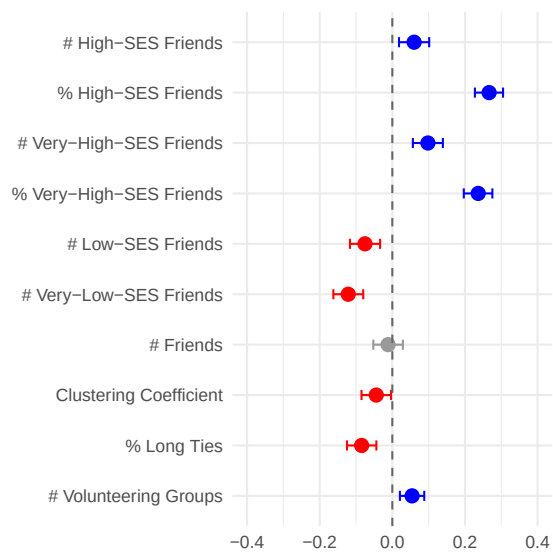
FIGURE S37: Correlations with wellbeing responses.



(A) Can most people in your neighbourhood be trusted?

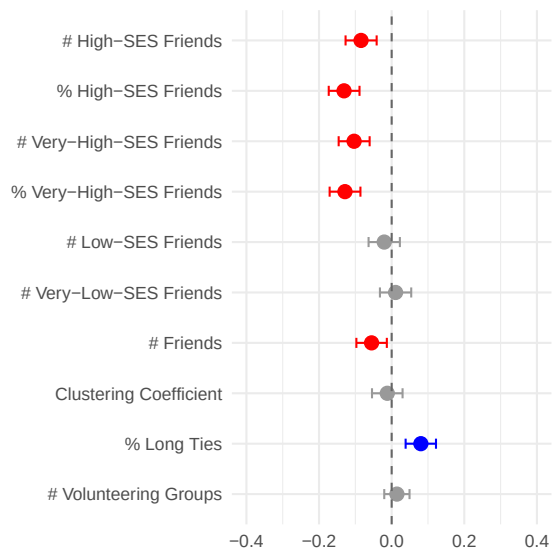


(B) Can most people in your country be trusted?

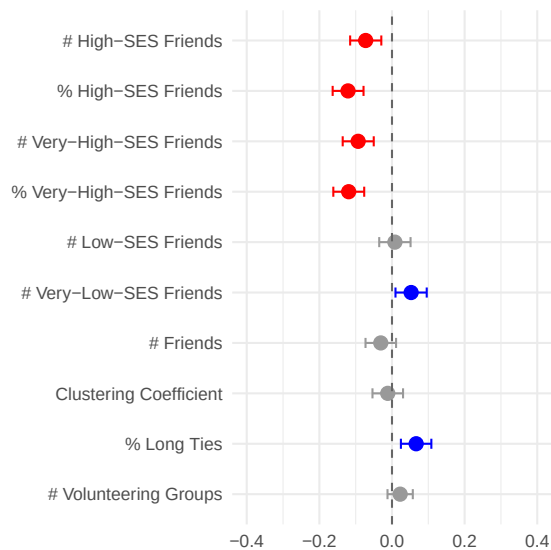


(C) Can most people in general be trusted?

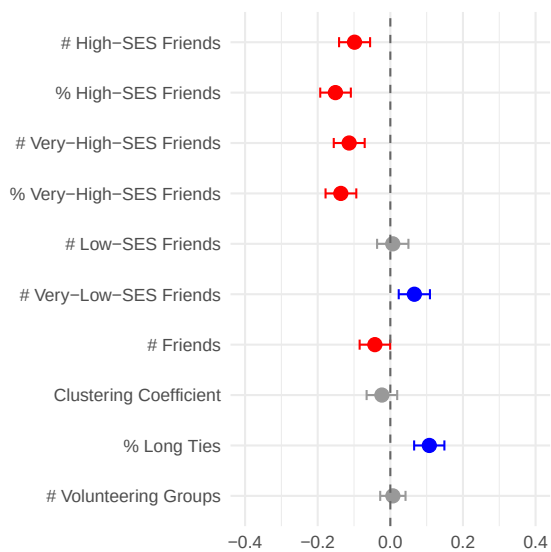
FIGURE S38: Correlations with trust responses.



(A) How often do you feel that you lack companionship?



(B) How often do you feel left out?



(C) How often do you feel isolated from others?

FIGURE S39: Correlations with connectedness responses.

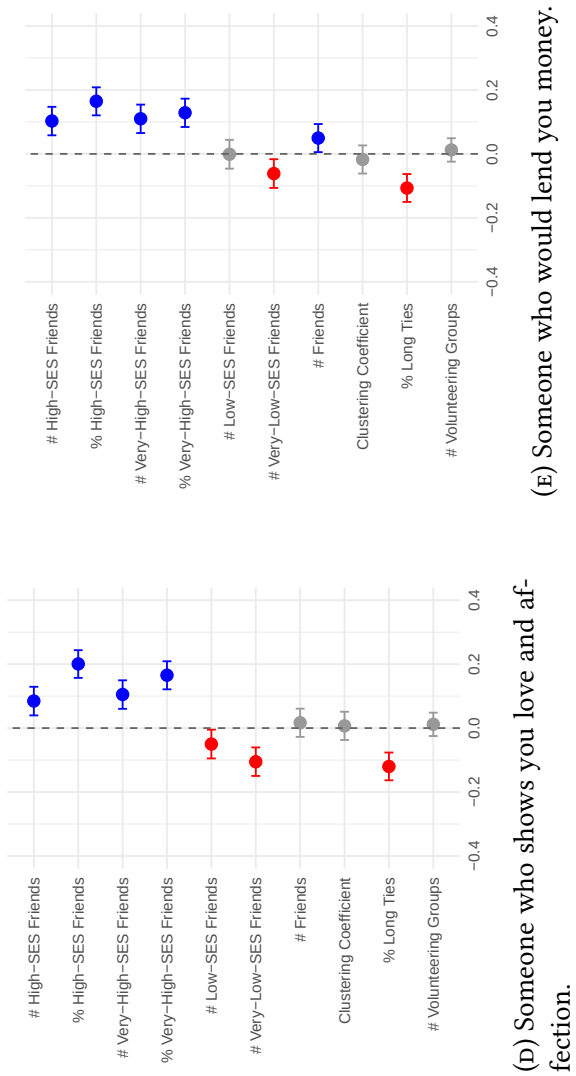
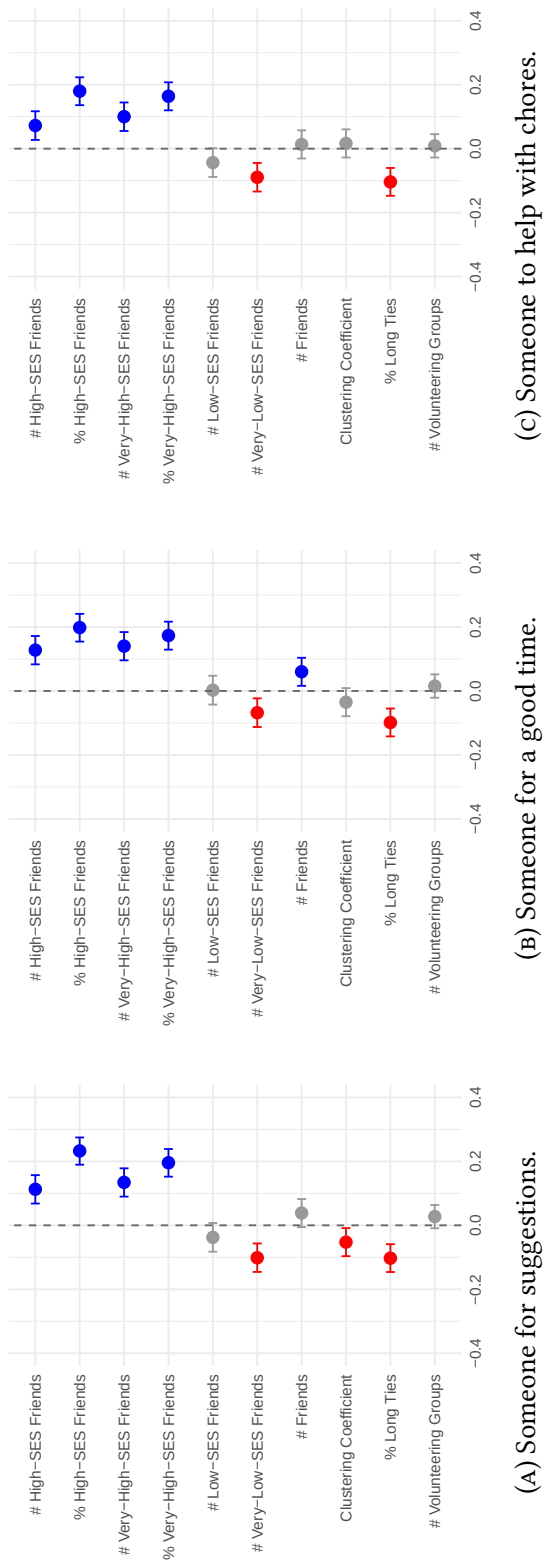
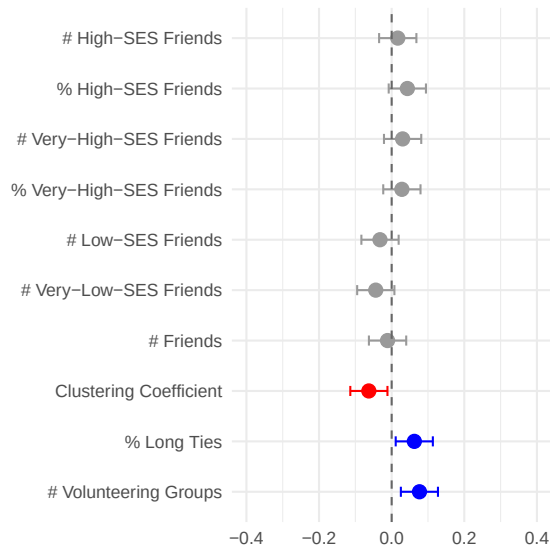
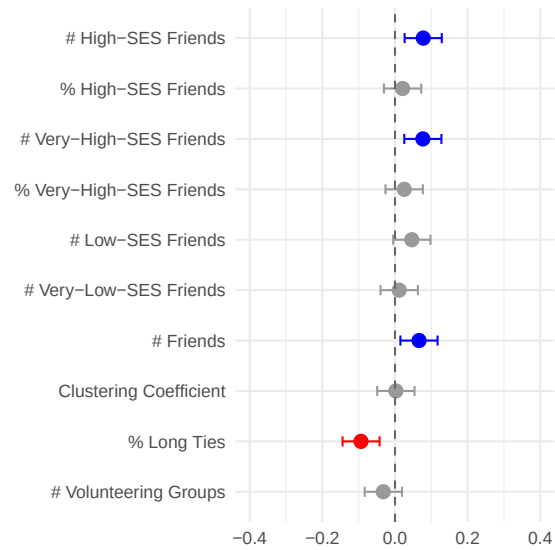


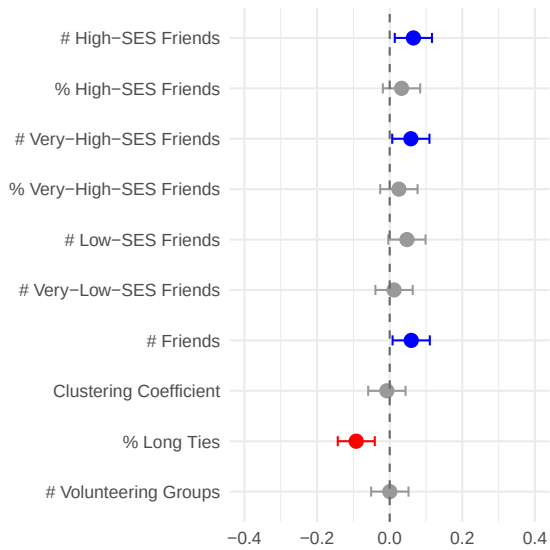
FIGURE S40: Correlations with social support responses.



