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

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Abstract

We construct a range of measures of social capital (the strength and structure of social networks) for the United Kingdom using data from Facebook covering 20.5 million adults. We make these measures publicly available. Low-socioeconomic-status (SES) individuals have far fewer high-SES friends than high-SES individuals do. Areas with more cross-SES friendships display higher levels of intergenerational economic mobility (higher adult earnings for children growing up in disadvantaged families). 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. Areas with more long ties (friendships between people with no mutual connections) also display substantially higher levels of intergenerational economic mobility, and long ties are especially likely to form outside the typical settings in which individuals make friends. The relationships between economic connectedness, long ties, and intergenerational economic mobility remain strong even after controlling for other area-level characteristics. We also make new estimates of intergenerational economic mobility in the UK publicly available, including the first estimates for areas in Scotland and Northern Ireland.

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Introduction

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 a social network and our behaviours and actions are deeply shaped by the structure of our social relations and the relations of our peers. We constantly make use of information and resources provided by those around us, and many of the most important facets of our lives are determined by interactions we have with others. For example, labour markets are heavily reliant on job referrals (*2*, *3*), and the types of jobs we look for are shaped by information provided by our contacts (*4*). Even before we ever apply for a job, our academic results are shaped by the inclinations of those around us (*5*, *6*). The individuals around us can also be a source of both credit and insurance (*7*, *8*), even in countries with well-established financial markets (*9*). Even our choice of where to live is shaped by the experiences and choices of 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 find that economic mobility is strongly predicted by two features of social networks: economic connectedness (EC)—the share of high-socioeconomic-status (SES) friends among low-SES individuals—and the long-tie ratio (LTR)—the share of connections from low-SES individuals in an area to peers with no mutual friends. We then examine how both ties to high-SES individuals and long ties are predicted by the settings (such as schools or workplaces) in which they form.

Our approach follows recent research by Chetty et al. (*14*), which similarly used data on Facebook friendships within the U.S. to show that economic connectedness (EC) is strongly related to economic mobility in the U.S. One contribution of this study is to show that this relationship holds outside of the U.S. context. We find that 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) more as an adult than a similar low-income child growing up in a local authority at the 10th percentile of the EC distribution (where 44% of their friends would have high SES).

Following Chetty et al. (*15*), we decompose differences in economic connectedness between low- and high-SES individuals into three components: differences in the settings where individuals make their friends (friending shares), differences in exposure to high-SES individuals within settings, and differences in friending bias (differences in connectedness within settings conditional on exposure). We find that differences in friending shares across settings account for around 9% of the gap in connectedness between low- and high-SES individuals. Differences in exposure account for roughly 32% of the gap. As a result, most of the gap in connectedness (59%) is attributable to differences in friending bias. The importance of friending bias as a determinant of connectedness emphasises an advantage of our data, where we directly observe friendships and interactions between individuals, over mobile phone co-location data which is also popular in the social capital literature and provides a complementary source of evidence on social capital (*16*–*19*).

A second, distinct, aspect of social capital we focus on is the prevalence of "long ties" in an area—friendships between individuals who do not share any mutual friends (*20*). We find that long ties are disproportionately likely to form outside of 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 growing up in a UK local authority at the 90th percentile of the LTR distribution (where 5.5% of friendships are long ties) can expect to earn £2,690 more than a similar child growing up in a local authority at the 10th percentile of the LTR distribution (where 3.3% of friendships are long ties). It seems unlikely that friendships between individuals with no mutual friends are special in terms of their impact compared to friendships between individuals with a small but non-zero number of mutual friends. Instead, we posit, the LTR's predictive power likely reflects broader properties of the network that matter, such as expansiveness and bridges between distinct social groups, and hence our results provide support for theories in sociology and economics emphasising these aspects of social networks (*21*–*25*).

The bivariate correlations between EC and the LTR with economic mobility are extremely large (0.57 and 0.70 respectively). For context, these correlations are roughly as large as the correlation between educational attainment in secondary schools (GCSEs) and economic mobility (0.60) and the correlation between average disposable income in an area and mobility (0.56). They are substantially larger than the absolute area-level correlations between economic mobility and other factors such as employment rates (0.19), unemployment rates (0.11), and the share of single-parent households (0.19), and larger than the share of black individuals (0.48), and measures of early-stage educational attainment (between 0.27 and 0.53).

EC and the LTR represent distinct forms of social capital. Both remain strongly predictive of economic mobility in multivariable regressions incorporating all of the measures of social capital we construct. They also both remain strong predictors even after controlling for other area-level characteristics such as income, educational attainment, and demographics.

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.1, and our economic mobility metrics in Appendix A.5. 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.

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 (*26*). We refer to this group as the *analytic sample*. Figure S1 shows that our analytic sample slightly over-represents females and younger adults, consistent with known social-media usage patterns (*27*, *28*).

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 S2 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 (*29*). 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 S3). 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.3 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 S17).

In order to construct SES measures for individuals while they were growing up we link individuals, where possible, to their parents (see Appendix A.4). 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.

Results

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 SES rank in the national distribution is associated with a 0.17 percentage point increase in the average SES rank of their friends. That association is even stronger when we restrict to an individual's close friends on the platform (using an internal metric validated against survey responses on closeness), where a 1 percentage point increase in an individual's SES is associated with a 0.21 percentage point increase in the average SES rank of their close friends on the platform, suggesting that income homophily is stronger for close friends.

Figure 1b also demonstrates the extent of homophily in the UK. Roughly 20% of the friends of individuals in the bottom decile of the SES distribution are also in the bottom decile of the SES distribution, while only 5% of the friends of individuals in the bottom decile of the SES distribution are from the highest decile.

Individuals with SES above the median for their birth cohort (henceforth "high-SES individuals") have both more friends and a higher proportion of their friends who are high-SES compared to below-median-SES (henceforth "low-SES") individuals. As a result, high-SES individuals have dramatically more high-SES friends than low-SES individuals, as demonstrated in 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 (*30*), and the *long-tie ratio*, which is the proportion of friends with whom the individual shares no mutual connections (*20*). Note that the long-tie ratio is equivalent to 1 subtract the *support ratio*, as defined by Jackson, Rodriguez-Barraquer, and Tan (*31*). Higher-SES individuals have less clustered networks (Figure S5), whilst the long-tie ratio shows no clear relationship with SES (Figure 1d). We note in Figures S4a and S4b 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. Full descriptions of all of our measures and how we construct them are available in Appendix A.1.

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 (*32*, *33*), EC is higher in Rural-Urban Fringe/Affluent Rural areas and lower in Industrial, Mining Legacy, and Multi-ethnic urban areas (Figure S7). EC correlates negatively with Brexit vote share (-0.2) and positively with EU referendum turnout (0.4), conditional on local SES composition (*34*). 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, where diverse connections are more common.

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, "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%) (Figure S7).

Social Capital and Economic Mobility

Area-Level Correlations

A central motivation for measuring social capital is its potential link to intergenerational economic mobility. Recent U.S. evidence shows that greater EC is associated with substantially higher economic mobility for disadvantaged children (*14*). 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. (*35*). Appendix A.5 details the construction of our mobility statistics, which we make publicly available. 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 (*36*). 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 S11).

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 (*37*, *38*). (We list all of our area-level characteristics in Appendix A.7.) Figure S12 shows that the LTR and EC correlate more strongly with economic mobility than most other economic, educational, health and demographic indicators we consider. Running a Lasso regression of economic mobility on all our social capital variables and these area-level characteristics, we find that both the LTR and EC are amongst the earliest selected predictors, 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 (38% increase) in annual 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 economic mobility amongst disadvantaged children. Empirical evidence suggests that social ties for which individuals share fewer mutual friends tend to be weaker in terms of intensity and closeness (*39*, *40*), and so our results provide further evidence in support of the theory that weak ties, in the language of Granovetter (*21*), who explicitly relates tie strength to the degree of overlap between two individuals' friendship networks, play an important rule in shaping economic outcomes.

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 S11, we show that our results are similar when running correlations at the more granular postcode district level. Figure S12 contextualizes the size of the correlations between our social capital variables and economic mobility versus the correlations between other local-authority-level predictors and mobility. We see that EC and the LTR are among the strongest predictors of upward mobility among all the variables we consider.

Contrasts with Results from the U.S.

While our findings on EC and economic mobility broadly mirror those from Chetty et al. (*14*) in the U.S., our finding that the LTR among low-SES individuals is highly predictive economic mobility is markedly stronger. They found the support ratio (which is equal to 1 minus the LTR) to only weakly predict economic 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 S18, 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 (*41*–*43*). We examine whether our Facebook-derived measures predict these outcomes.

In bivariate analyses, higher EC correlates with better GCSE results (Figure S14a), fewer preventable deaths (Figure S15a), and lower crime rates (Figure S16a). 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 S14c) and remains a moderate predictor in multivariable regressions (Figure S14d). For mortality, EC emerges as the strongest initial predictor (Figure S15c) and maintains this relationship when controlling for other variables (Figure S15d). Neither social capital measure shows robust associations with crime once compared to other predictors (Figures S16c and S16d).

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. (*15*) 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. We provide details of how we assign friendships to settings in Appendix A.3. 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 S17).

Figures S19 and S20 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). We give formal definitions for each of these three components of EC in Appendix A.2.

Figure 5 reveals three patterns. First, across all settings exposure is highest in universities, reflecting their predominantly affluent student populations. Second, low-SES users meet people of mixed socioeconomic backgrounds in hobby and recreation groups, whilst high-SES users encounter other high-SES individuals, suggesting that individuals with different backgrounds gravitate towards different activities within this 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, whilst there are equal numbers of cross-SES friendships in each direction, these cross-class friendships make up a smaller percentage of their larger social networks.

We quantify how much each of these three components contributes to the overall EC gap between low- and high-SES individuals. Figure 5d presents a counterfactual decomposition. If low-SES individuals formed friendships across settings with the same relative proportions as high-SES individuals, that would close 9% of the gap. Closing the gap in exposure within settings would then subsequently close an additional 32% of the gap. As a result, the remaining disparity (59% of the total gap) is attributable to differences in friending bias. We provide complete details of our decomposition, as well as a more detailed walkthrough of the exercise, in Appendix B.2.

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. See Appendix B.3 for further analysis of multiplexing patterns.

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.

Discussion

This paper introduces UK-wide, fine-grained measures of social capital constructed from Facebook friendship networks covering roughly 20.5 million adults. We showed that EC and the LTR are two of strongest predictors of economic mobility in the UK, and outlined the determinants of each of these metrics of social capital. We make all of the social capital and mobility metrics we construct publicly available at the Humanitarian Data Exchange to facilitate further research on both social capital and economic mobility.

The main limitation of our analysis is that it is observational, not causal. However, we believe that the statistics we make publicly available can facilitate future studies focusing on causation. Analyses to date of the causal impact of social networks has largely leveraged quasi-random variation in the *pool of peers* from which individuals can make friends (*5*, *6*, *44*, *45*). The estimates of friending bias we make publicly available will be helpful for such quasi-experimental designs that leverage shifts in peer composition in determining the extent to which variation in peer composition translates into genuine variation in friendship networks.

Additionally, we have focused on area-level relationships between social capital and outcomes. We have avoided relating individual-level measures of social capital to individual outcomes since we are concerned that individual-level relationships between social capital and outcomes would be driven in part by an individual's SES growing up, and measurement error in individual predictions of SES would make this factor hard to control for fully. However, the strength and direction of our local-authority-level results are similar when we analyse at the much smaller postcode-district level.

Overall, our findings provide evidence for classic theories in economics and sociology that emphasize the role of connections spanning distinct social groups (*21*–*25*), and we have outlined the settings in which connections that span social groups are most likely to form. We hope that the measures of social capital we make publicly available will facilitate further research on both the determinants of social capital and the relationship between social capital and a wide range of outcomes.

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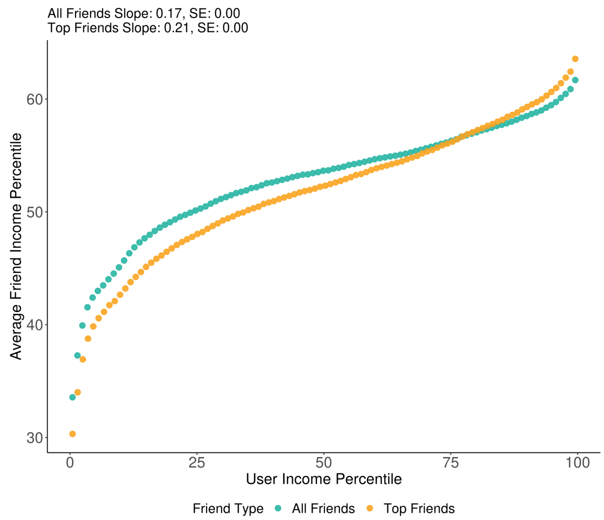
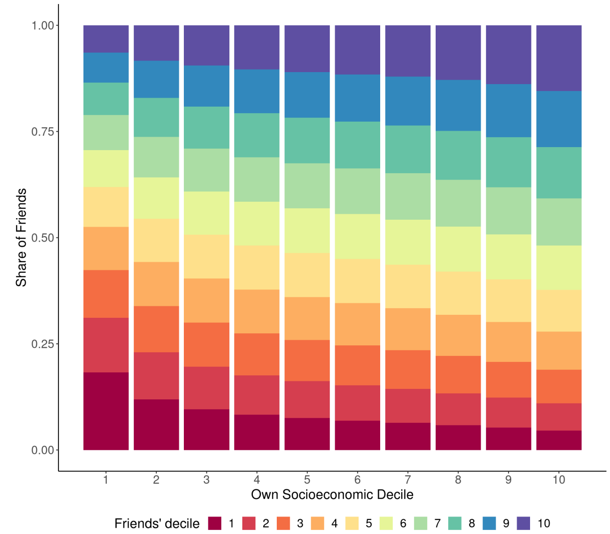
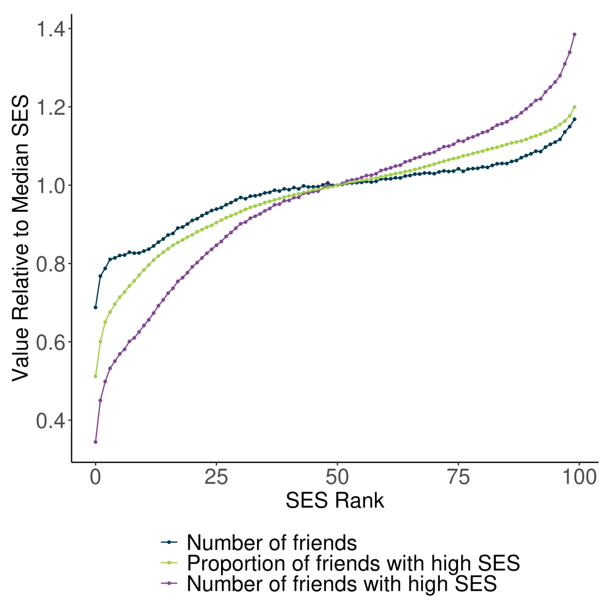


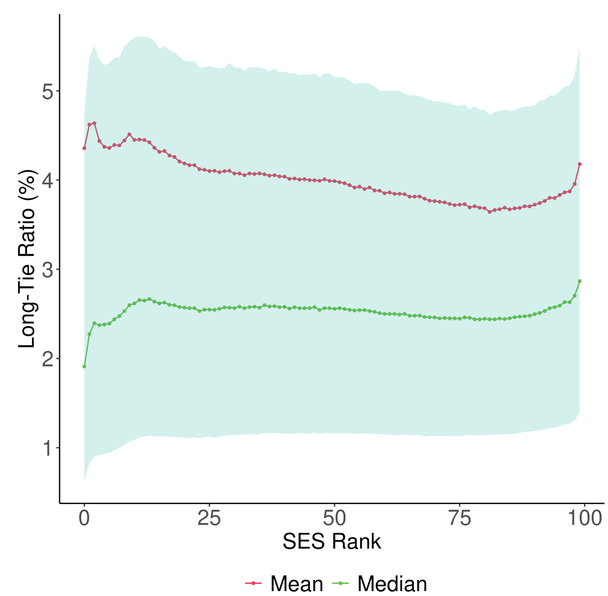
(A) Own SES rank vs. mean friend SES rank.