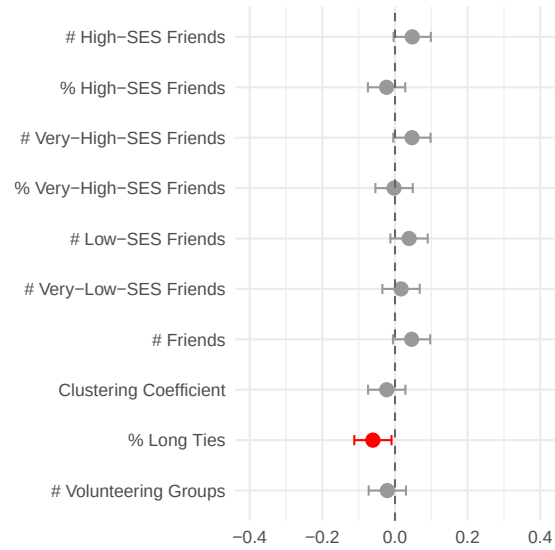
(A) Overall, how worried are you about the state of the world?



(B) Overall, how satisfied are you with your life nowadays?

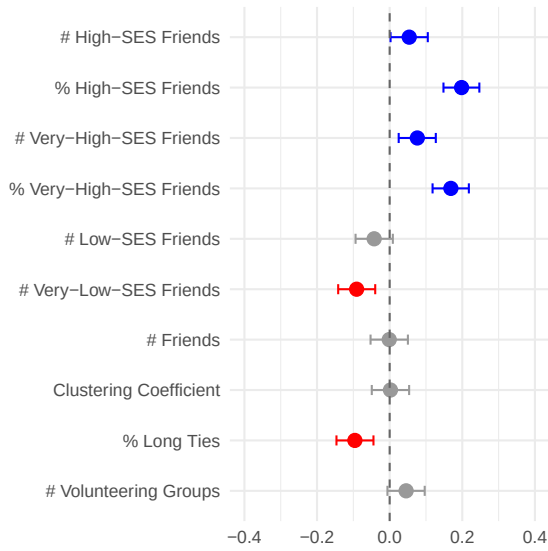


(c) Overall, how happy did you feel yesterday?

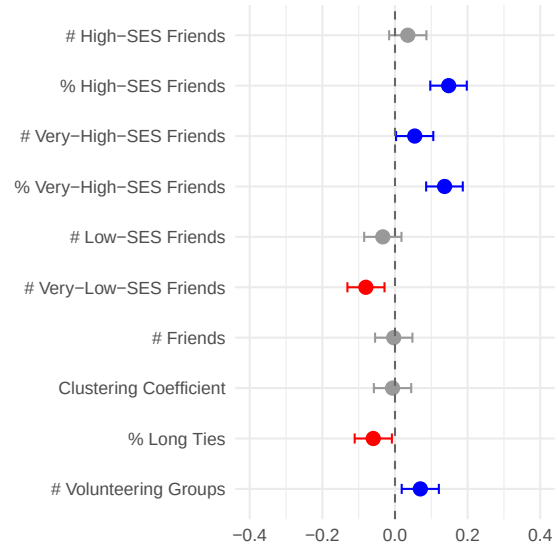


(D) Overall, to what extent do you feel the things you do in your life are worthwhile?

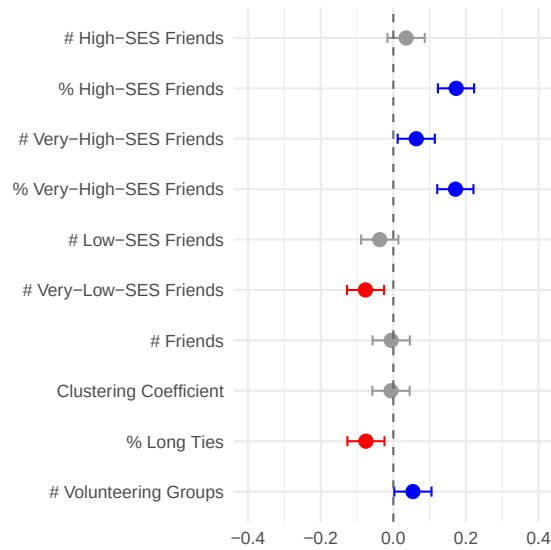
FIGURE S41: Partial correlations with wellbeing responses, after partialling out age, income, and gender.



(A) Can most people in your neighbourhood be trusted?

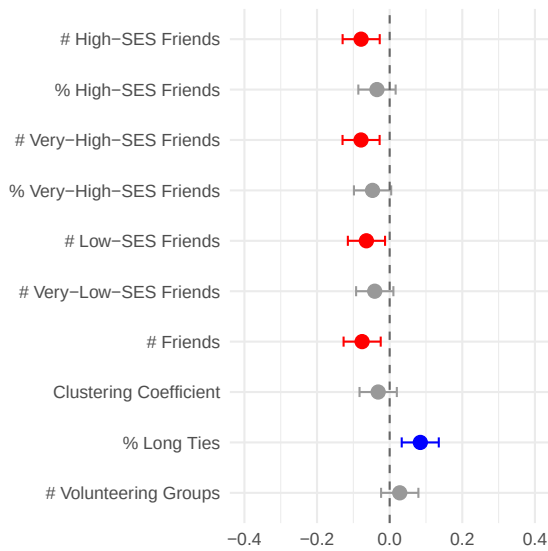


(B) Can most people in your country be trusted?

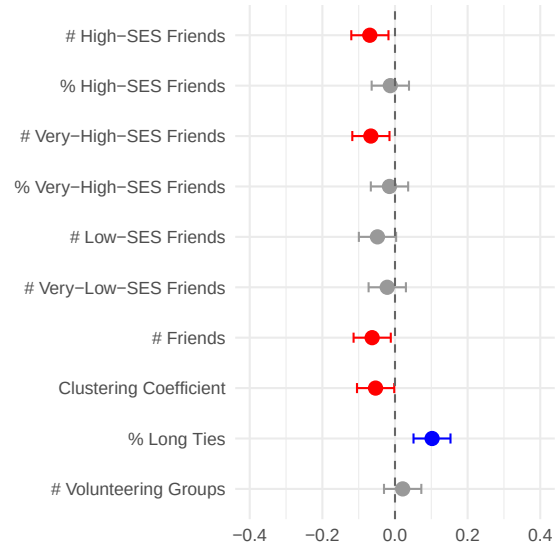


(C) Can most people in general be trusted?

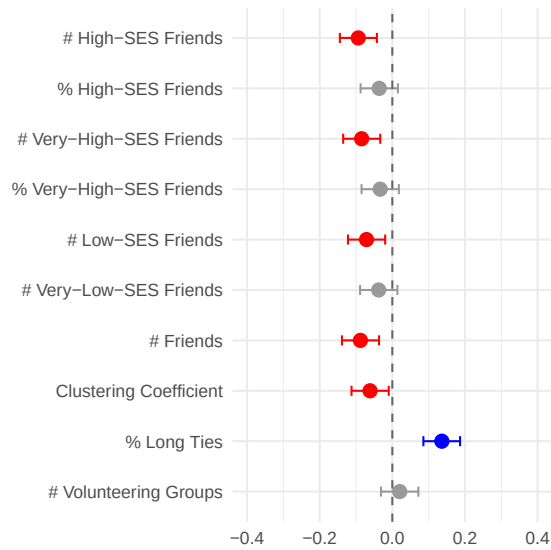
FIGURE S42: Partial correlations with trust responses, after partialling out age, income, and gender.



(A) How often do you feel that you lack companionship?

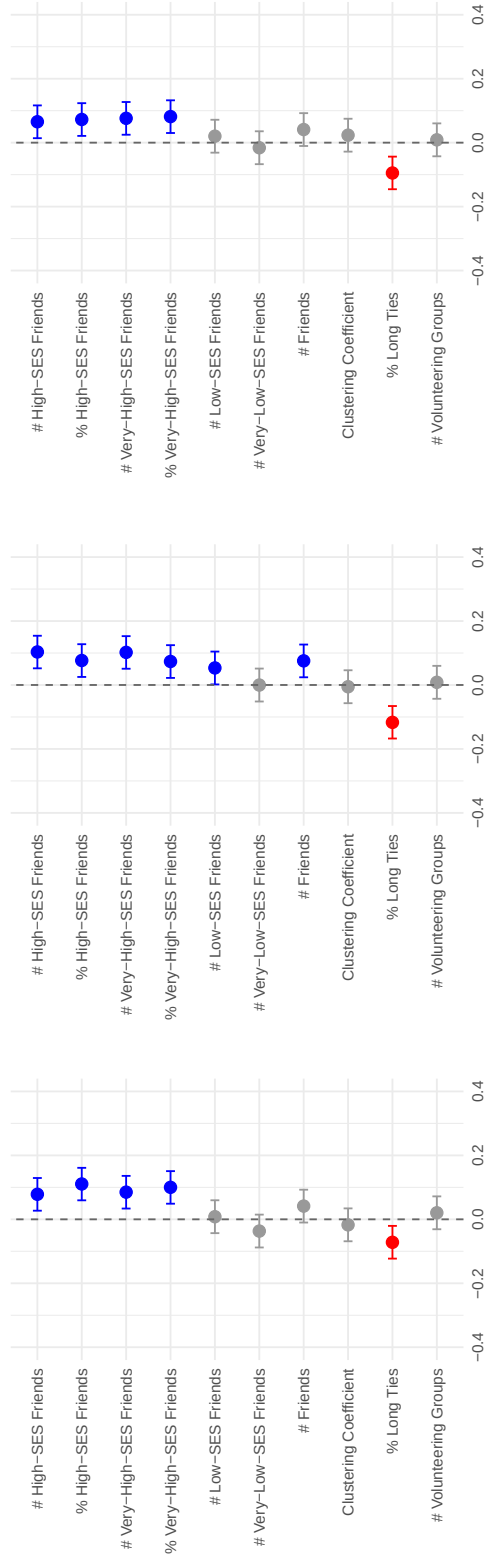


(B) How often do you feel left out?



(C) How often do you feel isolated from others?

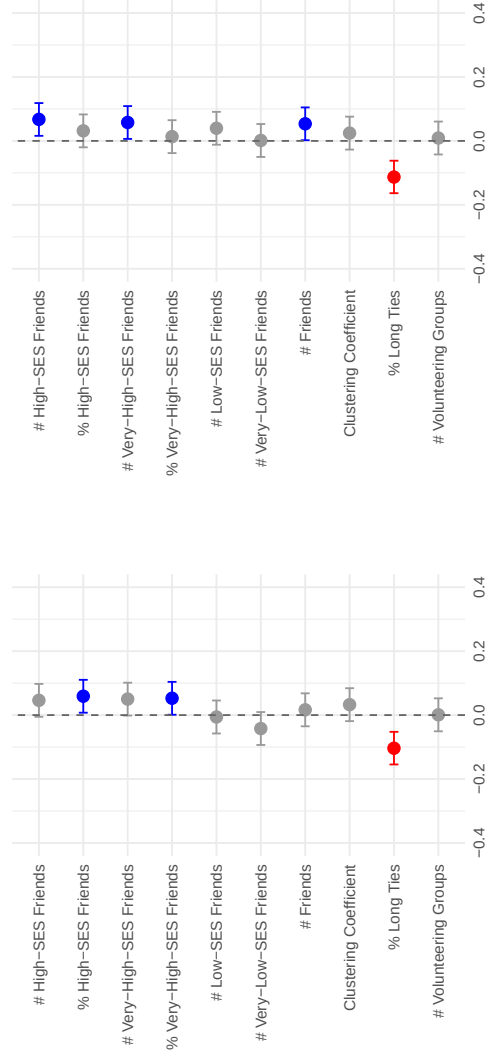
FIGURE S43: Partial correlations with connectedness responses, after partialling out age, income, and gender.



(A) Someone for suggestions.

(B) Someone for a good time.

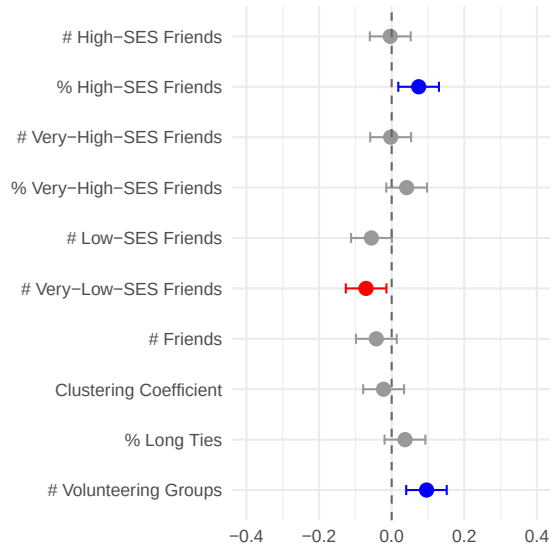
(C) Someone to help with chores.



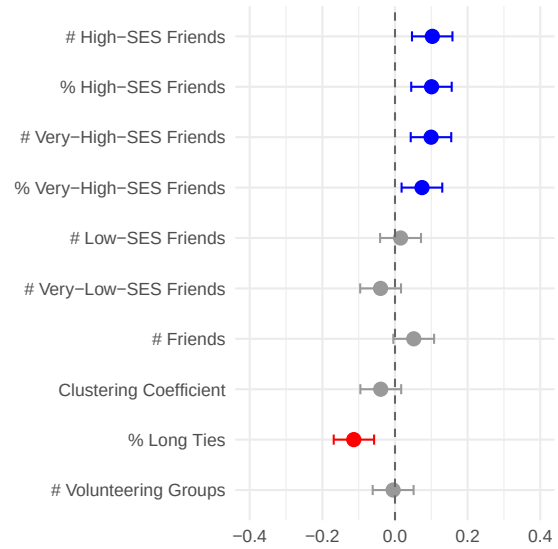
(D) Someone for love and affection.

(E) Someone to lend you money.

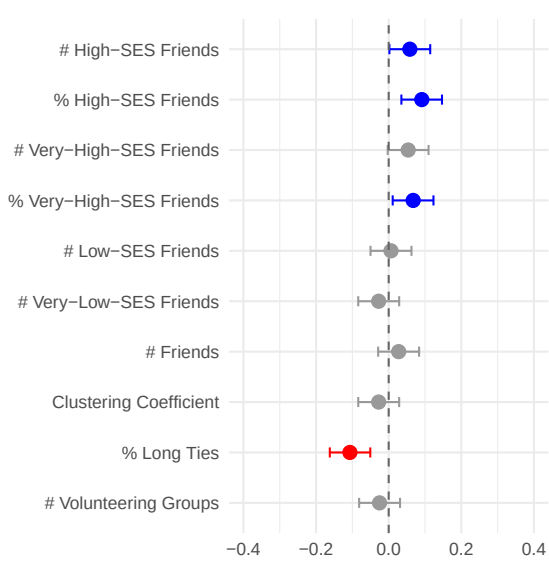
FIGURE S44: Partial correlations with social support responses, after partialling out age, income, and gender.



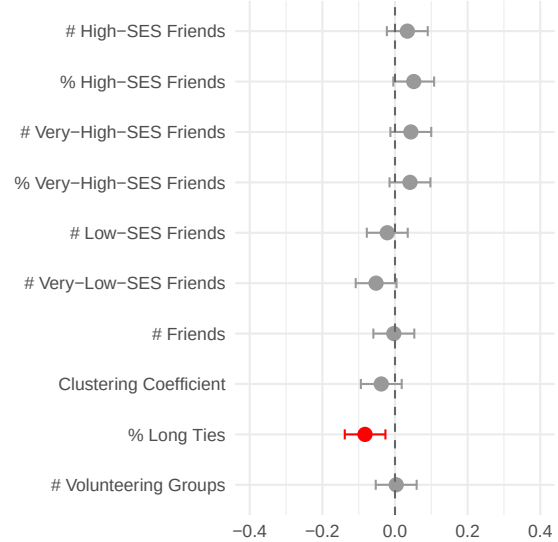
(A) Overall, how worried are you about the state of the world?



(B) Overall, how satisfied are you with your life nowadays?

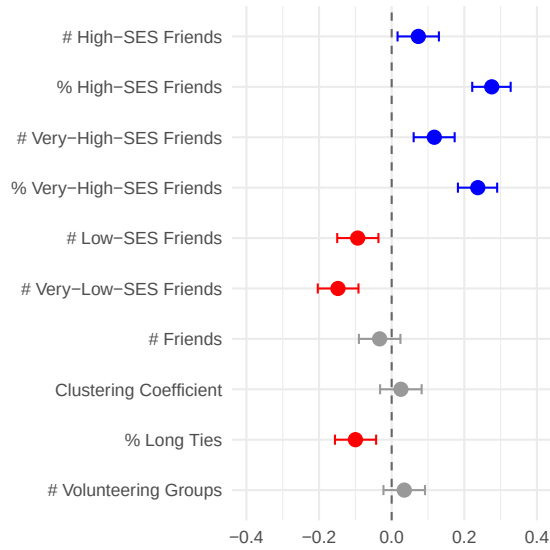


(C) Overall, how happy did you feel yesterday?

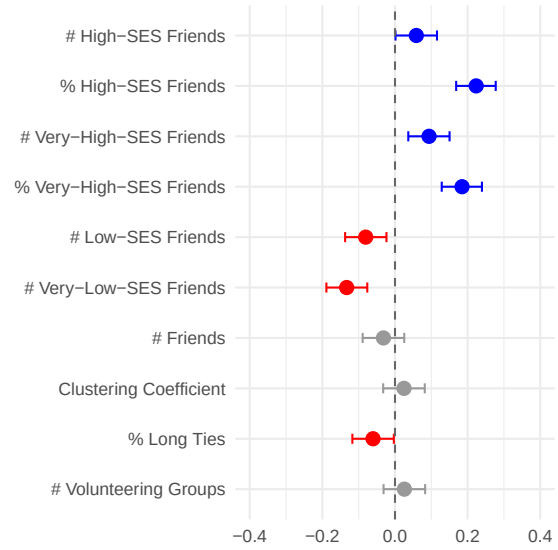


(D) Overall, to what extent do you feel the things you do in your life are worthwhile?

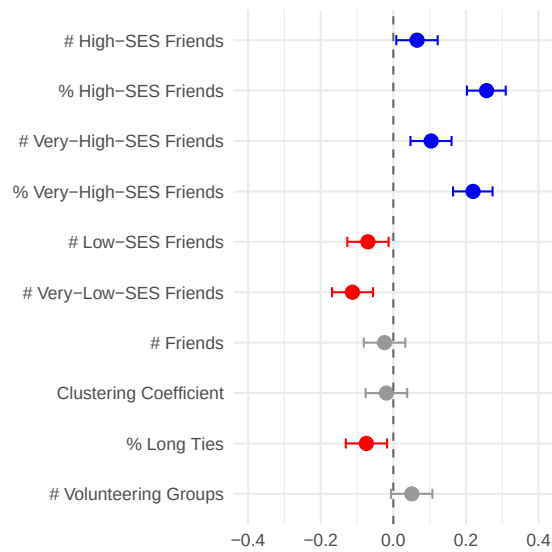
FIGURE S45: Correlations with wellbeing responses for low-SES respondents.



(A) Can most people in your neighbourhood be trusted?

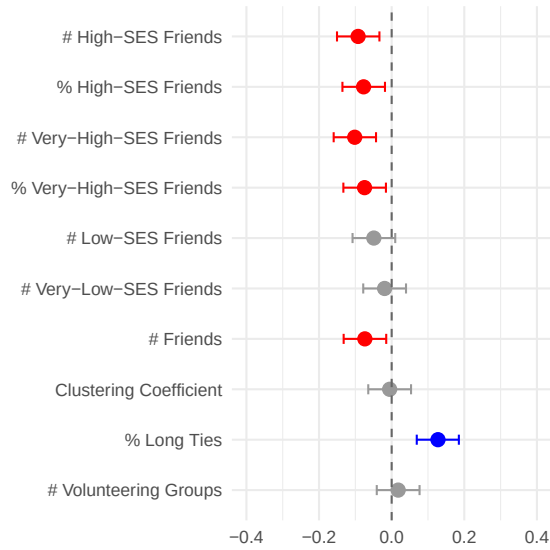


(B) Can most people in your country be trusted?

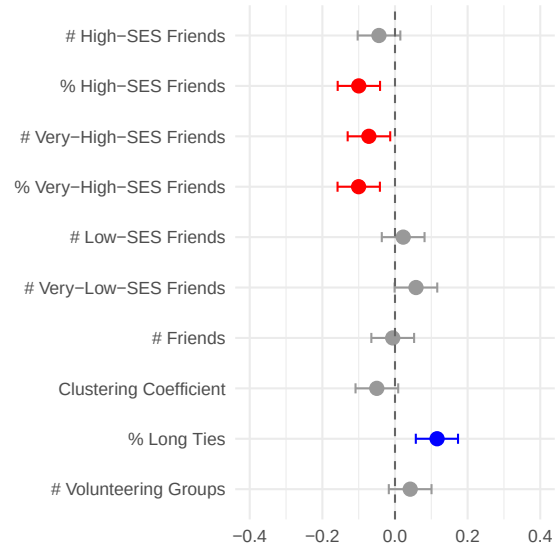


(C) Can most people in general be trusted?