(B) SES decile to SES decile friendship shares.



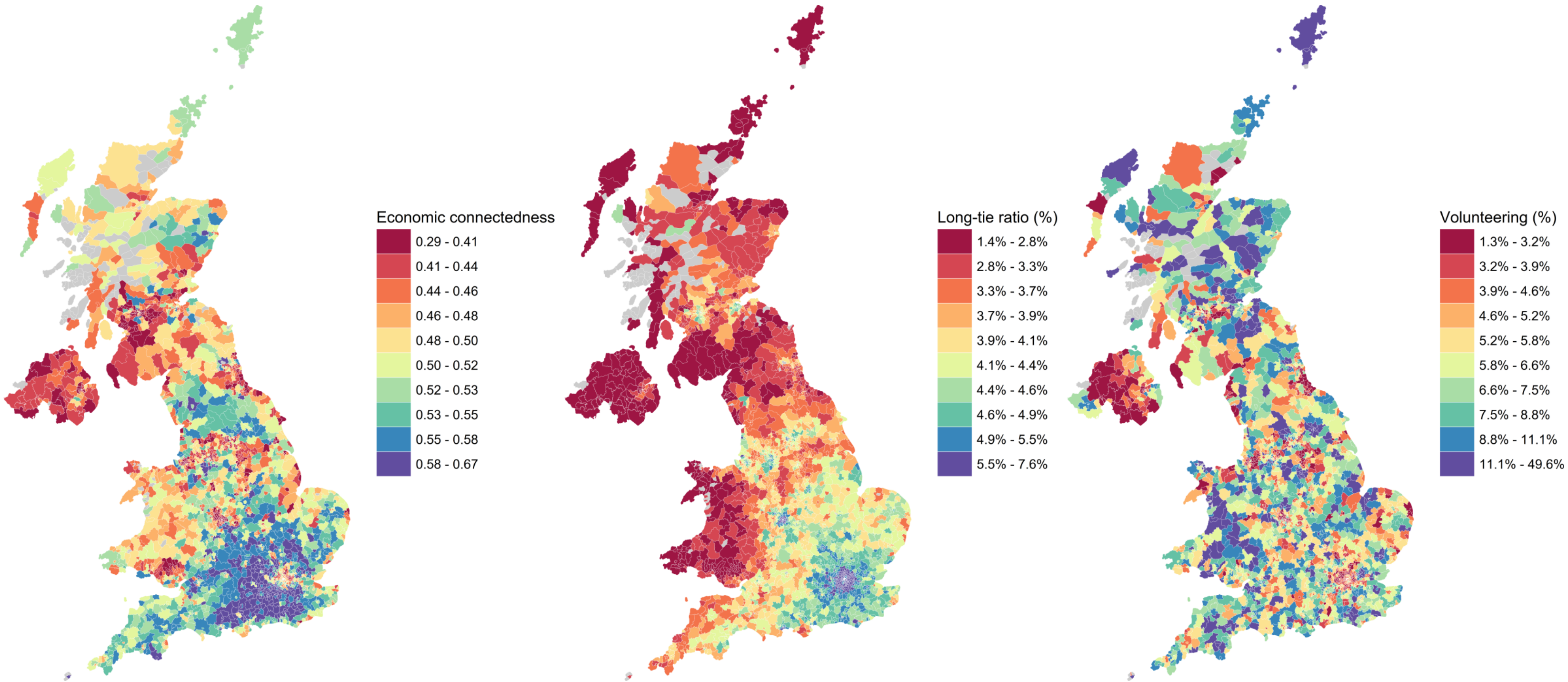
(C) Number of friends by own SES.



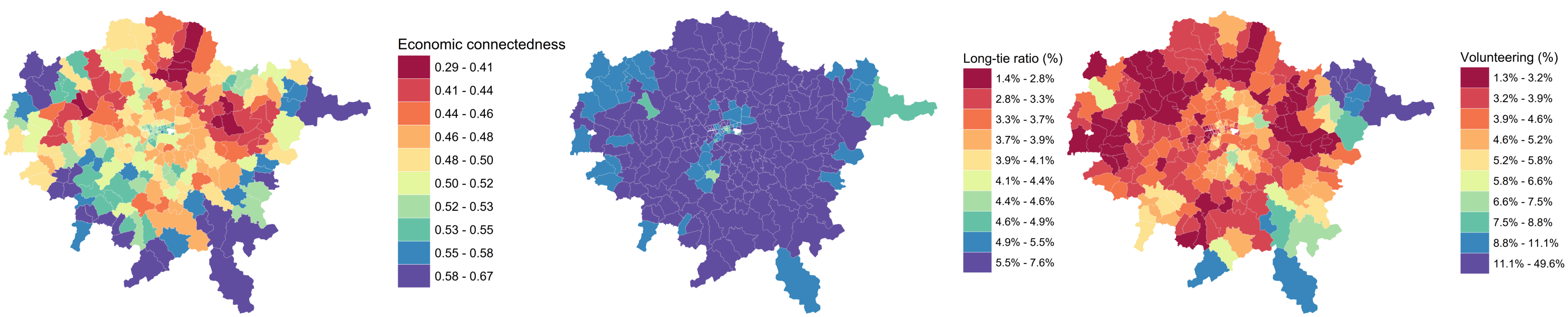
(D) Long-tie ratio, by SES.

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.

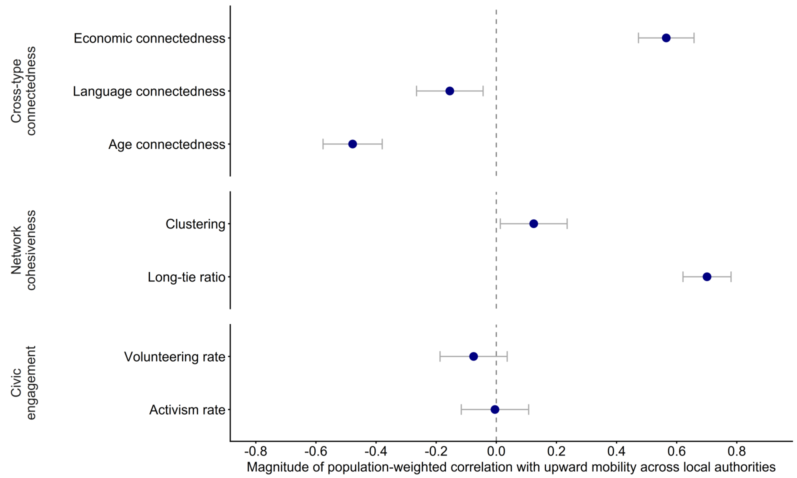


(A) Geographic distribution of social capital measures by postcode district across the UK.

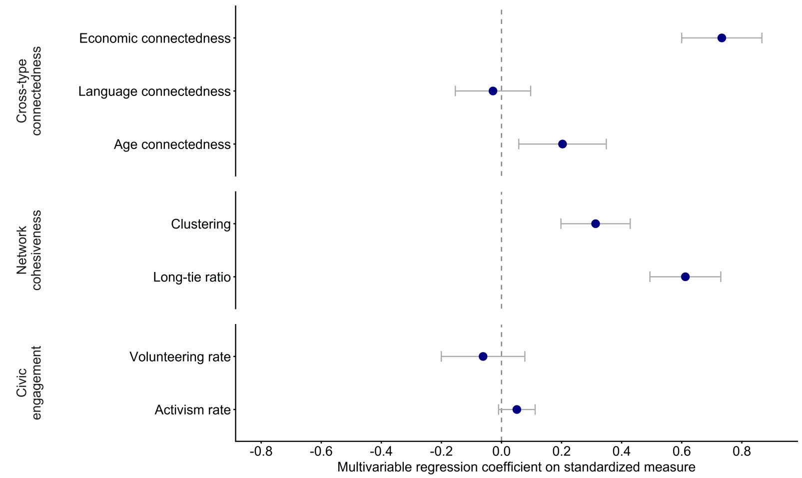


(B) Geographic distribution of social capital measures by postcode district in London.

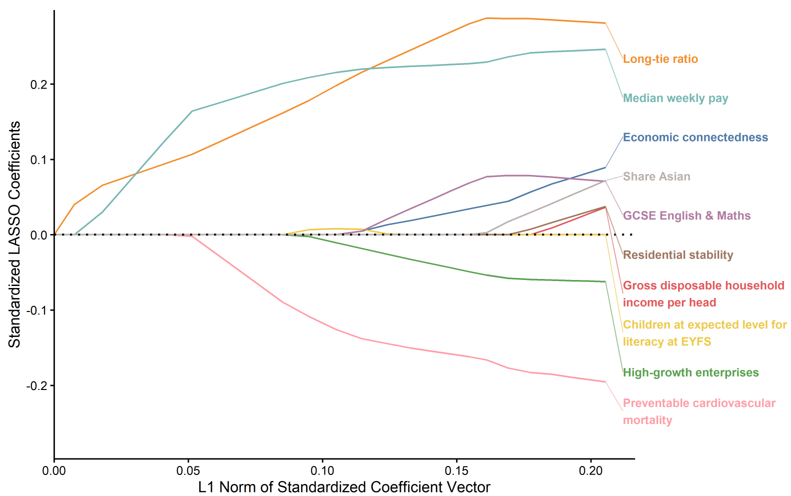
FIGURE 2: Geographic distribution of social capital measures by postcode district. Panel (a) reports values for all UK postcode districts, while panel (b) zooms in on postcode districts within Greater London. Darker shading corresponds to higher levels of social capital.



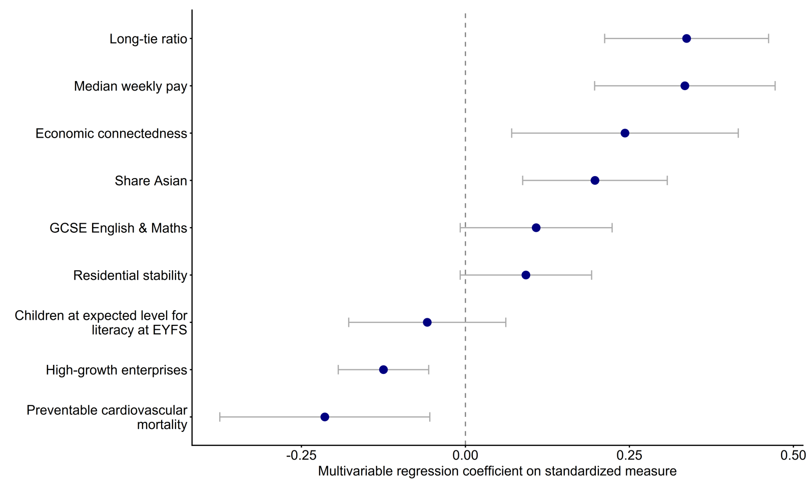
(A) Bivariate correlations



(B) Multivariate correlations



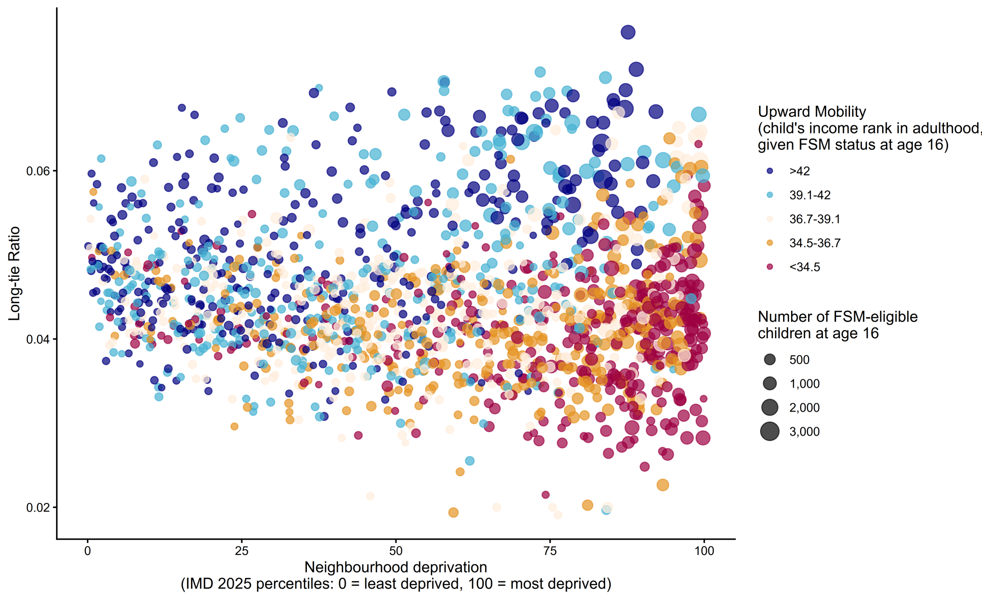
(C) LASSO regularization paths



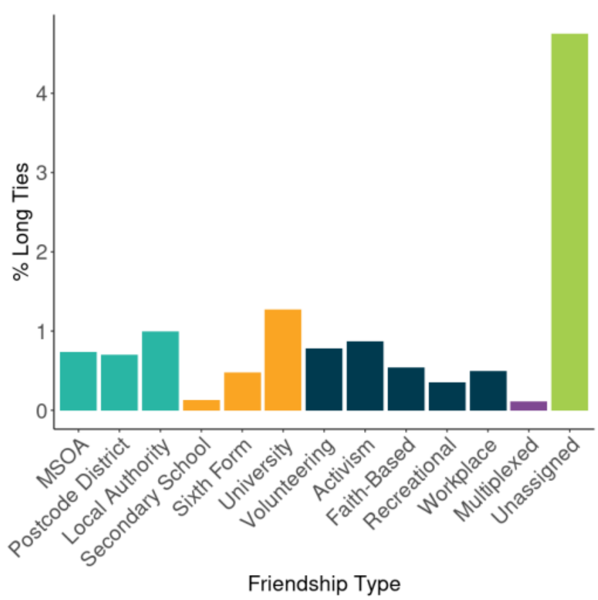
(D) With neighbourhood covariates

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 (*37*, *38*) (All variables used are specified in A.7). Panel (D) uses the leading variables selected by the LASSO.



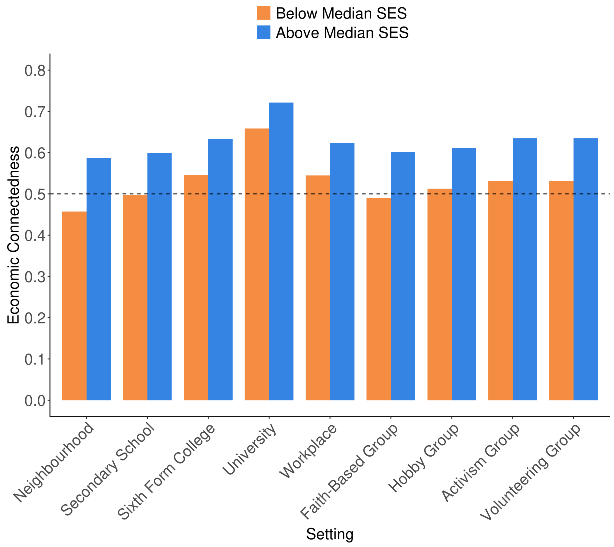
(A) Long-tie ratio, neighbourhood deprivation, and economic mobility (postcode-district level).