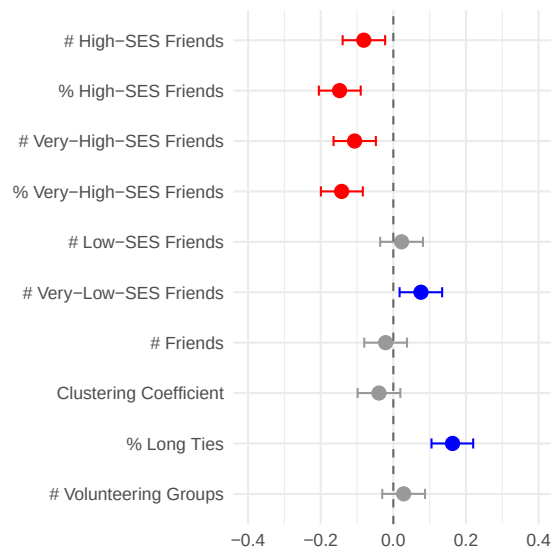
FIGURE S46: Correlations with trust responses for low-SES respondents.



(A) How often do you feel that you lack companionship?

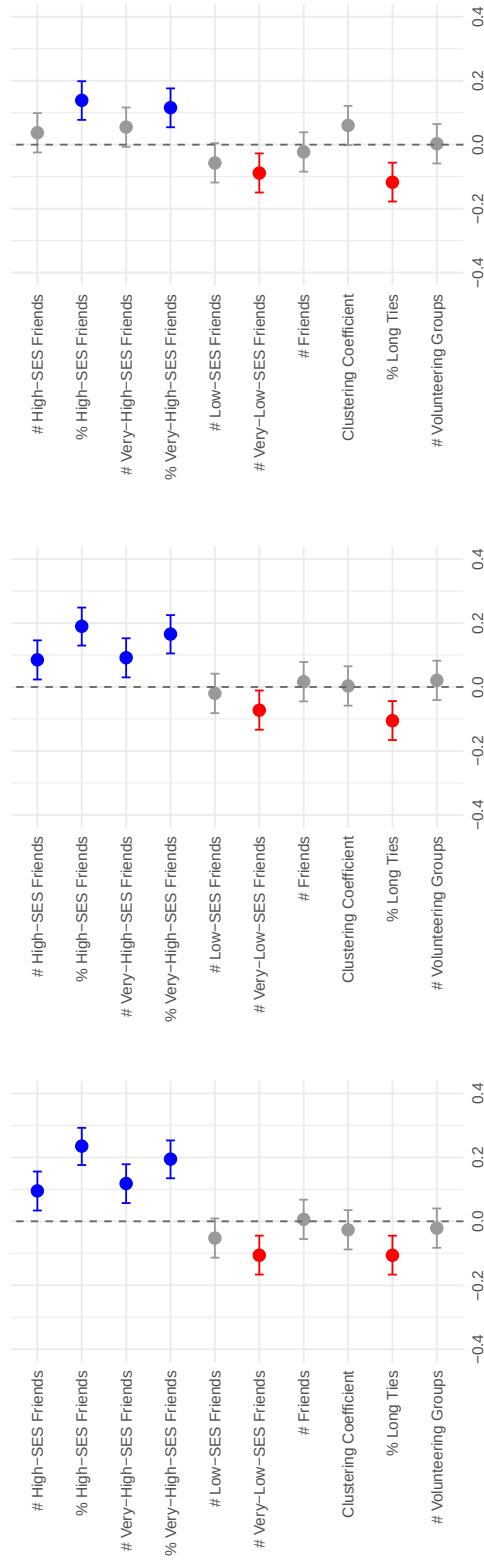


(B) How often do you feel left out?



(C) How often do you feel isolated from others?

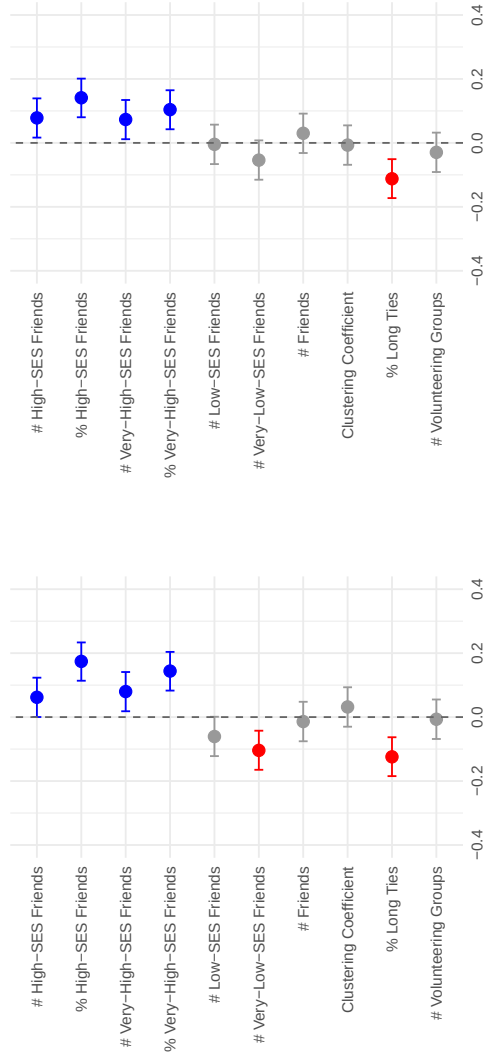
FIGURE S47: Correlations with connectedness responses for low-SES respondents.



(A) Someone for suggestions.

(B) Someone for a good time.

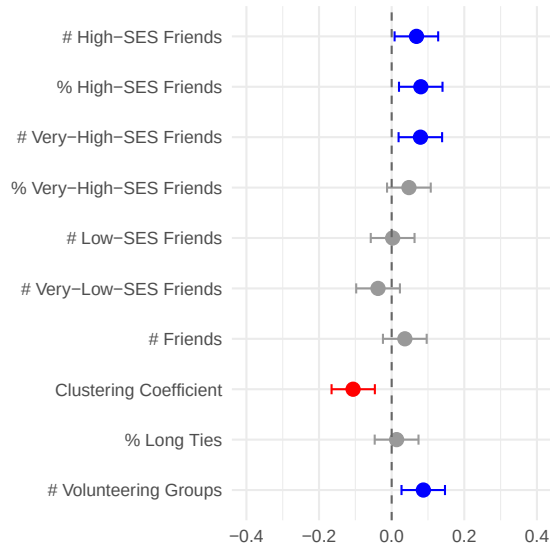
(C) Someone to help with chores.



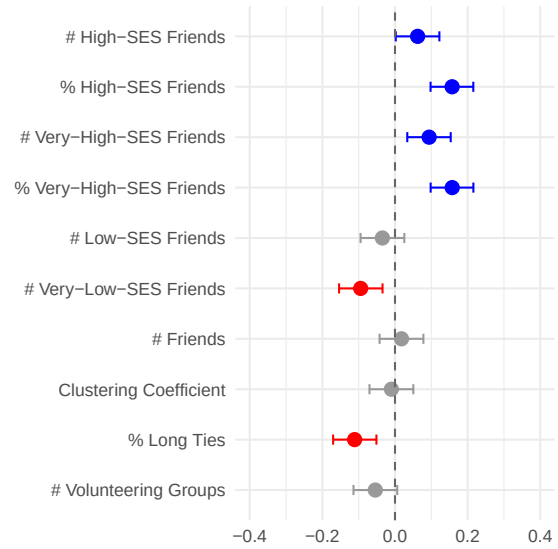
(D) Someone for love and affection.

(E) Someone to lend you money.

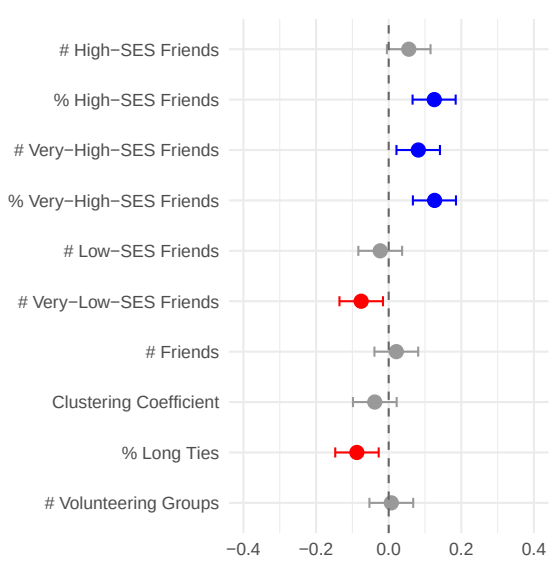
FIGURE S48: Correlations with social support responses for low-SES respondents.



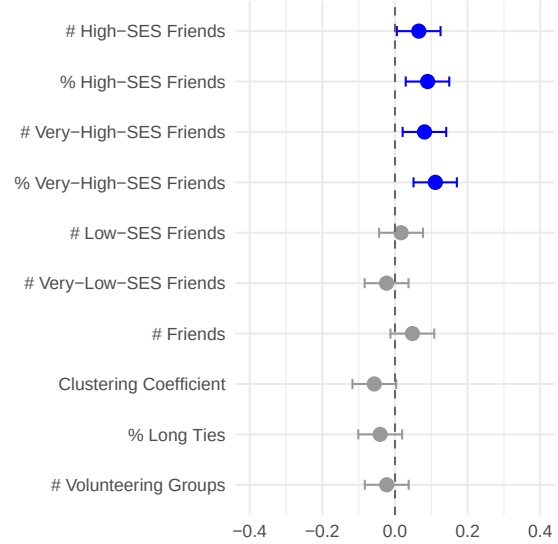
(A) Overall, how worried are you about the state of the world?



(B) Overall, how satisfied are you with your life nowadays?

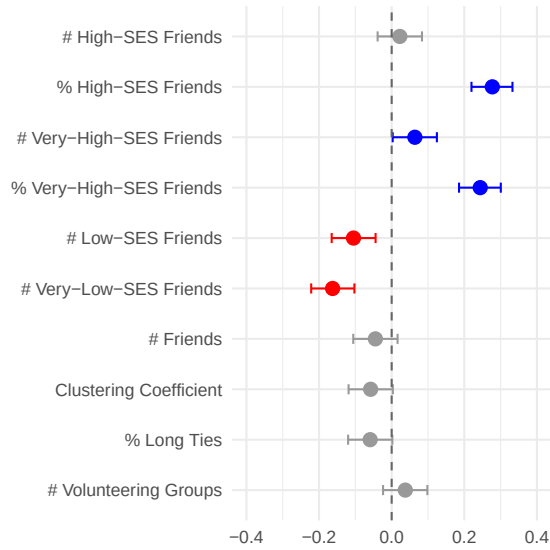


(c) Overall, how happy did you feel yesterday?

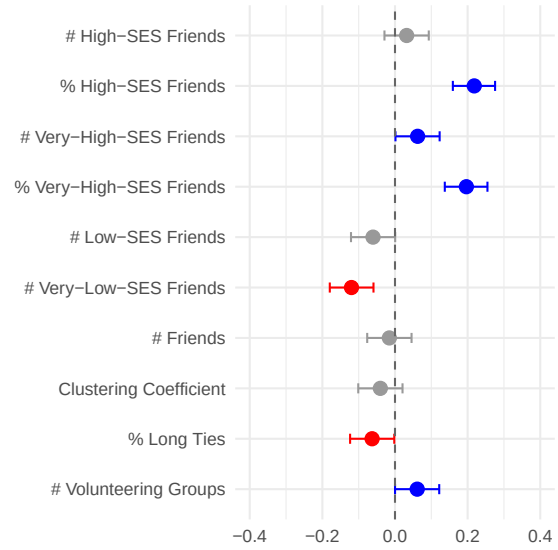


(D) Overall, to what extent do you feel the things you do in your life are worthwhile?

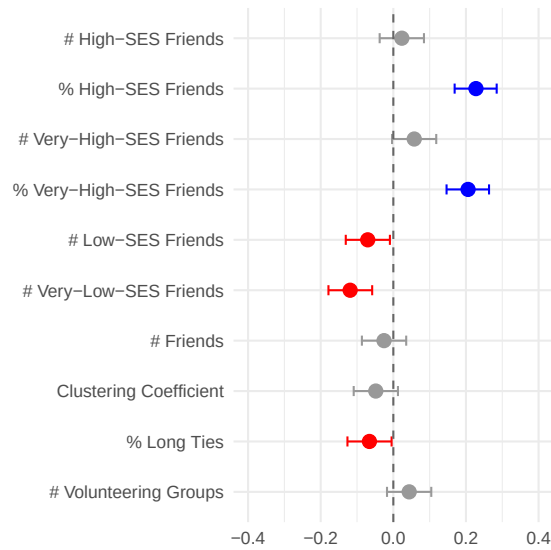
FIGURE S49: Correlations with wellbeing responses for high-SES respondents.



(A) Can most people in your neighbourhood be trusted?

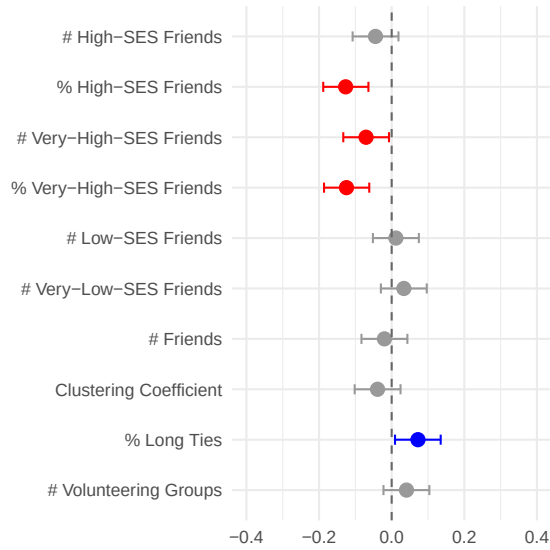


(B) Can most people in your country be trusted?

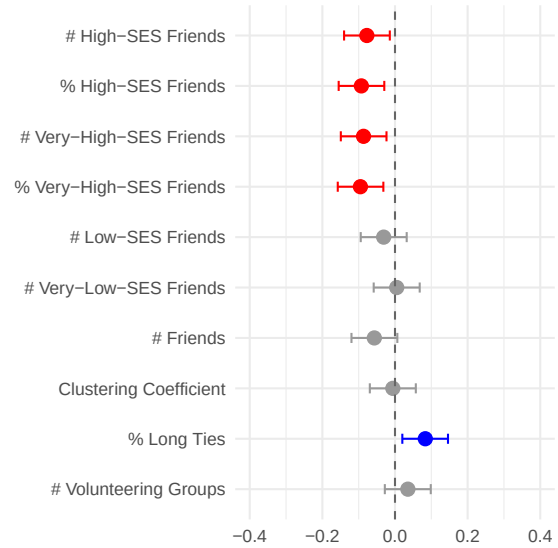


(C) Can most people in general be trusted?

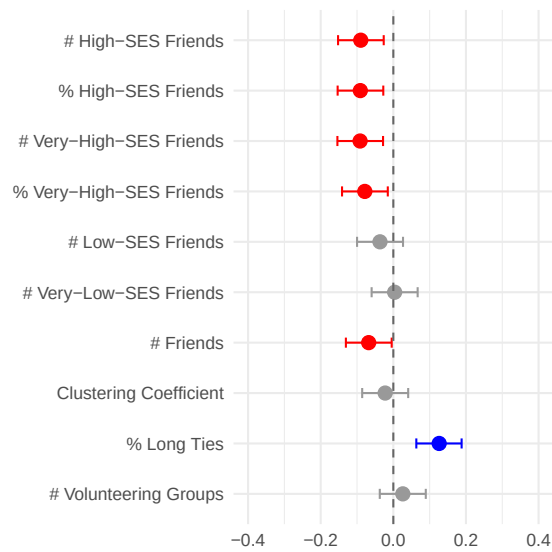
FIGURE S50: Correlations with trust responses for high-SES respondents.



(A) How often do you feel that you lack companionship?

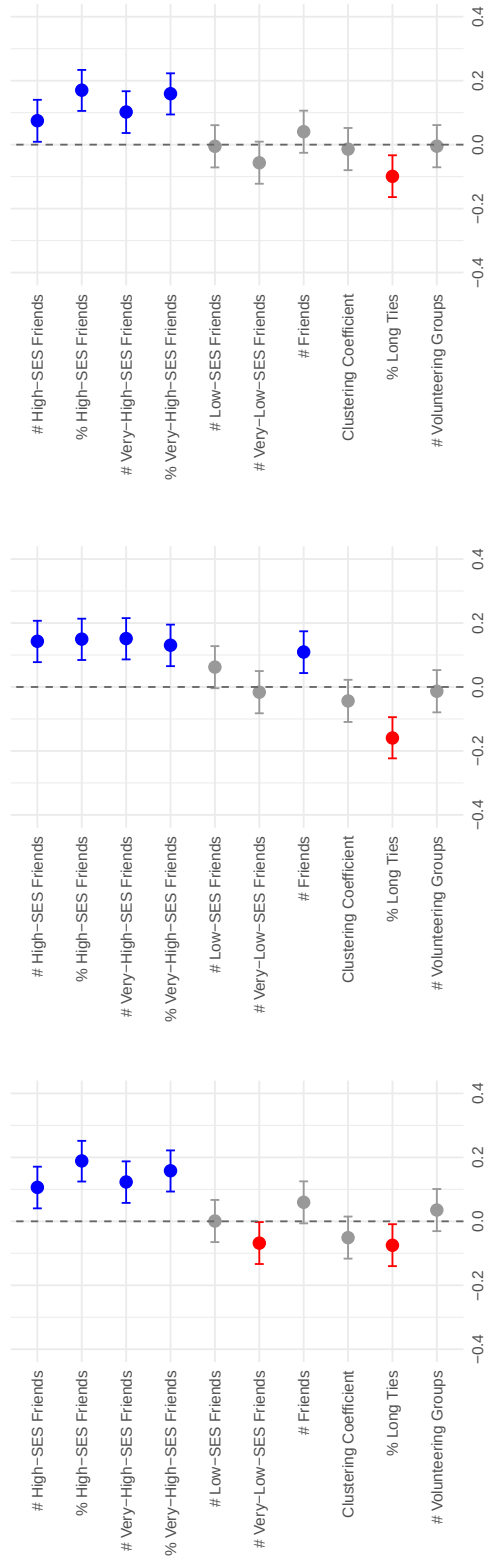


(B) How often do you feel left out?



(C) How often do you feel isolated from others?

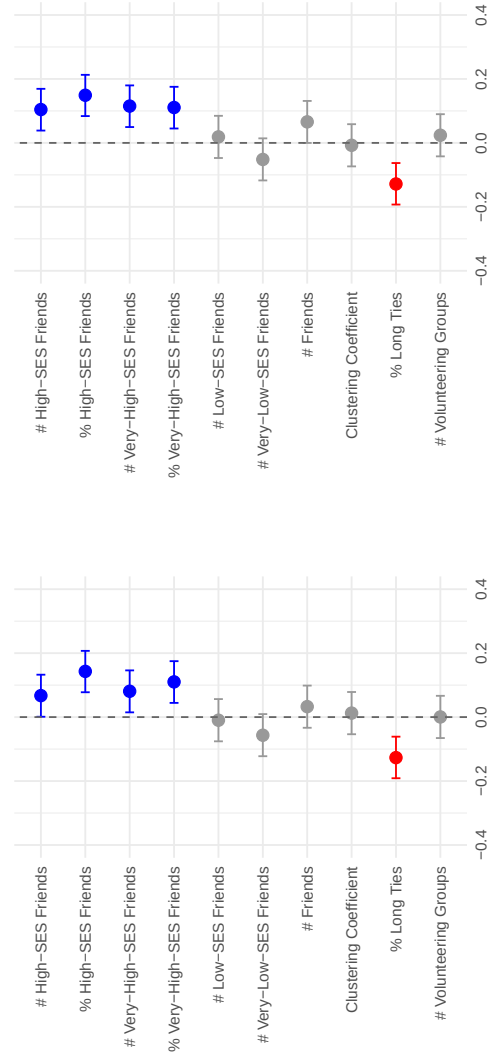
FIGURE S51: Correlations with connectedness responses for high-SES respondents.



(A) Someone for suggestions.

(B) Someone for a good time.

(C) Someone to help with chores.



(D) Someone for love and affection.

(E) Someone to lend you money.

FIGURE S52: Correlations with social support responses for high-SES respondents.