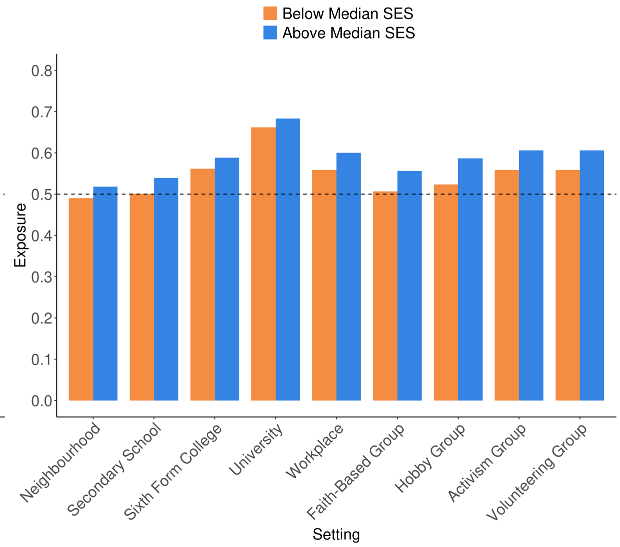
(B) Proportion of friendships that are long ties, within each setting.

FIGURE 4: Long-tie ratios

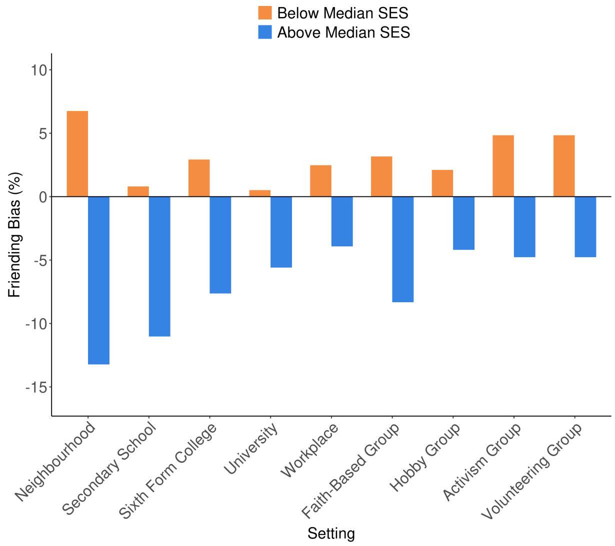
Notes for Figure 4b: Each bar represents the proportion of friendships we assign to the relevant setting that are long ties. (That is, where the two individuals at each end of the friendship do not have any mutual friends, even in other settings.) "Multiplexed" friendships are friendships we are able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



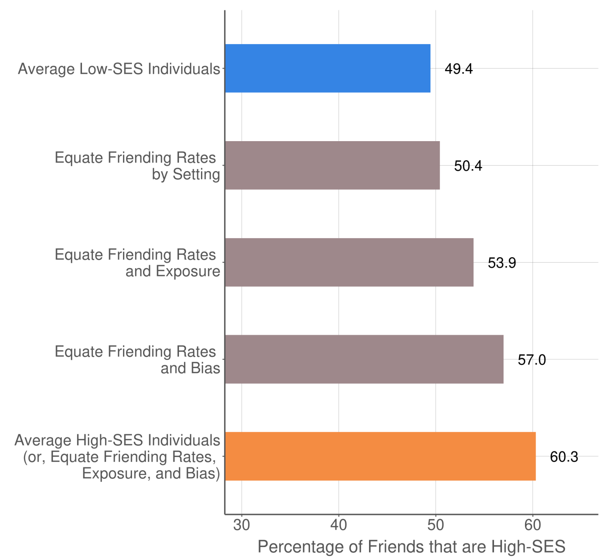
(A) Economic Connectedness



(B) Exposure



(C) Friending Bias



(D) Decomposition of EC Differences

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

A Materials and Methods

A.1 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. (*14*).

A.1.1 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 (*21*), which refers to bonds between acquaintances with less frequent social interaction, often connecting people who are not in the same immediate social circle. Putnam (*46*) 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

$$\mathrm{IEC}_i \;=\; \frac{\left|\{\, j \in F_i : \mathrm{SES}_j > p_{50}(b_j)\,\}\right|}{|F_i|}.$$

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

$$\mathrm{EC}_c \;=\; \frac{1}{|L_c|}\sum_{i \in L_c} \mathrm{IEC}_i.$$

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:

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

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.1.2 Social Cohesion

Social cohesion reflects the structural characteristics of social networks. Bourdieu (47) 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 (21) 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 (46) 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:

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

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 $m^c_{ij} \equiv [(\mathbf{A}^c)^2]_{ij}$ 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 $j \in F^c_i$ is an unsupported ("long") tie if $m^c_{ij} = 0$. The individual measure is

$$\text{LongTieRatio}^c_i = \frac{1}{|F^c_i|} \sum_{j \in F^c_i} \mathbf{1}\{\, m^c_{ij} = 0 \,\} \, ,$$

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

$$\text{LongTieRatio}_c = \frac{1}{|L_c|} \sum_{i \in L_c} \text{LongTie}^c_i \, .$$

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 (*31*). We use the term "long-tie ratio" throughout the paper for consistency.

A.1.3 Civic Engagement

Putnam (*46*) 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.2 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

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

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

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

and overall EC for i averages across settings:

$$\mathrm{EC}_i = \sum_s w_{is}\, \mathrm{EC}_{is}.$$

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

$$\mathrm{FB}_{\cdot s} \;=\; 1 - \frac{\mathrm{EC}_{\cdot s}}{p_{\cdot s}},$$

so $\mathrm{FB}_{\cdot s} = 0$ 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 $\mathrm{EC}_{cs} = \frac{1}{|L_c|} \sum_{i \in L_c} \mathrm{EC}_{is}$,

$$\mathrm{EC}_c = \sum_s w_{cs}\, (1 - \mathrm{FB}_{cs})\, p_{cs}.$$

This identity makes explicit the three determinants of EC.

A.3 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.

A.4 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.5 Constructing Intergenerational Economic Mobility Estimates for the UK

A.5.1 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. (*35*), 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 (*48*), 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. (*35*) from the 1986–1988 birth cohorts to 1986–1992. Our updated local-authority estimates correlate strongly with Carneiro et al. (*35*) (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.5.2 National PCA-Based Mobility Measures

Following the general approach of previous research (*49*), we construct a continuous childhood SES index using Principal Component Analysis (PCA) applied to multiple area-level indicators from the 2001 Census (*50*) and the 2004 Index of Multiple Deprivation (*51*), 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 (*50*), 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 (*51*) 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. (*49*) for adjacent cohorts, indicating that our index successfully recovers familiar intergenerational economic mobility gradients.

A.5.3 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.4.

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) (*14*).

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.6 Other Outcome Data

A.6.1 Educational Attainment

We measure educational attainment using the Department for Education's school-level Key Stage 4 performance data for 2023/24 (*52*). 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 (*53*). 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.6.2 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 (*54*). 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 that social capital influences such as health norms, information flow, and mutual support (*42*).

A.6.3 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 (*55*). 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 (*56*).

A.7 External Covariates

We use the following area characteristics from government statistics (*37*, *38*). 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 MSOA-level population flagged as urban, using 2021 Census usual resident counts and aggregating to local authorities via an MSOA–LAD crosswalk.
- 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.

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 S19). 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.4.) 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 $1 - \mathrm{EC}/\mathrm{Exposure}$ within the institution.

There is large heterogeneity across institutions. Table S4 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, Drayton, and Erve (*57*). Figure S24 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 S25 plots our university-level EC (based on parental SES) against Britton, Drayton, and Erve (*57*)'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 S19). 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 S26 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 S19), 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 S19), yet they exhibit the highest friending bias (Figure 5). Table S5 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. (*15*), 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.2.

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.3 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 S19, 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* (*58*, *59*). Understanding multiplexity is important because multiplexed relationships, by virtue of their value in multiple settings, may enable greater levels of cooperation in relationships (*60*) and experimental evidence shows that the degree of multiplexity in relationships affects the speed with which new information spreads through a society (*61*).

Figure S27 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 them do not remain in the same area upon graduating.

We follow Chandrasekhar et al. (*61*) 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 $\boldsymbol{A}^s$ denote the adjacency matrix including only friendships in setting s (with entries a^s_{ij}), 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 S28, 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 (*61*), although in that study the notion of multiplexing is across different types of support as opposed to friendships and conenctions 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.

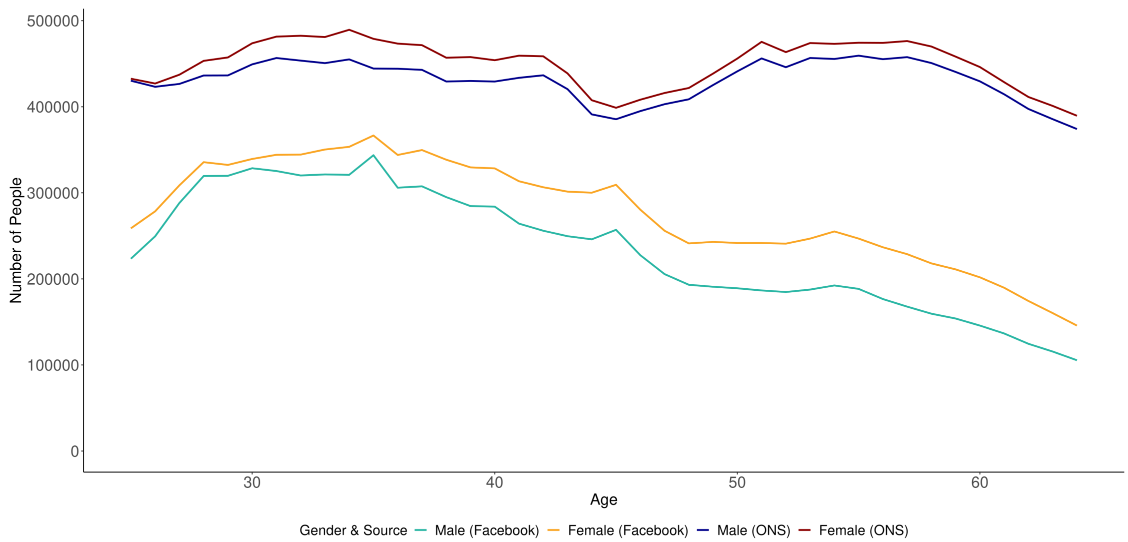


FIGURE S1: Age Distribution by Gender in the Analytic Sample.

Notes for Figure S1: The ONS series uses data from (*26*) 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).

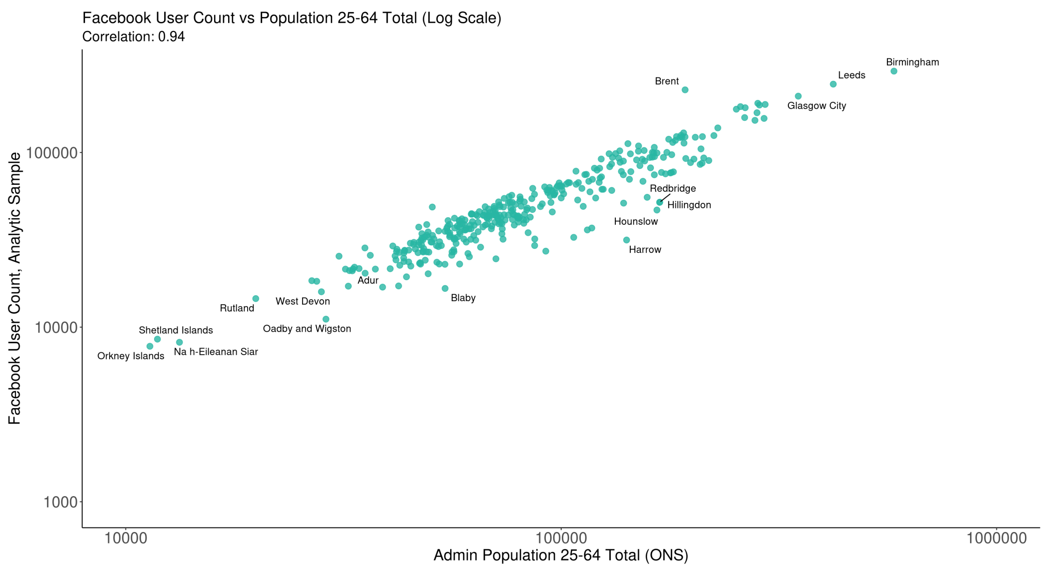


FIGURE S2: Correlation between analytic-sample user counts and administrative population counts for 25–64 year-olds by administrative area.

Notes for Figure S2: The ONS series uses data from (*26*) 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.