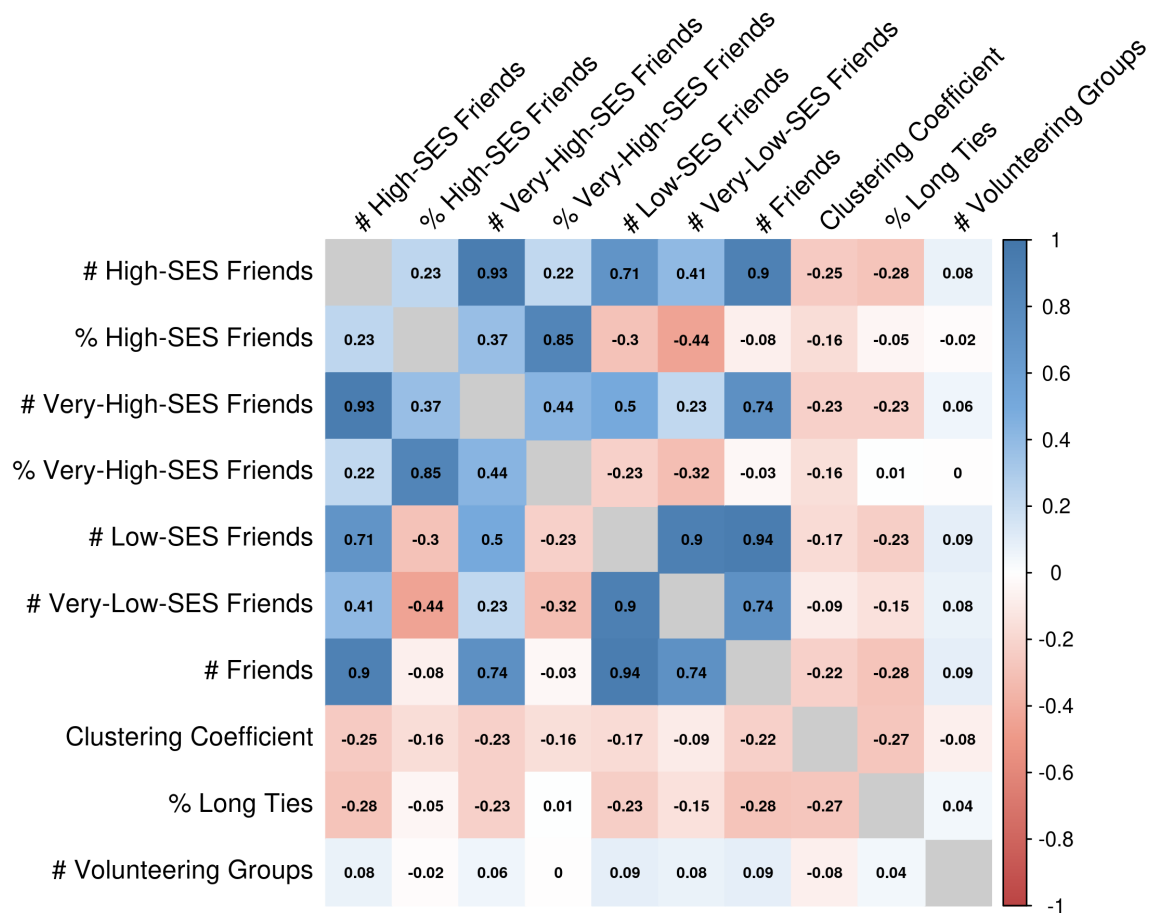


FIGURE S53: Respondent-level correlations between social capital metrics.

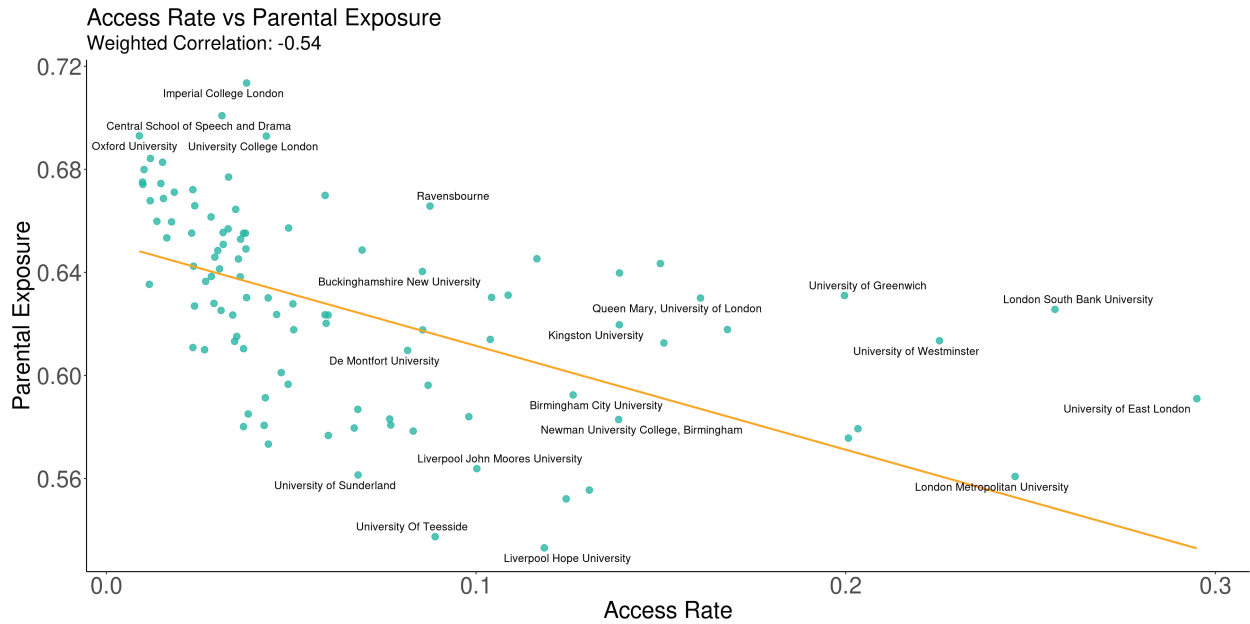


FIGURE S54: Parental exposure vs. FSM access rates across universities.

Notes: Parental exposure is the share of students with above-median parental SES among those linked to parents. Access rate is the share of entrants who received FSM in school [78].

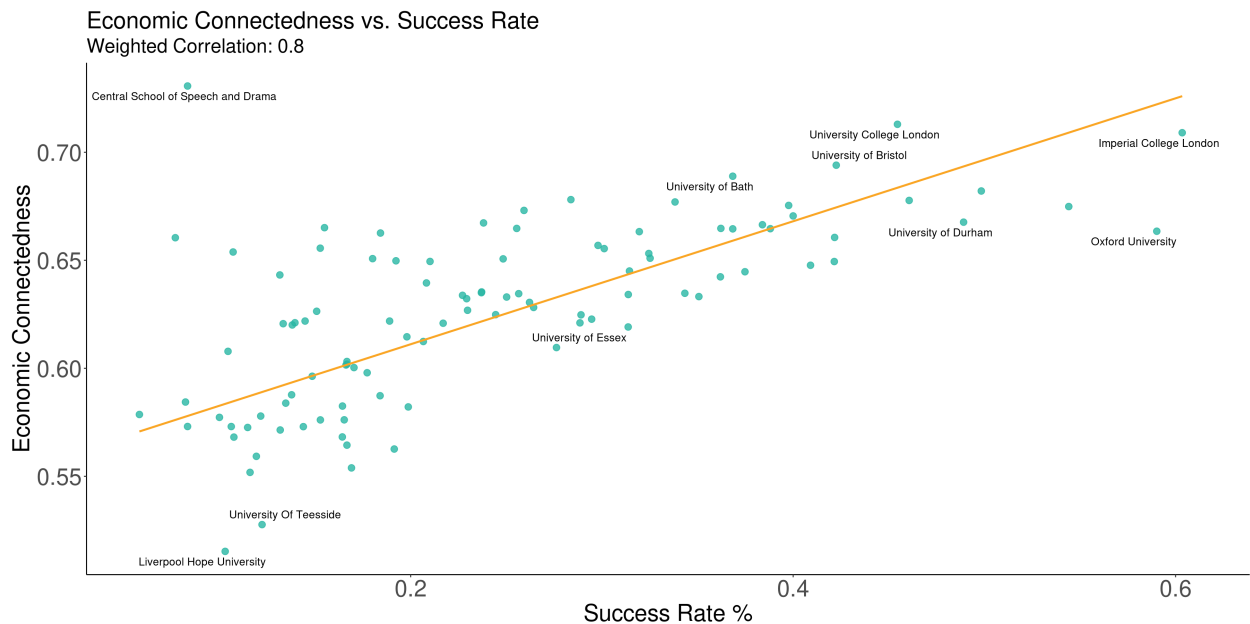


FIGURE S55: University EC (parental SES) vs. success rates for FSM students.

Notes: University EC is computed using parental SES among within-university friendships. Success rate is the share of FSM students reaching the top 20% of the earnings distribution by age 30 [78]. Correlation ≈ 0.82 .

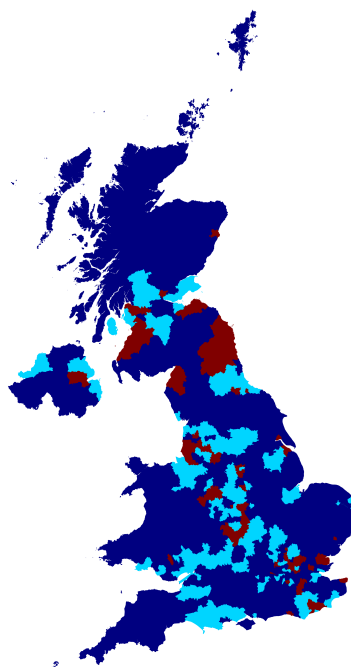


FIGURE S56: Friending bias in hobby & recreation groups by local authority district.
Notes: Dark blue LADs: friending bias in hobby/recreation groups $< 2.2\%$ (the analytic-sample average within these groups). Light blue: between 2.2% and 3.3% (overall friending bias across all friendships). Dark red: $> 3.3\%$.

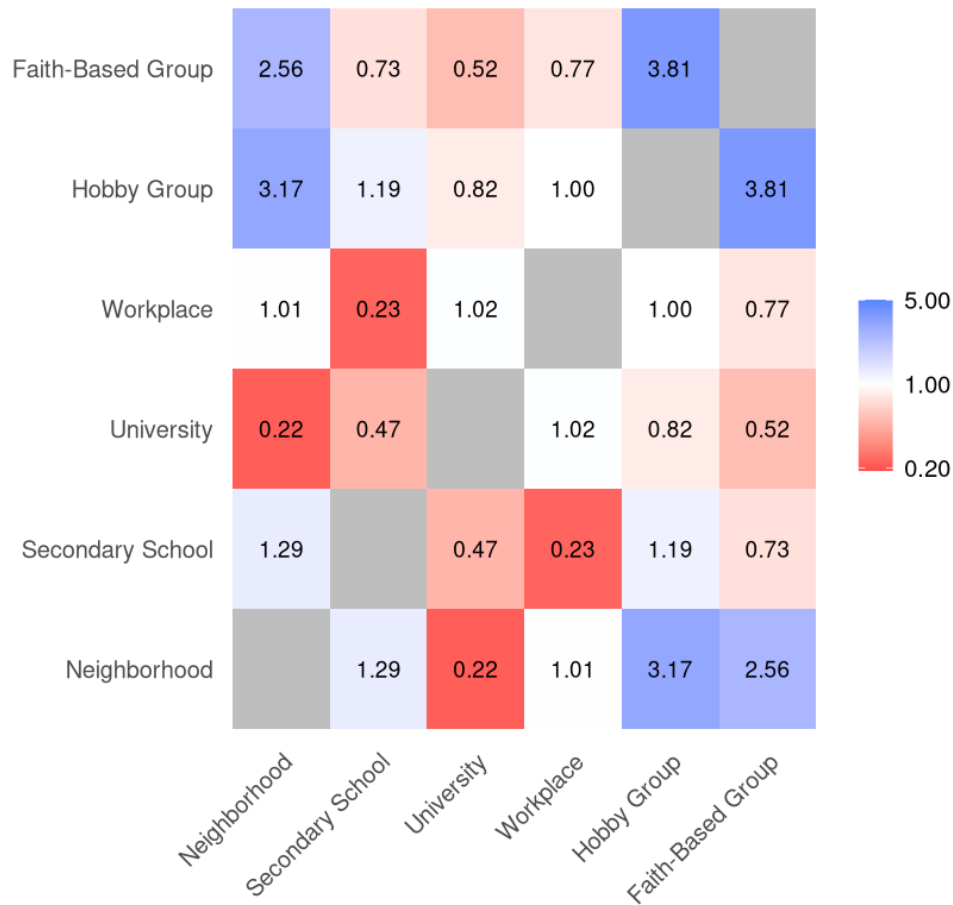


FIGURE S57: Relative probabilities of friendships spanning two settings.