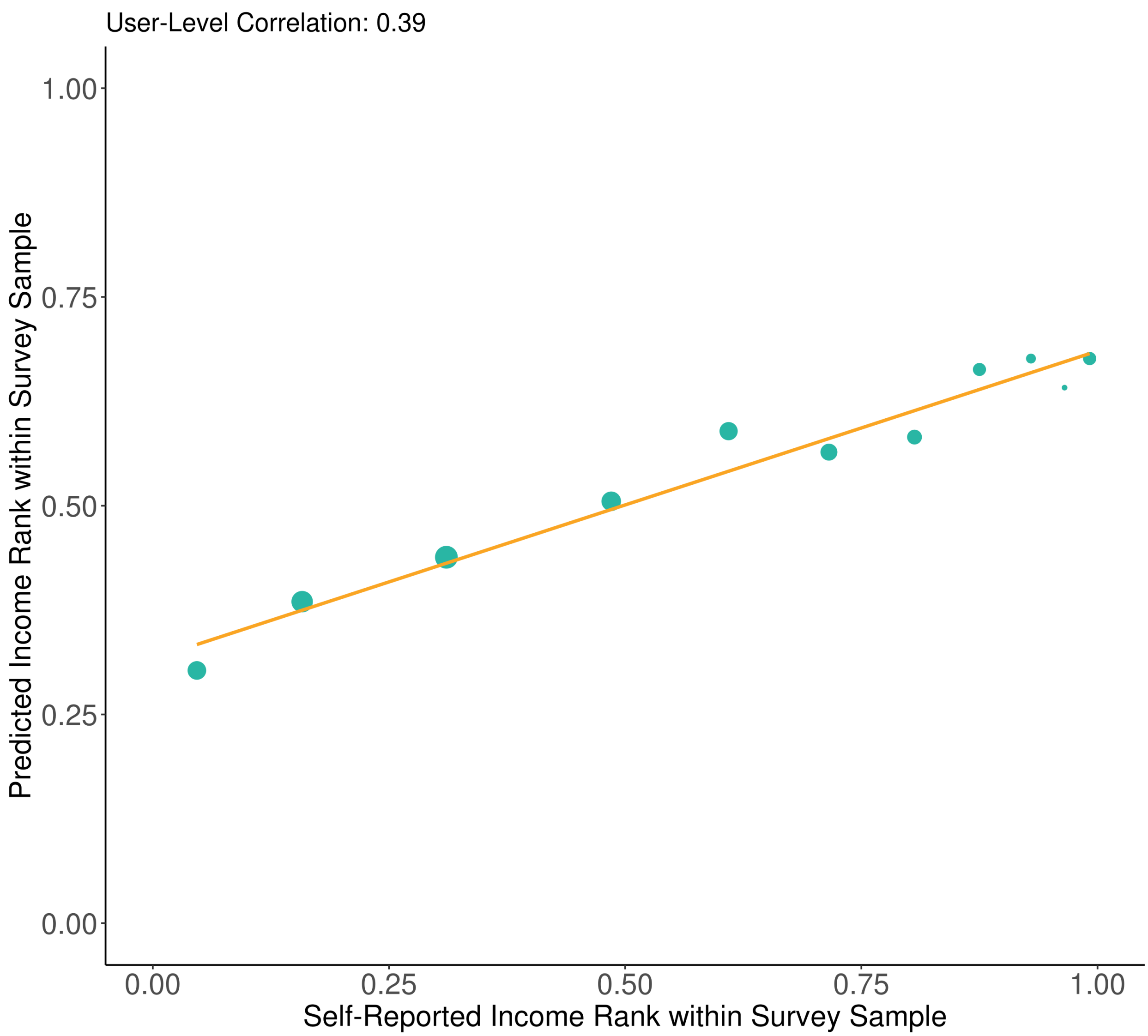
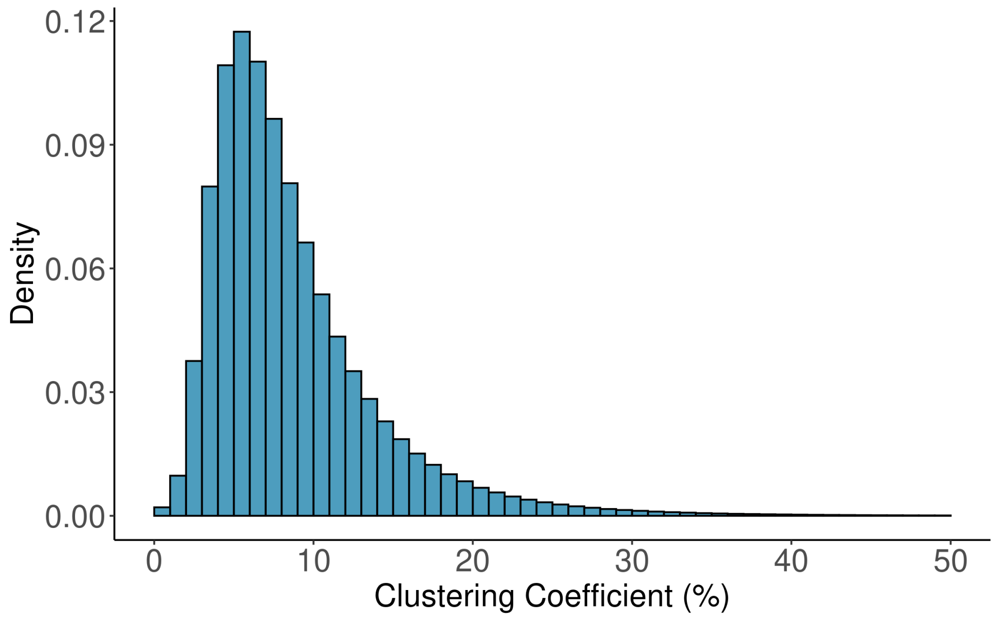
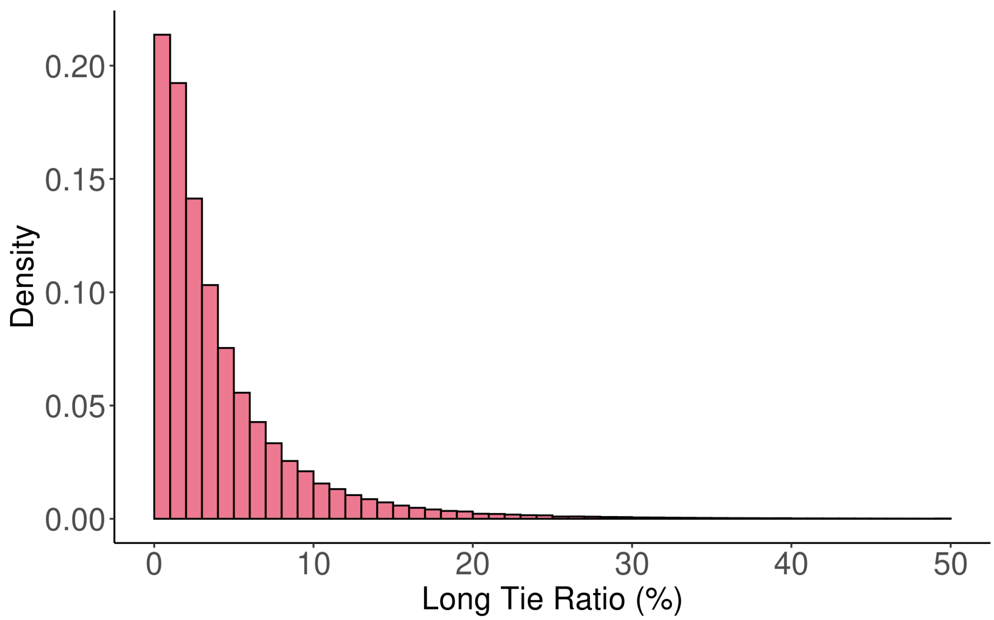


FIGURE S3: Binned scatter plot of self-reported income vs. predicted SES for 2,138 respondents to our well-being survey.



(A) Clustering Coefficient



(B) Long-Tie Ratio

FIGURE S4: User-level histograms for the local clustering coefficient and long-tie ratio.

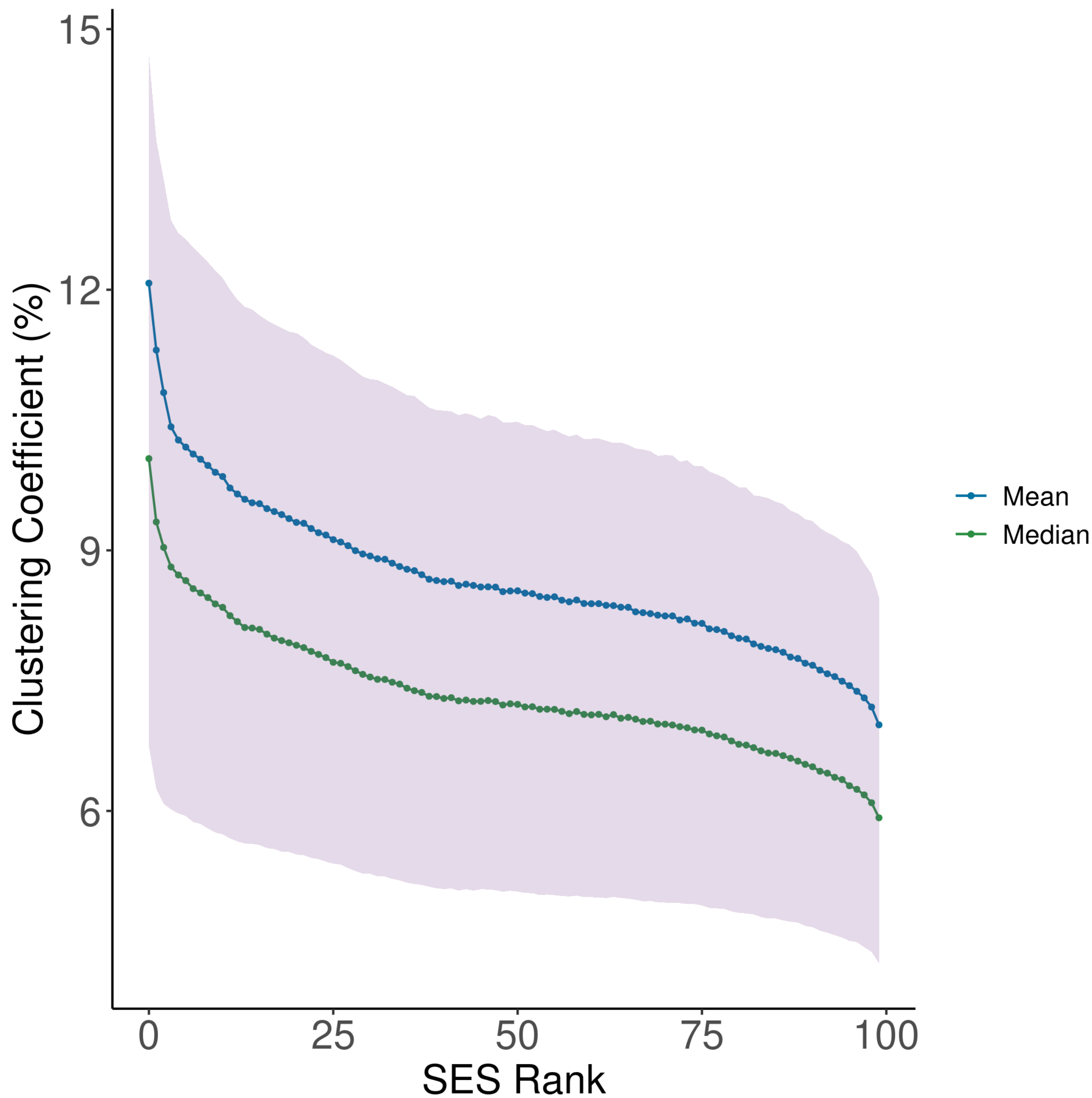


FIGURE S5: Local clustering coefficient, by SES.

Notes for Figure S5: 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.

FIGURE S6: User-level correlations between SES and cohesivesness metrics.

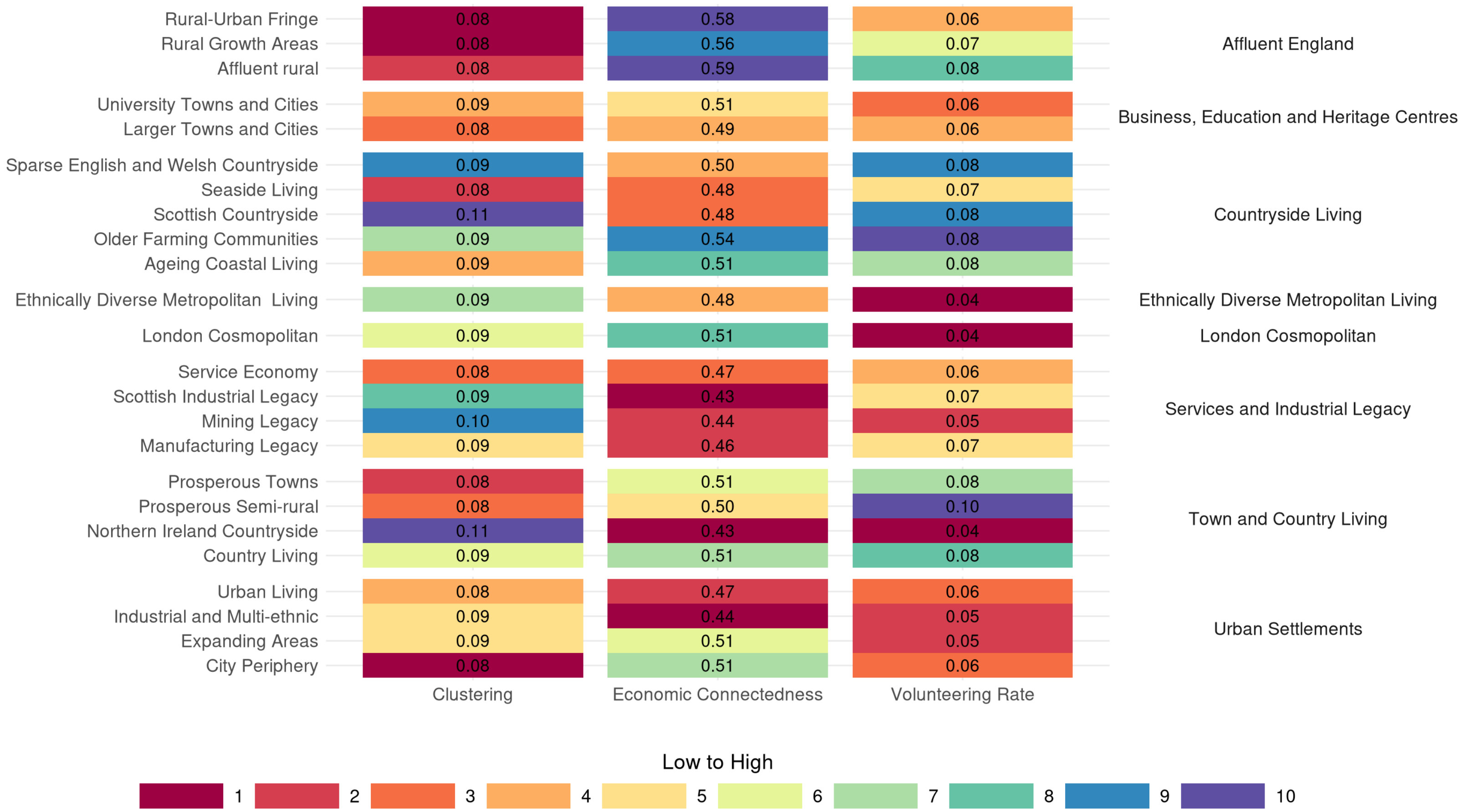
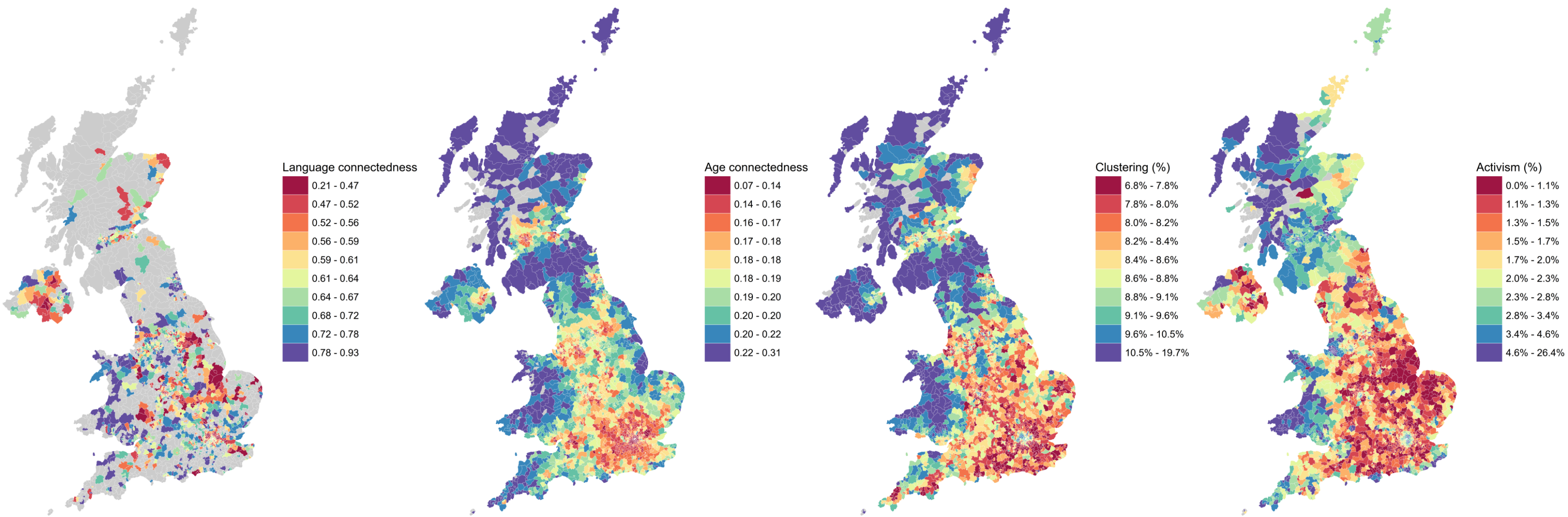
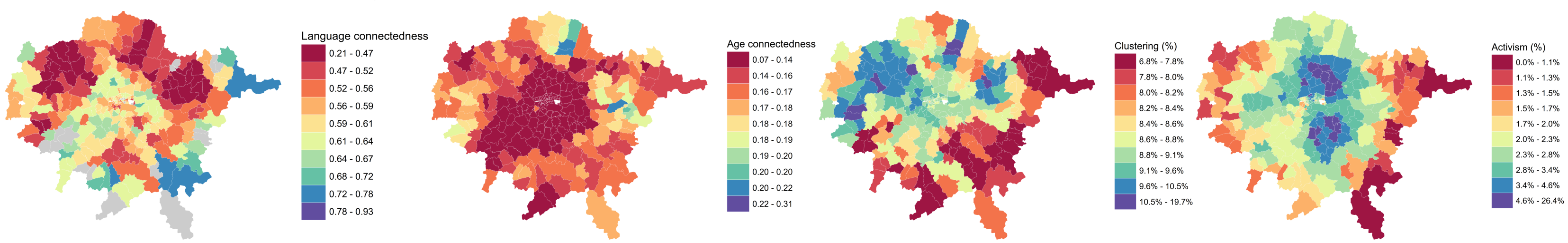


FIGURE S7: Social capital by ONS Area Classifications.



(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 S8: 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.

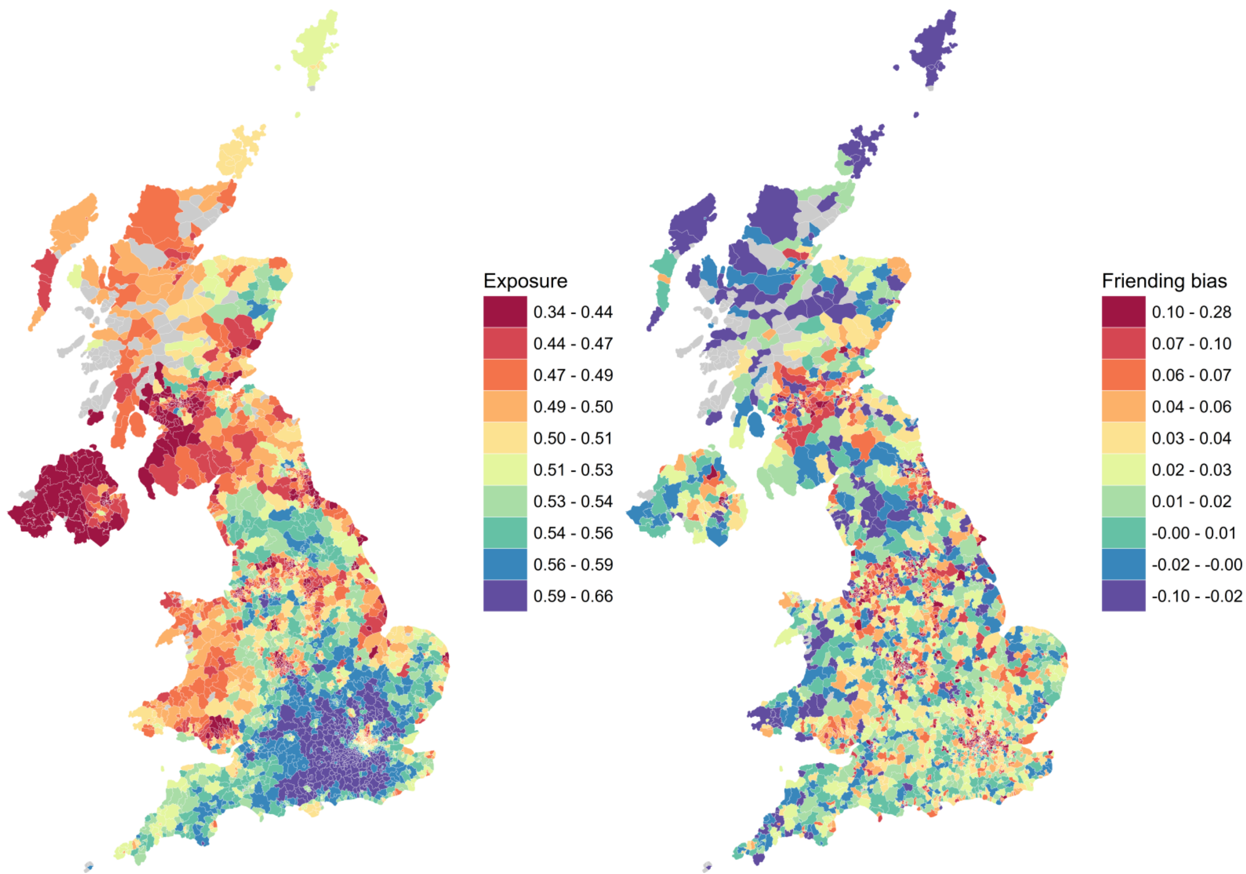


FIGURE S9: Exposure and friending bias by postcode district across the UK.

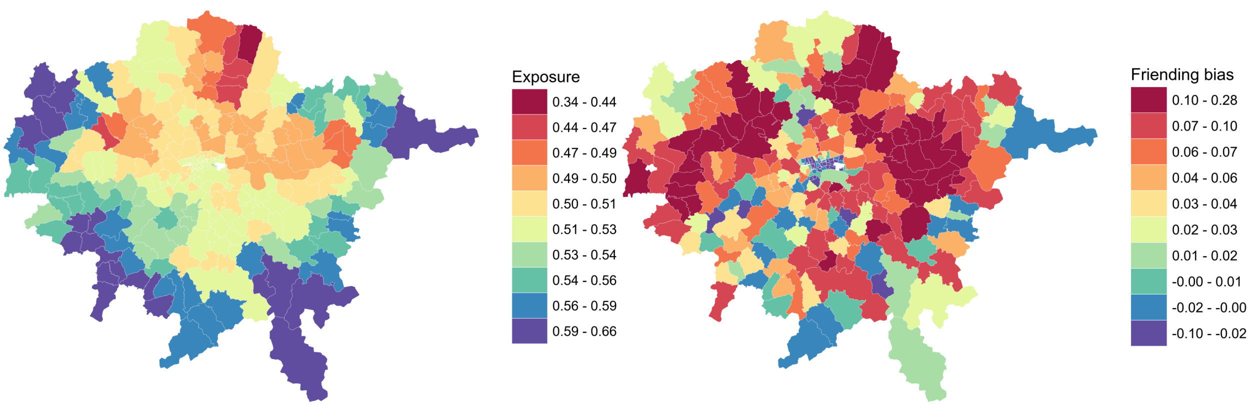
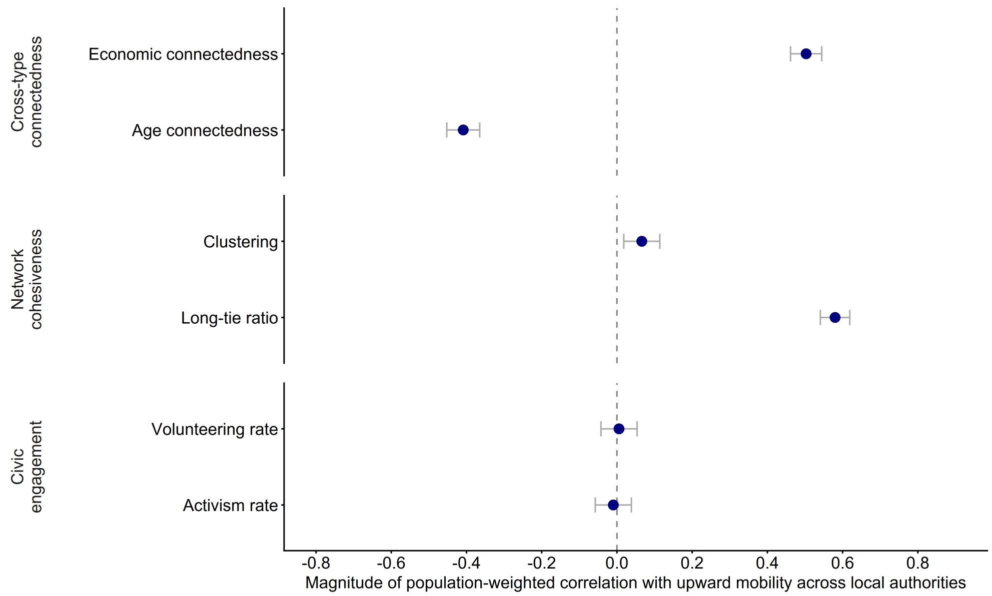
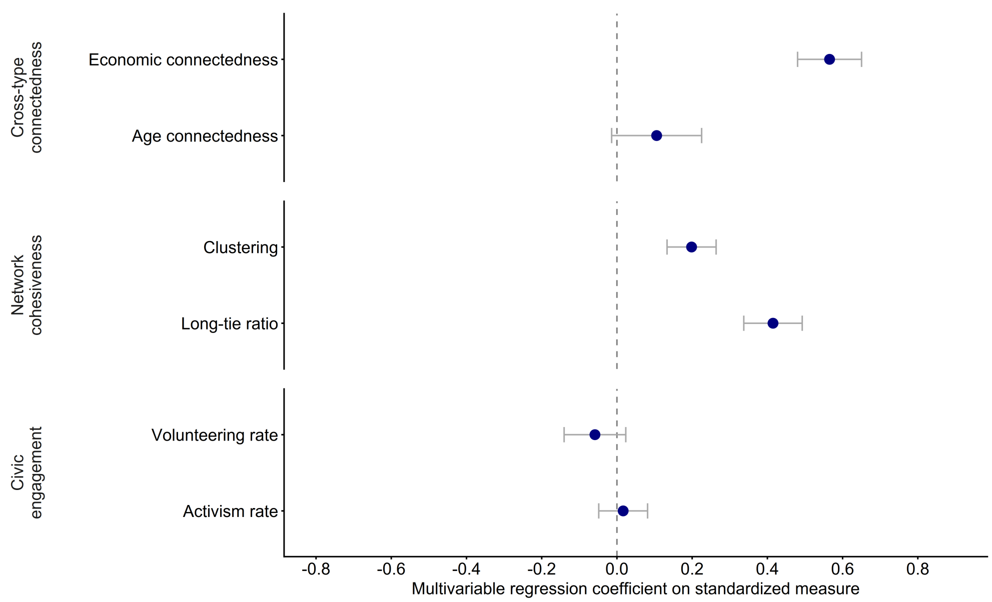


FIGURE S10: Exposure and friending bias by postcode district in Greater London.



(A)



(B)

FIGURE S11: 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 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 S12: Local authority-level bivariate correlations between economic mobility and area characteristics. *Notes:* Demographic variables are sourced from (*38*). All other area statistics are sourced from (*37*). Details on all variables appear in A.7. All correlations are weighted by by the number of FSM–eligible pupils in each local authority. Intervals represent coefficient standard errors.

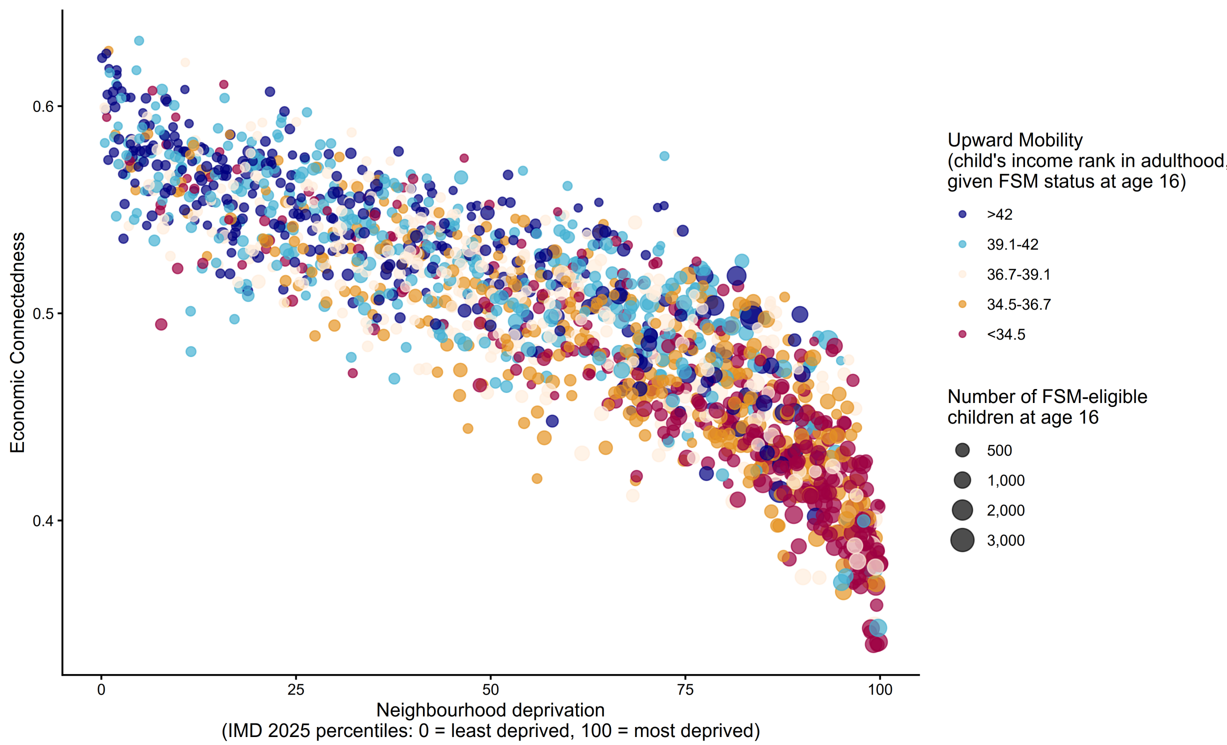
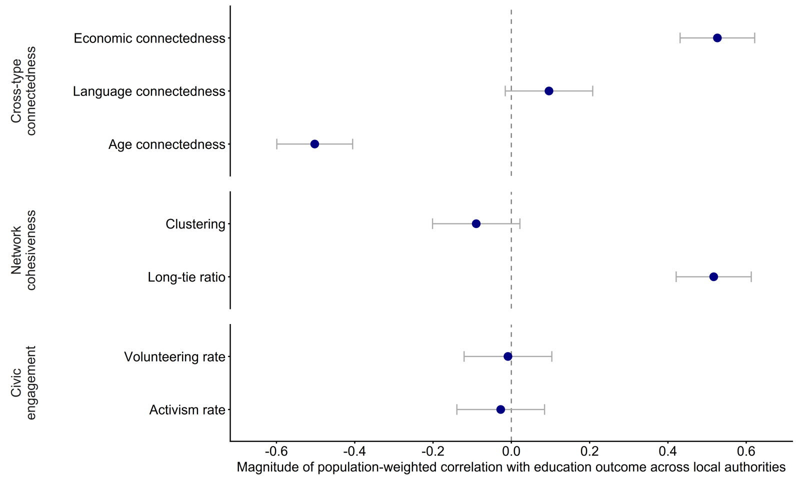
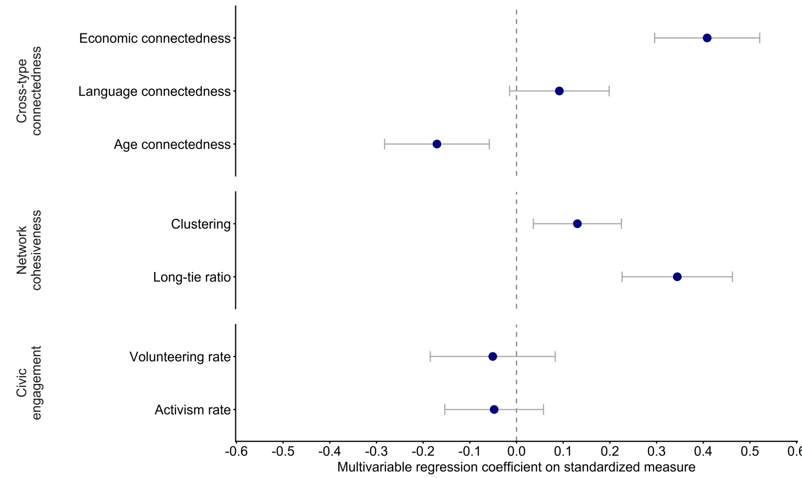


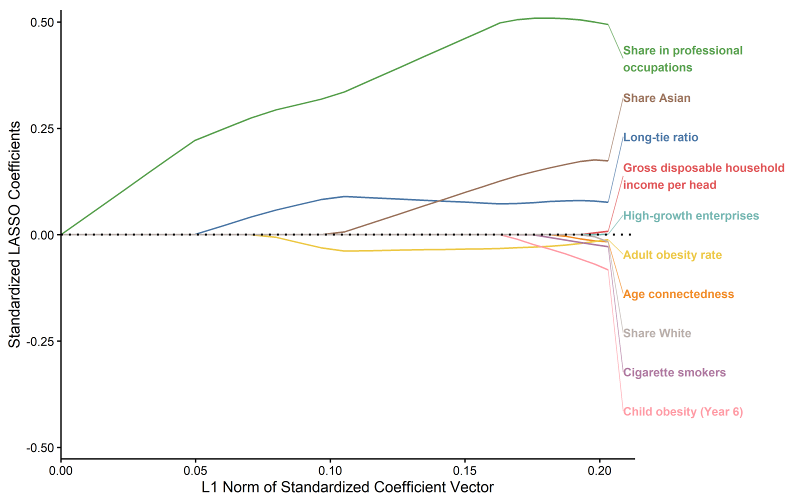
FIGURE S13: Economic connectedness, neighbourhood deprivation, and economic mobility (England, postcode-district level).