Notes for Figure S57: The entry in each cell is calculated as follows. First, we calculate the proportion of all friendships that we assign to the setting designated in the row that we *also* assign to the setting designated in the column. Second, we calculate the fraction of all friendships that we assign the setting. The values displayed in each cell are the ratio of the first quantity to the second. Cells are shaded by value on a log scale.

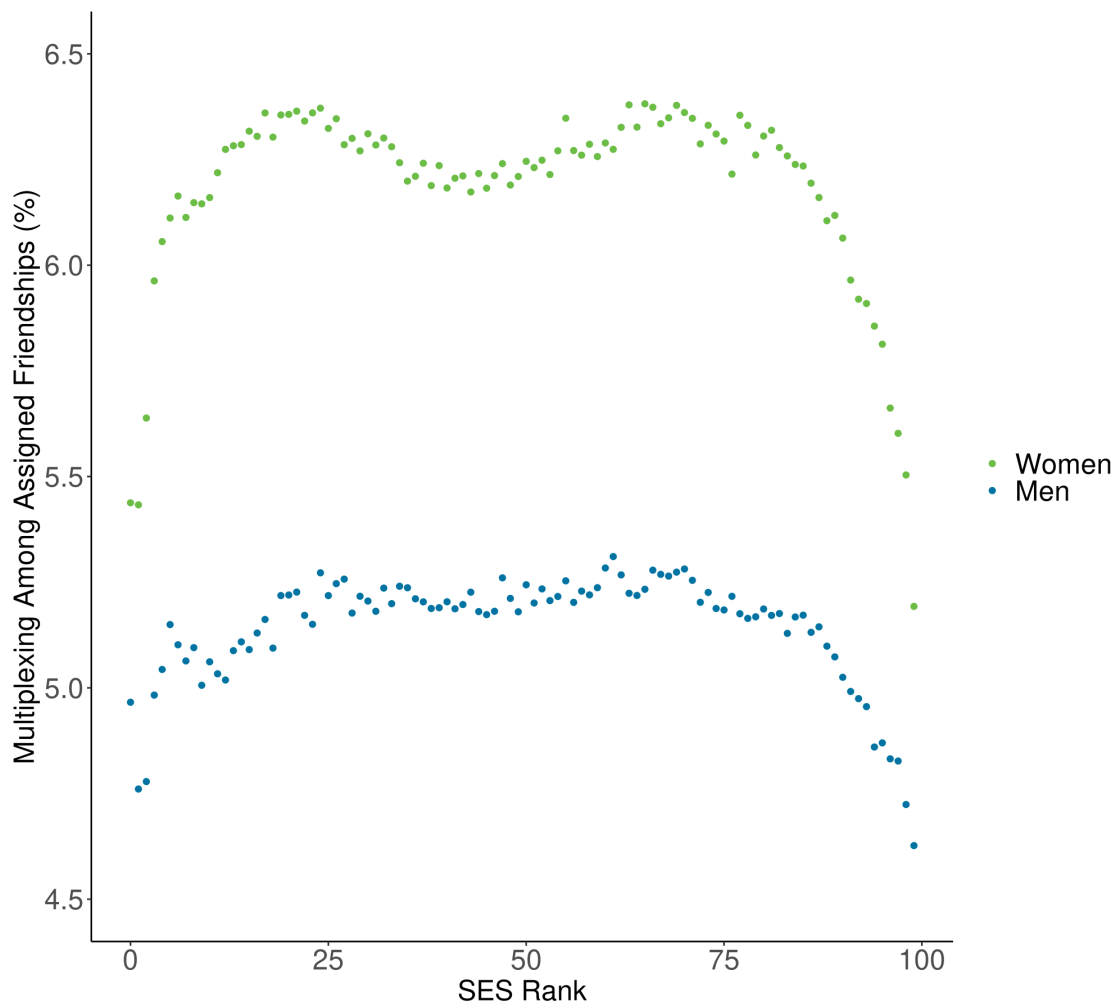
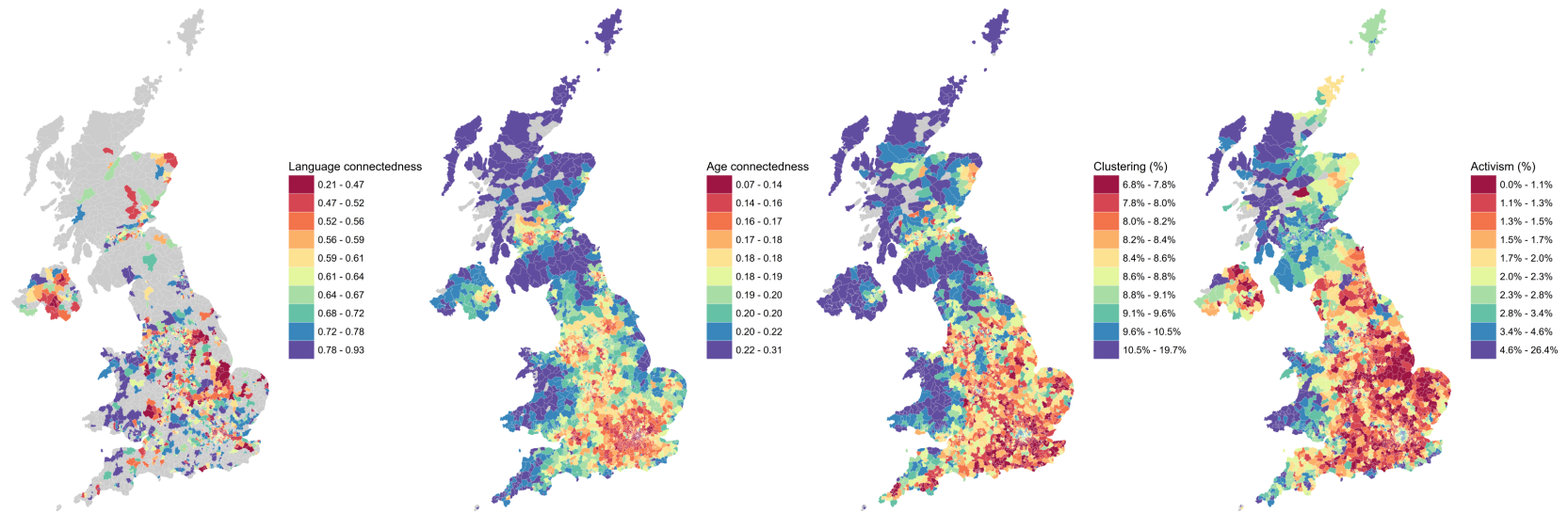


FIGURE S58: Multiplexing by SES rank and gender.

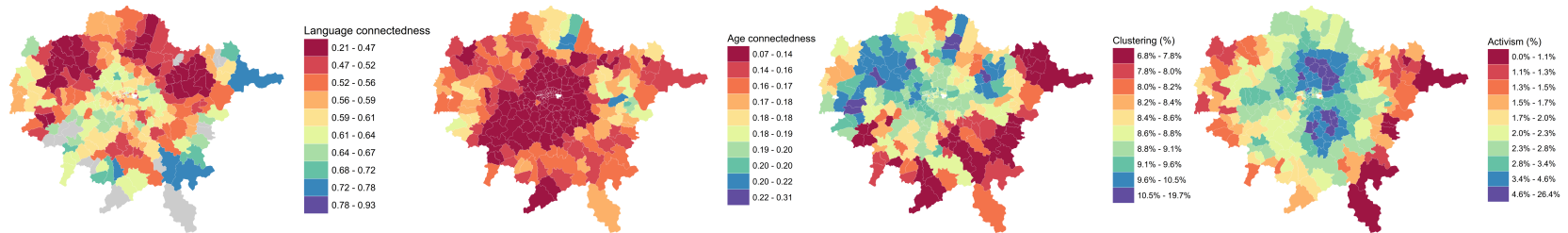
Notes for Figure S58: Each dot corresponds to the average multiplexing index for individuals of a given SES rank and gender. The multiplexing index for each individual is calculated as the proportion of their friendships assigned to at least one setting that are assigned to two or more settings.



FIGURE S59: User-level correlations between SES and cohesiveness metrics.



(A) Geographic distribution of social capital measures by postcode district across the UK.



(B) Geographic distribution of social capital measures by postcode district in London.

FIGURE S60: Geographic distribution of social capital measures by postcode district. Panel (a) reports values for all UK postcode districts, while panel (b) zooms in on postcode districts within Greater London. Darker shading corresponds to higher levels of social capital.

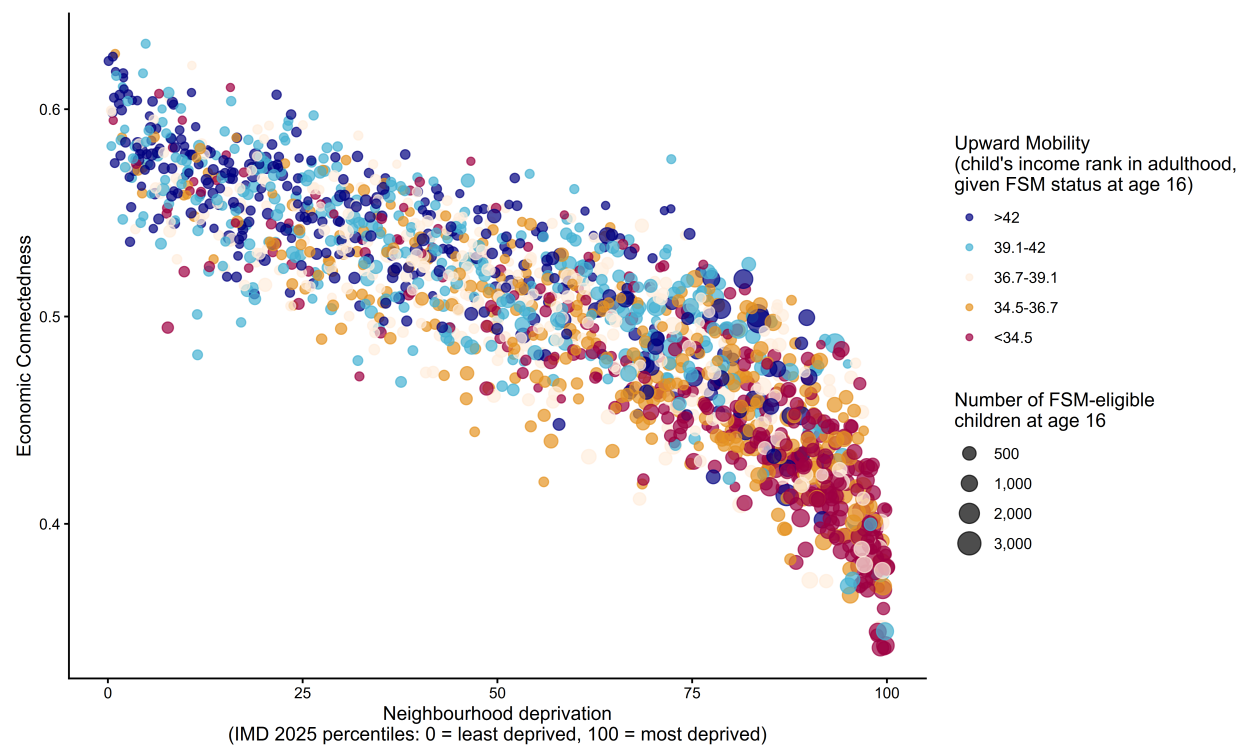


FIGURE S61: Economic connectedness, neighbourhood deprivation, and economic mobility (England, postcode-district level).