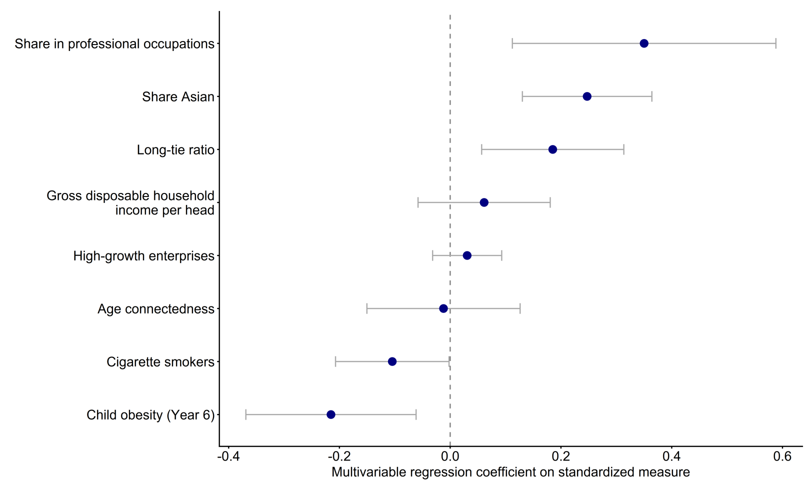
(A) Bivariate correlations



(B) Multivariate correlations



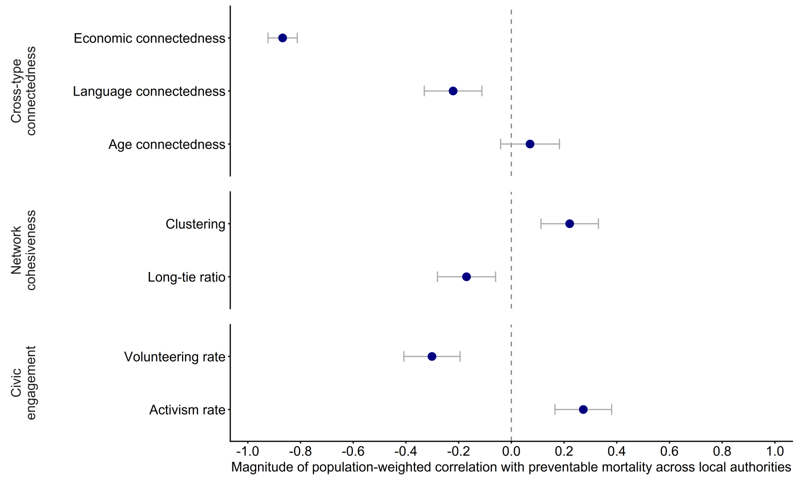
(C) LASSO regularization paths



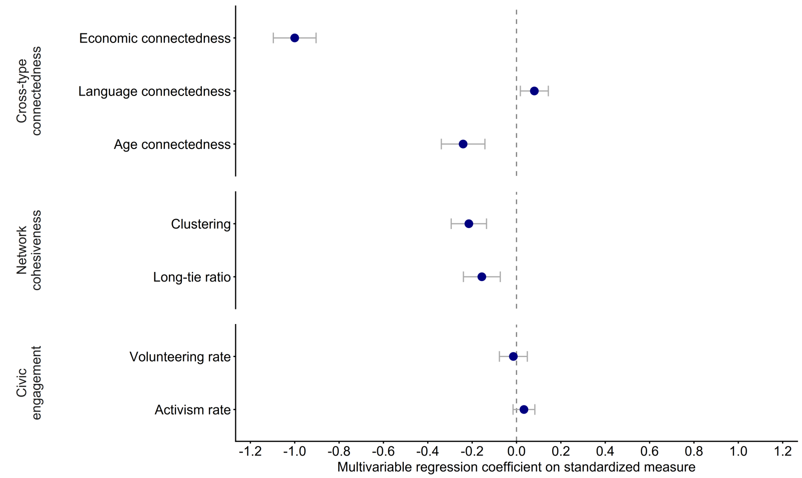
(D) With neighbourhood covariates

Figure S14: Local authority-level relationships between educational attainment and measures of social capital.

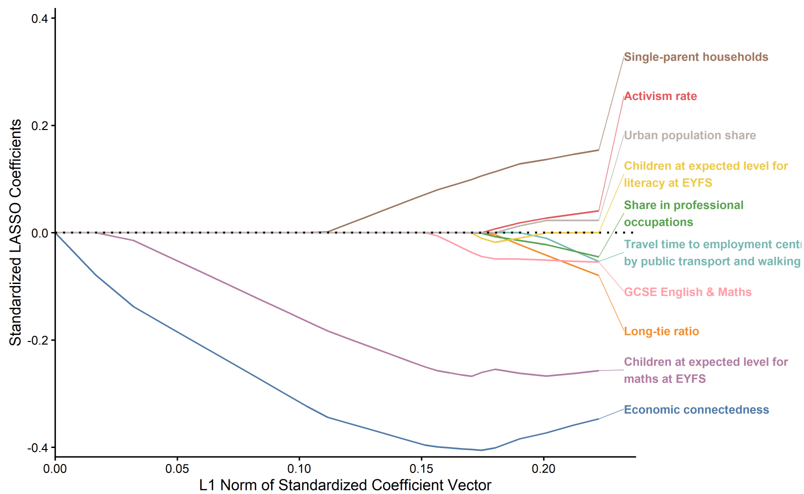
Notes for Figure S14: All correlations and regressions reported are at the local-authority level and are weighted by the number of pupils in the local authority. Error bars represent 95% confidence intervals constructed from heteroskedasticity-robust standard errors. Panel (C) shows the L1-penalized 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 (*37*, *38*) (All variables used are specified in A.7). Panel (D) uses the leading variables selected by the LASSO.)



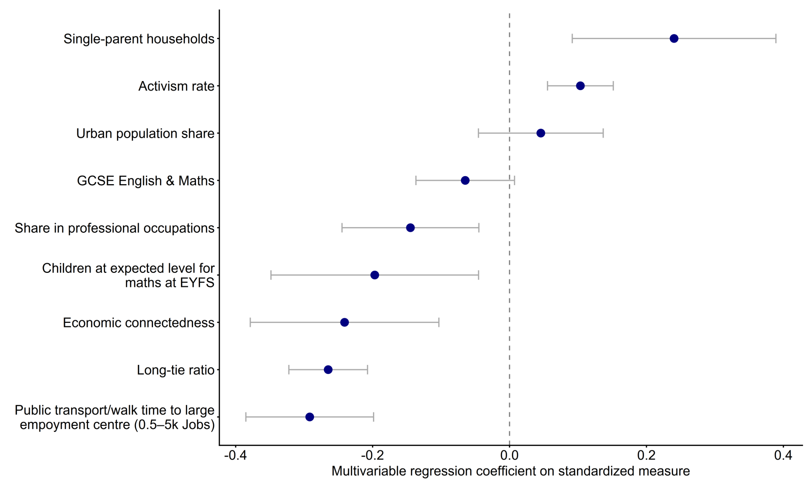
(A) Bivariate correlations



(B) Multivariate correlations



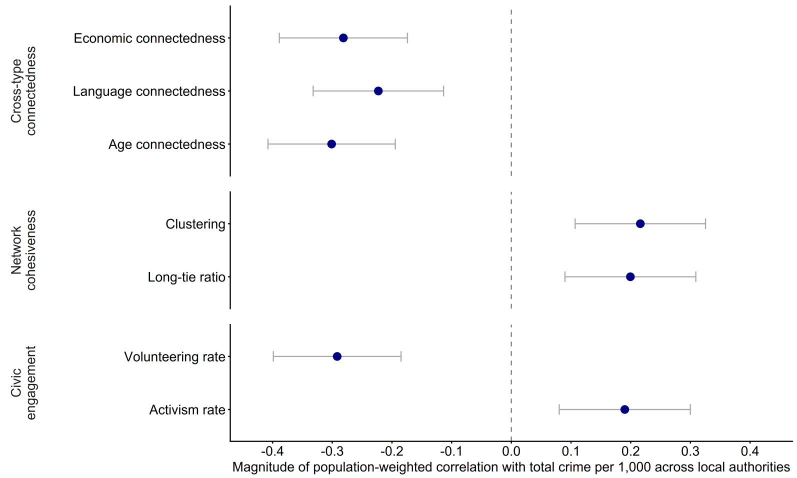
(C) LASSO regularization paths



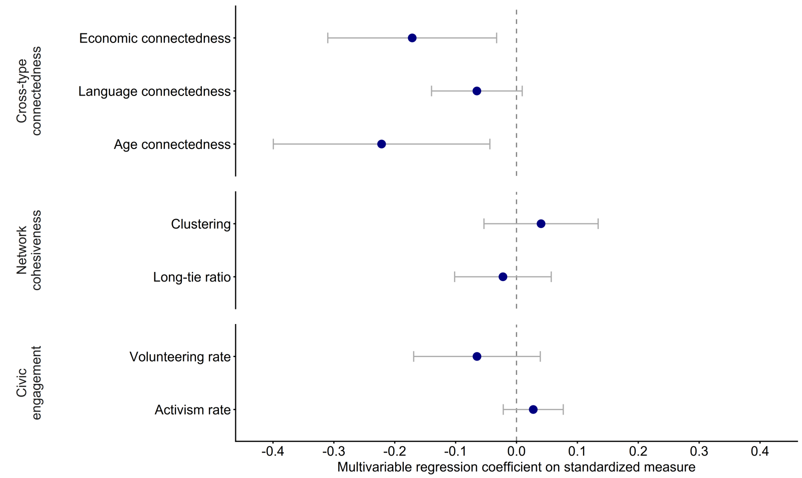
(D) With neighbourhood covariates

Figure S15: Local authority-level relationships between preventable mortality and measures of social capital.

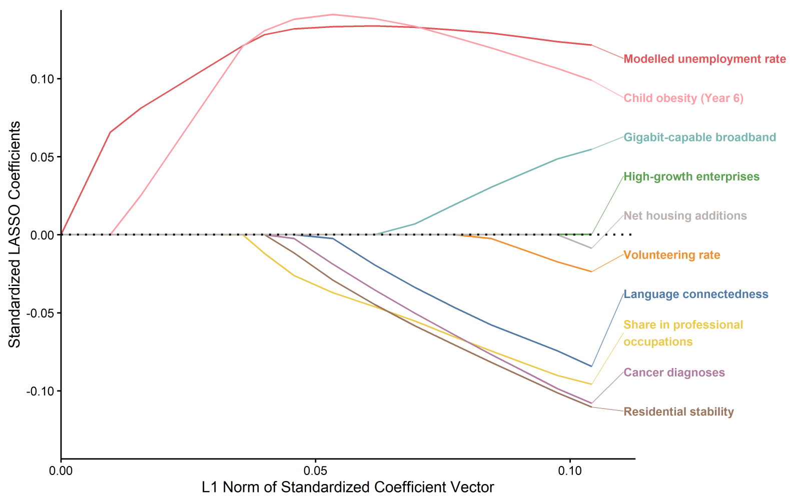
Notes for Figure S15: All correlations and regressions reported are at the local-authority level and are weighted by the local authority population. Error bars represent 95% confidence intervals constructed from heteroskedasticity-robust standard errors. Panel (C) shows the L1-penalized LASSO regularization paths from a model of preventable mortality on the full set of social-capital measures and other neighbourhood characteristics drawn from government statistics (*37*, *38*) (All variables used are specified in A.7). Panel (D) uses the leading variables selected by the LASSO.)



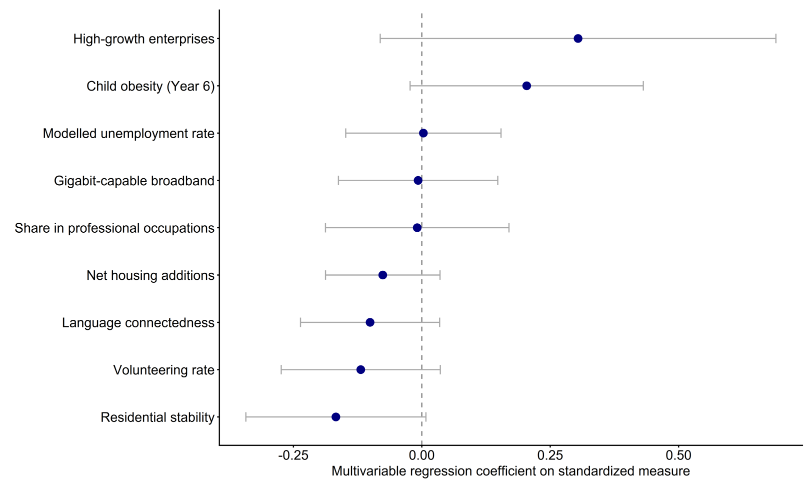
(A) Bivariate correlations



(B) Multivariate correlations



(C) LASSO regularization paths



(D) With neighbourhood covariates

Figure S16: Local authority-level relationships between crime and measures of social capital.

Notes for Figure S16: 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 (*37*, *38*) (All variables used are specified in A.7). Panel (D) uses the leading variables selected by the LASSO.)