TABLE S1: Universities with High/Low Economic Connectedness, Exposure, and Friending Bias

Rank	Economic Connectedness (higher = better)	Exposure (share above-median SES)	Friending Bias (higher = worse)
High 1	Central School of Speech and Drama (0.73)	Imperial College London (0.71)	University of the Arts London (0.07)
High 2	University College London (0.71)	Central School of Speech and Drama (0.70)	Liverpool Institute for Performing Arts (0.06)
High 3	Imperial College London (0.71)	Oxford University (0.69)	Oxford University (0.04)
High 4	University of Bristol (0.69)	University College London (0.69)	Liverpool Hope University (0.03)
High 5	University of Bath (0.69)	University of Exeter (0.68)	University Campus Suffolk (0.03)
Low 1	Liverpool Hope University (0.52)	Liverpool Hope University (0.53)	University of East London (-0.05)
Low 2	University Of Teesside (0.53)	University Of Teesside (0.54)	University of Bolton (-0.05)
Low 3	University of Wolverhampton (0.55)	University of Bolton (0.55)	Central School of Speech and Drama (-0.04)
Low 4	Liverpool John Moores University (0.55)	University of Wolverhampton (0.56)	London South Bank University (-0.04)
Low 5	University of Sunderland (0.56)	London Metropolitan University (0.56)	University College Falmouth (-0.03)

Notes: All metrics use parental SES. EC is the share of above-median (by parental SES) friends among below-median students' within-university friendships. Exposure is the share of students with above-median parental SES. Friending bias = $1 - \text{EC}/\text{Exposure}$; *higher values indicate less cross-SES mixing (worse)*.

TABLE S2: Top and bottom local authority districts by social connection metrics

Rank	Economic Connectedness	Exposure	Friending Bias
Top 1	E07000089 (Hart — 0.67)	E07000207 (Elmbridge — 0.70)	E09000014 (Haringey — 0.13)
Top 2	E07000214 (Surrey Heath — 0.66)	E07000089 (Hart — 0.70)	E06000039 (Slough — 0.12)
Top 3	E07000207 (Elmbridge — 0.65)	E07000240 (St Albans — 0.69)	E09000010 (Enfield — 0.11)
Top 4	E06000041 (Wokingham — 0.64)	E07000214 (Surrey Heath — 0.68)	E07000241 (Welwyn Hatfield — 0.11)
Top 5	E07000216 (Waverley — 0.64)	E06000041 (Wokingham — 0.68)	E07000123 (Lancashire — 0.10)
Bottom 1	E09000014 (Haringey — 0.30)	E09000014 (Haringey — 0.34)	E06000053 (Isles of Scilly — -0.05)
Bottom 2	N09000003 (Belfast — 0.33)	N09000003 (Belfast — 0.36)	S12000027 (Shetland Islands — -0.05)
Bottom 3	E09000010 (Enfield — 0.33)	N09000005 (Derry & Strabane — 0.36)	S12000023 (Orkney Islands — -0.04)
Bottom 4	E06000002 (Middlesbrough — 0.34)	W06000019 (Blaenau Gwent — 0.37)	S12000013 (Na h-Eileanan Siar — -0.04)
Bottom 5	S12000049 (Glasgow City — 0.35)	E06000002 (Middlesbrough — 0.37)	N09000006 (Fermanagh & Omagh — -0.03)

Notes: EC is the share of above-median-SES friends among below-median-SES residents' within-neighbourhood friendships. Exposure is the share of above-median-SES residents in the LAD. Friending bias is $1 - \text{EC}/\text{Exposure}$.

TABLE S3: Bivariate associations between social capital and outcomes

	Economic mobility		Educational attainment	Preventable mortality	Crime
	LA-level	PCD-level			
Economic connectedness	0.57 (0.05)	0.50 (0.02)	0.53 (0.05)	-0.87 (0.03)	-0.28 (0.05)
Language connectedness	-0.15 (0.06)	- (-)	0.10 (0.06)	-0.22 (0.06)	-0.22 (0.06)
Age connectedness	-0.48 (0.05)	-0.41 (0.02)	-0.50 (0.05)	0.07 (0.06)	-0.30 (0.05)
Clustering	0.12 (0.06)	0.07 (0.02)	-0.09 (0.06)	0.22 (0.06)	0.22 (0.06)
Long-tie ratio	0.70 (0.04)	0.58 (0.02)	0.52 (0.05)	-0.17 (0.06)	0.20 (0.06)
Volunteering rate	-0.08 (0.06)	0.01 (0.02)	-0.01 (0.06)	-0.30 (0.05)	-0.29 (0.05)
Activism rate	0.00 (0.06)	-0.01 (0.02)	-0.03 (0.06)	0.27 (0.05)	0.19 (0.06)
Observations	308	1670	308	309	309

Notes: Coefficients with standard errors in parentheses from separate bivariate correlations of each outcome on each social capital measure. Economic mobility is measured at both local authority (LA) and postcode district (PCD) level; other outcomes are at LA level. Economic mobility correlations are weighted by the number of FSM-eligible pupils in the relevant geography (local authority or postcode district). Educational attainment correlations are weighted by the number of pupils in the local authority. Preventable mortality and crime correlations are weighted by total population in the local authority. Owing to incomplete geographical coverage, Language connectedness is excluded from the postcode district-level analysis.

TABLE S4: Multivariate associations between social capital and outcomes

	Economic mobility		Educational attainment	Preventable mortality	Crime
	LA-level	PCD-level			
Economic connectedness	0.73 (0.07)	0.57 (0.04)	0.41 (0.06)	-1.00 (0.05)	-0.17 (0.07)
Language connectedness	-0.03 (0.06)	- (-)	0.09 (0.05)	0.08 (0.03)	-0.07 (0.04)
Age connectedness	0.20 (0.07)	0.11 (0.06)	-0.17 (0.06)	-0.24 (0.05)	-0.22 (0.09)
Clustering	0.31 (0.06)	0.20 (0.03)	0.13 (0.05)	-0.21 (0.04)	0.04 (0.05)
Long-tie ratio	0.61 (0.06)	0.41 (0.04)	0.34 (0.06)	-0.16 (0.04)	-0.02 (0.04)
Volunteering rate	-0.06 (0.07)	-0.06 (0.04)	-0.05 (0.07)	-0.01 (0.03)	-0.06 (0.05)
Activism rate	0.05 (0.03)	0.02 (0.03)	-0.05 (0.05)	0.03 (0.02)	0.03 (0.03)
Adjusted R^2	0.76	0.62	0.50	0.82	0.21
Observations	308	1670	307	308	308

Notes: Coefficients with standard errors in parentheses from multivariate regressions including all listed social capital variables simultaneously. Economic mobility models are weighted by the number of FSM-eligible pupils in the relevant geography (local authority or postcode district). The educational attainment model is weighted by the number of pupils in the local authority. The preventable mortality and crime models are weighted by total population in the local authority. Outcomes and predictors are standardised to mean 0 and standard deviation 1. Intervals are 95% confidence intervals using heteroskedasticity-robust standard errors. Postcode district-level analysis standard errors are clustered by postcode area. Owing to incomplete geographical coverage, Language connectedness is excluded from the postcode district-level analysis.

TABLE S5: Multivariate regressions with other area-level covariates

(A) Economic mobility		(B) Educational attainment	
Economic connectedness	0.24 (0.09)	Long-tie ratio	0.19 (0.07)
Long-tie ratio	0.34 (0.06)	Age connectedness	-0.01 (0.07)
Median weekly pay	0.33 (0.07)	Gross disposable household income per head	0.06 (0.06)
Residential stability	0.09 (0.05)	Child obesity (Year 6)	-0.22 (0.08)
High-growth enterprises	-0.12 (0.04)	Share in professional occupations	0.35 (0.12)
GCSE English & Maths	0.11 (0.06)	Share Asian	0.25 (0.06)
Share Asian	0.20 (0.06)	High-growth enterprises	0.03 (0.03)
Children at expected level for literacy at EYFS	-0.06 (0.06)	Cigarette smokers	-0.10 (0.05)
Preventable cardiovascular mortality	-0.21 (0.08)	Adjusted R^2	0.59
Adjusted R^2	0.82	Observations	288
Observations	288		
(C) Preventable mortality		(D) Crime	
Economic connectedness	-0.24 (0.07)	Language connectedness	-0.10 (0.07)
Long-tie ratio	-0.26 (0.03)	Volunteering rate	-0.12 (0.08)
Activism rate	0.10 (0.02)	Share in professional occupations	-0.01 (0.09)
Share in professional occupations	-0.14 (0.05)	Net housing additions	-0.08 (0.06)
Children at expected level for maths at EYFS	-0.20 (0.08)	Modelled unemployment rate	0.00 (0.08)
Single-parent households	0.24 (0.08)	Residential stability	-0.17 (0.09)
GCSE English & Maths	-0.06 (0.04)	Gigabit-capable broadband	-0.01 (0.08)
Urban population share	0.05 (0.05)	Child obesity (Year 6)	0.20 (0.12)
Travel time to employment centre by public transport and walking	-0.29 (0.05)	High-growth enterprises	0.30 (0.20)
Adjusted R^2	0.88	Adjusted R^2	0.38
Observations	288	Observations	274

Notes: Panels (A)–(D) report coefficients with standard errors in parentheses from LA-level multivariate regressions for each outcome. Social-capital predictors are listed first in each panel. Covariates were chosen via outcome-specific LASSO models using social-capital measures and neighbourhood statistics [41, 42] (full variable list in A.8; LASSO paths in Figs. 3c, S7c, S8c, and S9c). The economic mobility model is weighted by the number of FSM-eligible pupils in the relevant geography (local authority or postcode district). The educational attainment model is weighted by the number of pupils in the local authority. The preventable mortality and crime models are weighted by total population in the local authority. Variables are standardised to mean 0 and standard deviation 1; heteroskedasticity-robust standard errors.