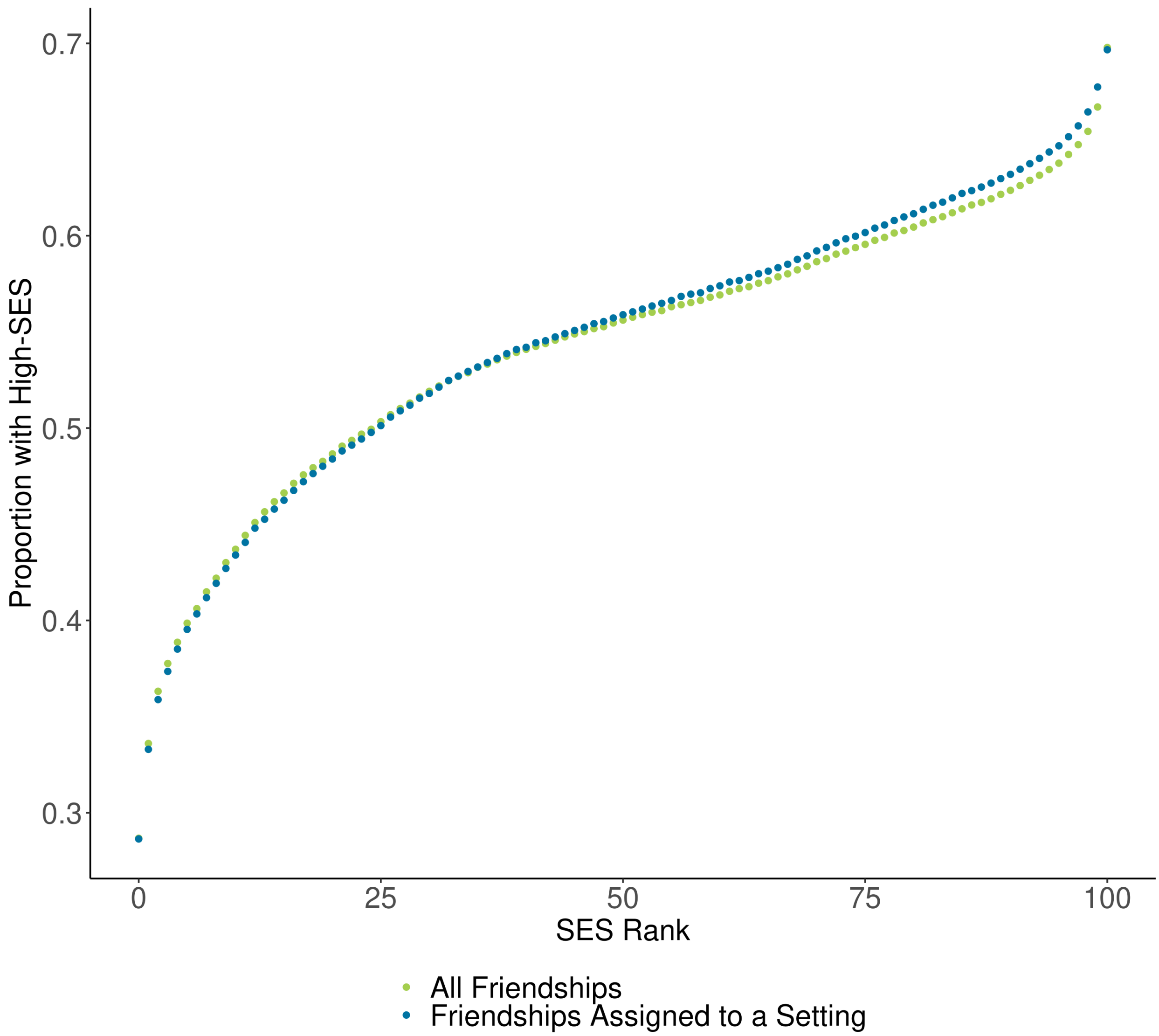


FIGURE S17: High-SES share among all friendships vs. among friendships assigned to a setting, by ego SES.

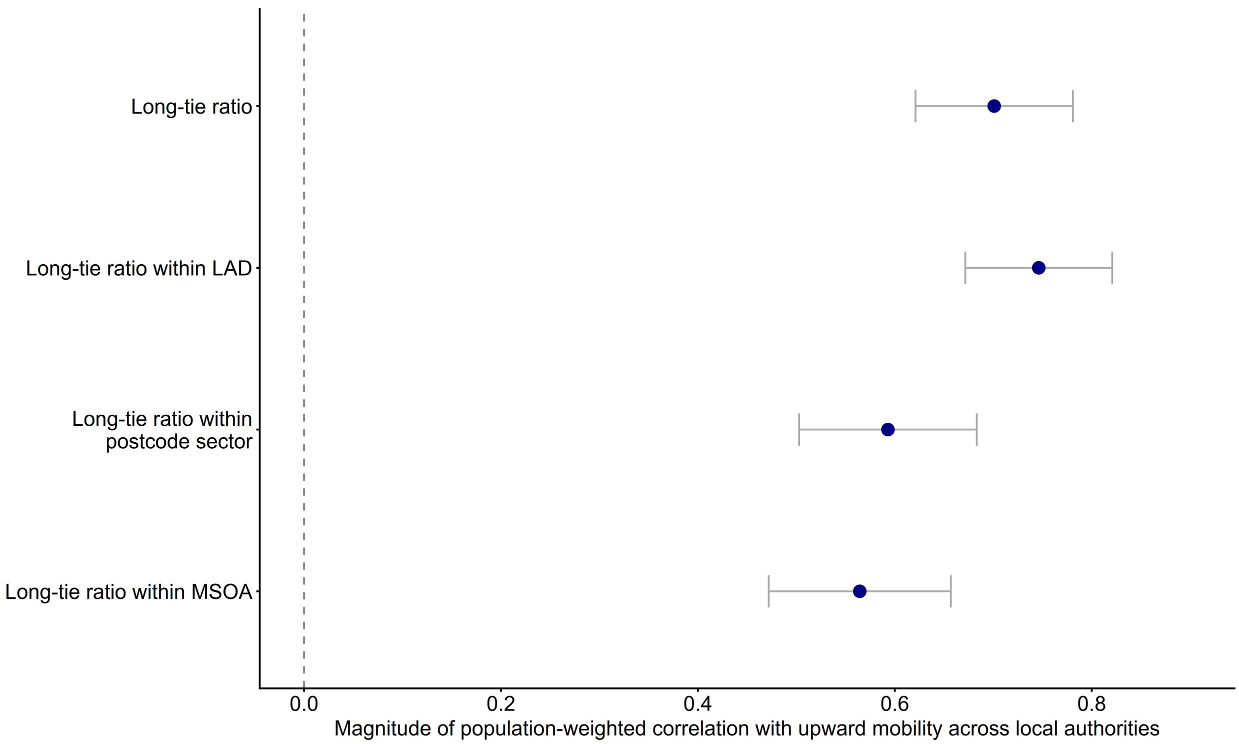


FIGURE S18: Long-tie ratio relationship with economic mobility by geographic friendship restrictions.

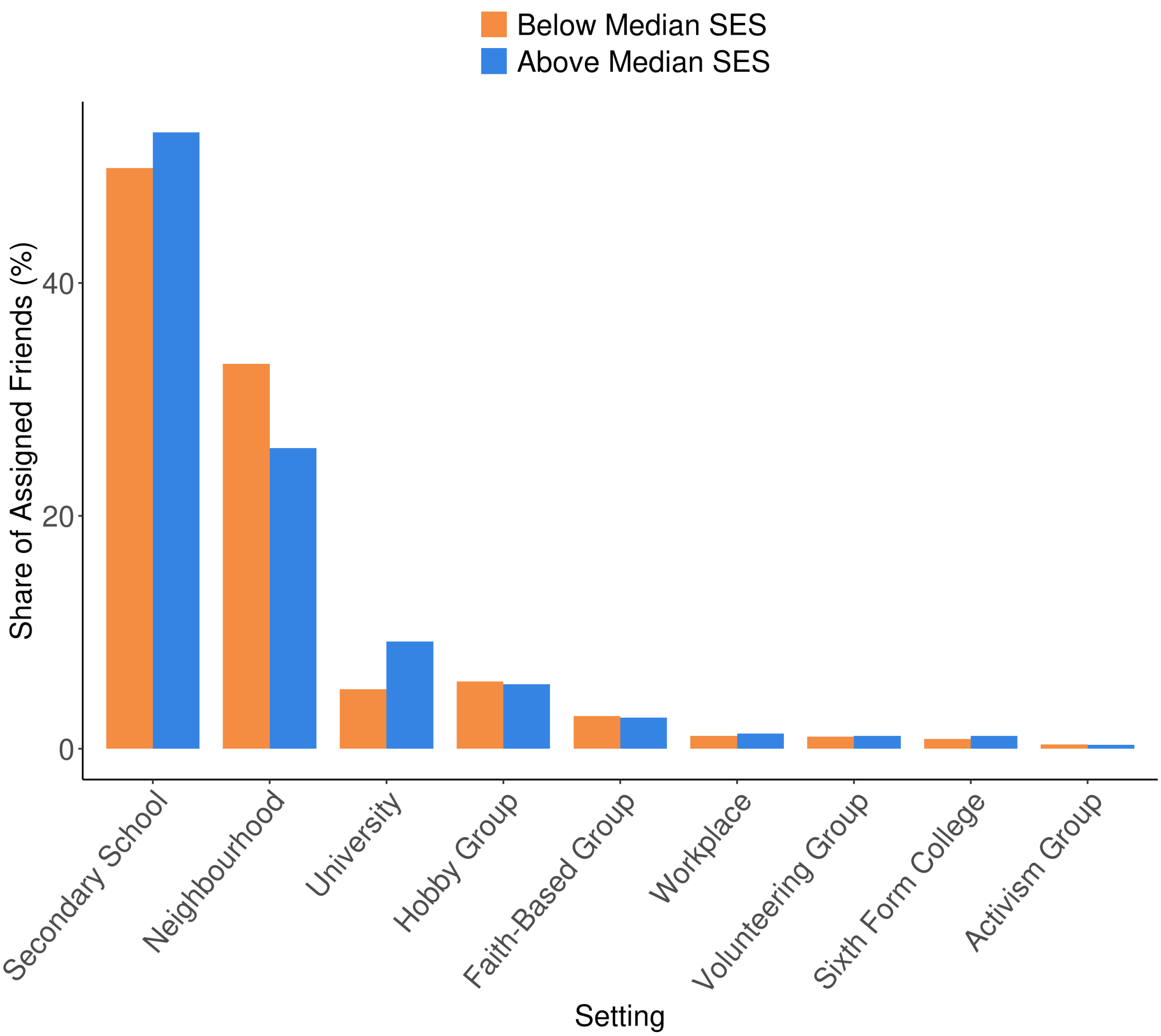


Figure S19: Friending shares by setting, for below- vs. above-median SES users.

Notes for Figure S19: 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.

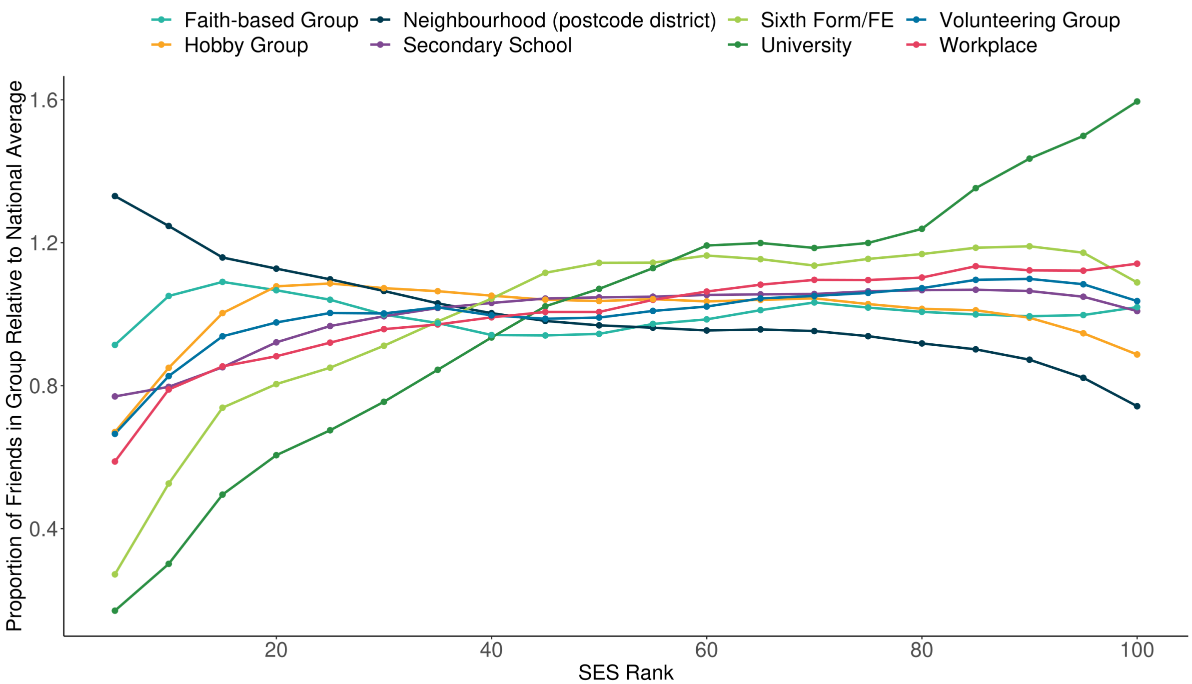


FIGURE S20: Relative friending shares by setting and SES ventile.

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

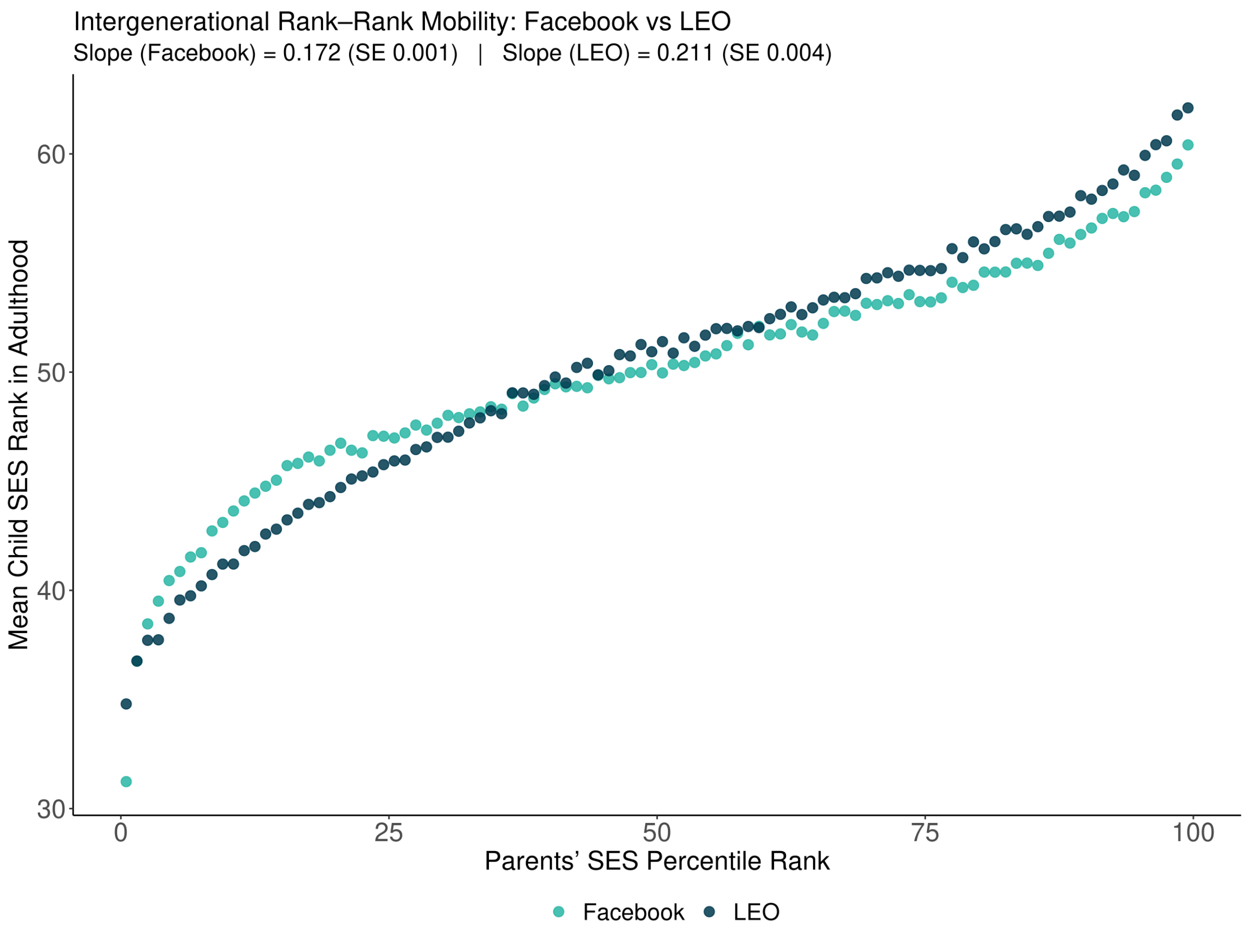


FIGURE S21: Intergenerational persistence of socioeconomic status in Facebook and LEO data.

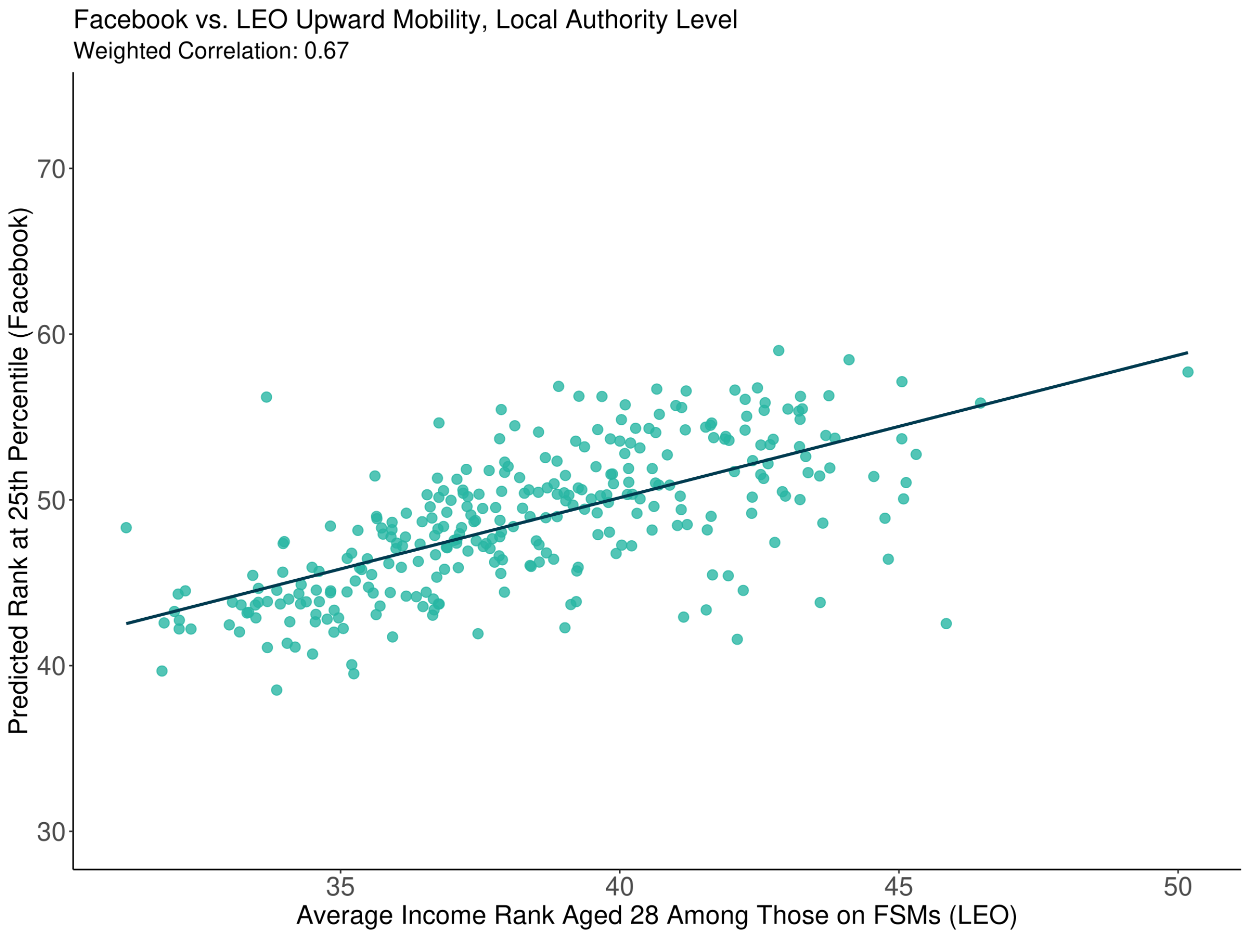


FIGURE S22: Correlation between Facebook and LEO economic mobility estimates at local-authority level (England).

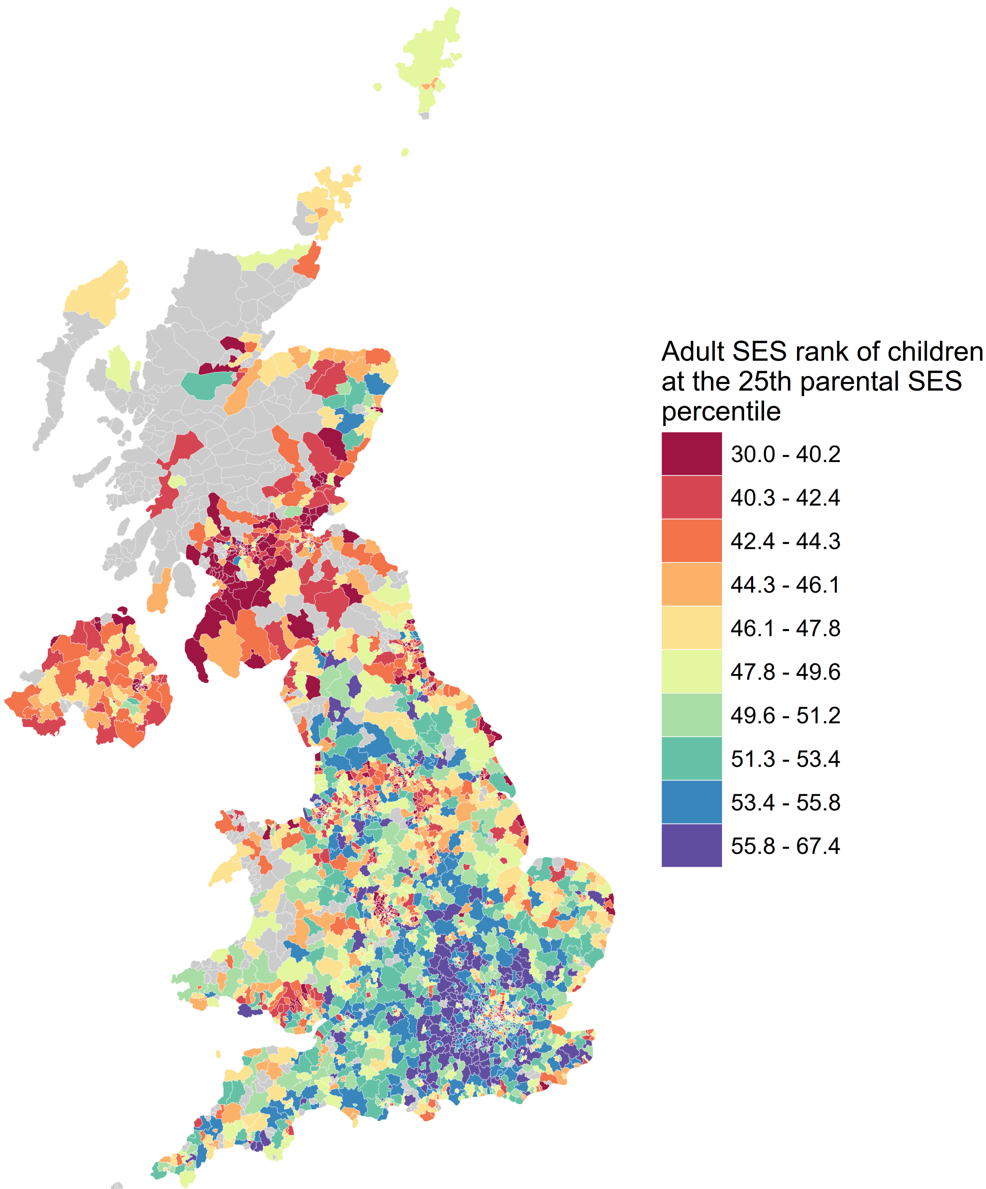


FIGURE S23: Geographic distribution of economic mobility in the UK by postcode district (Facebook-based).

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.

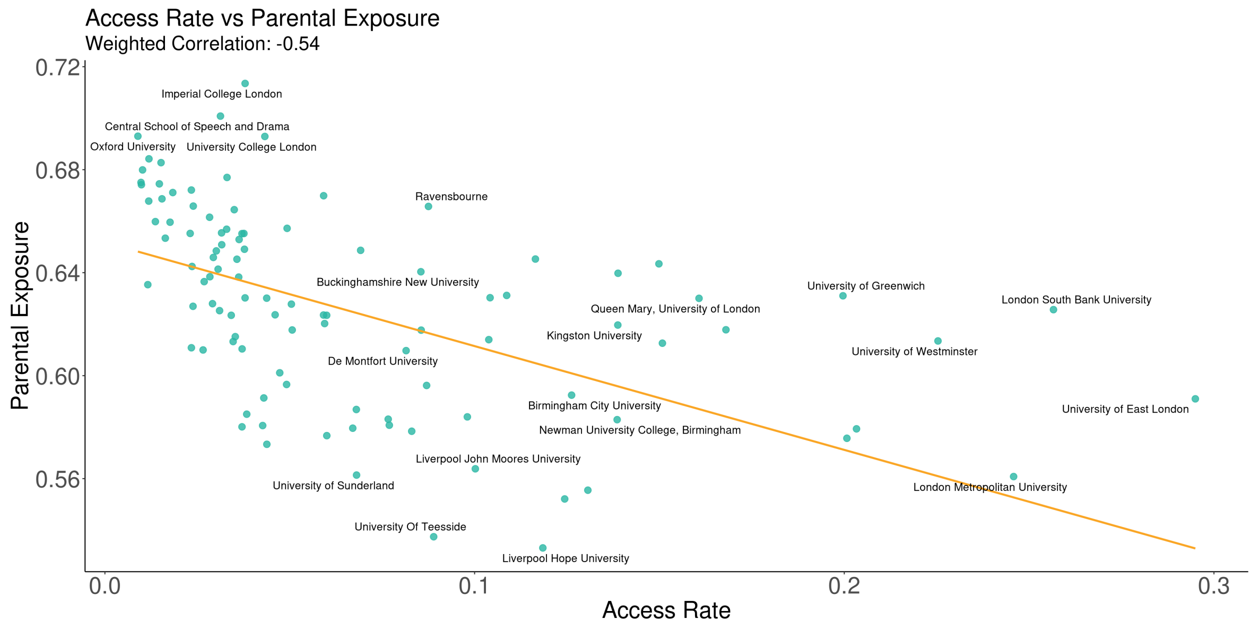


Figure S24: Parental exposure vs. FSM access rates across universities.

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 (57).

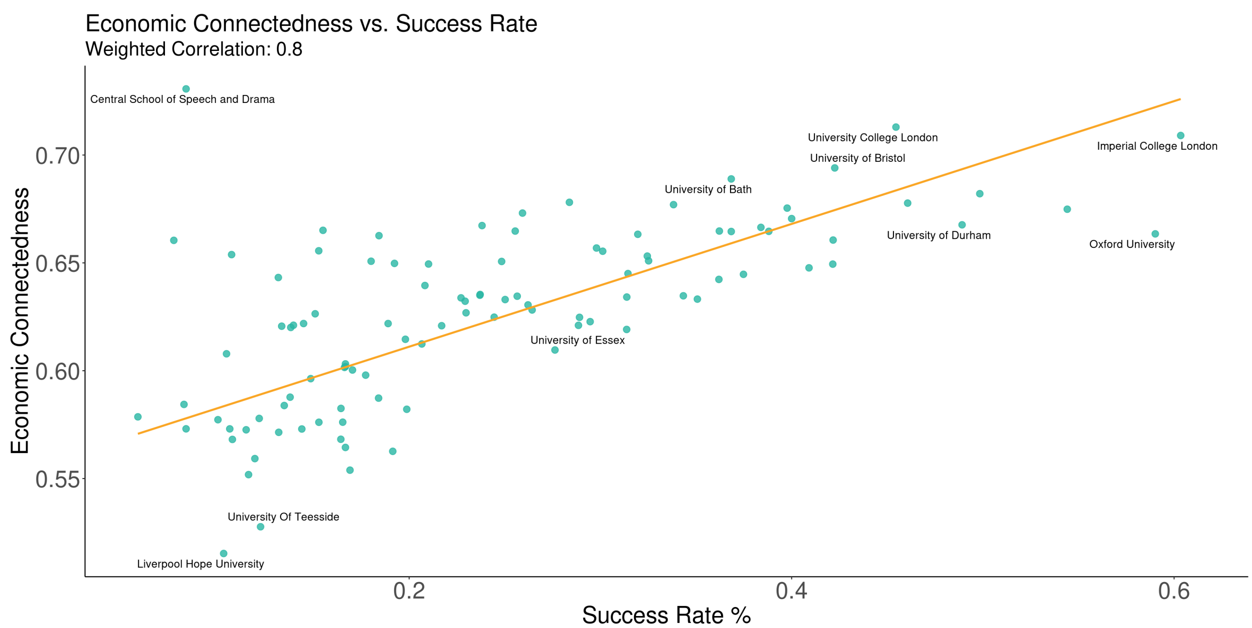


Figure S25: University EC (parental SES) vs. success rates for FSM students.
Notes: University EC is computed using parental SES among within-university friendships. Success rate is the share of FSM students reaching the top 20% of the earnings distribution by age 30 (57). Correlation ≈ 0.82.

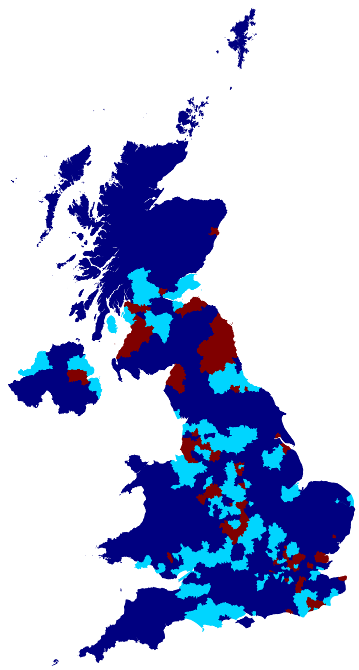


Figure S26: Friending bias in hobby & recreation groups by local authority district.
Notes: Dark blue LADs: friending bias in hobby/recreation groups $<$ 2.2% (the analytic-sample average within these groups). Light blue: between 2.2% and 3.3% (overall friending bias across all friendships). Dark red: $>$ 3.3%.

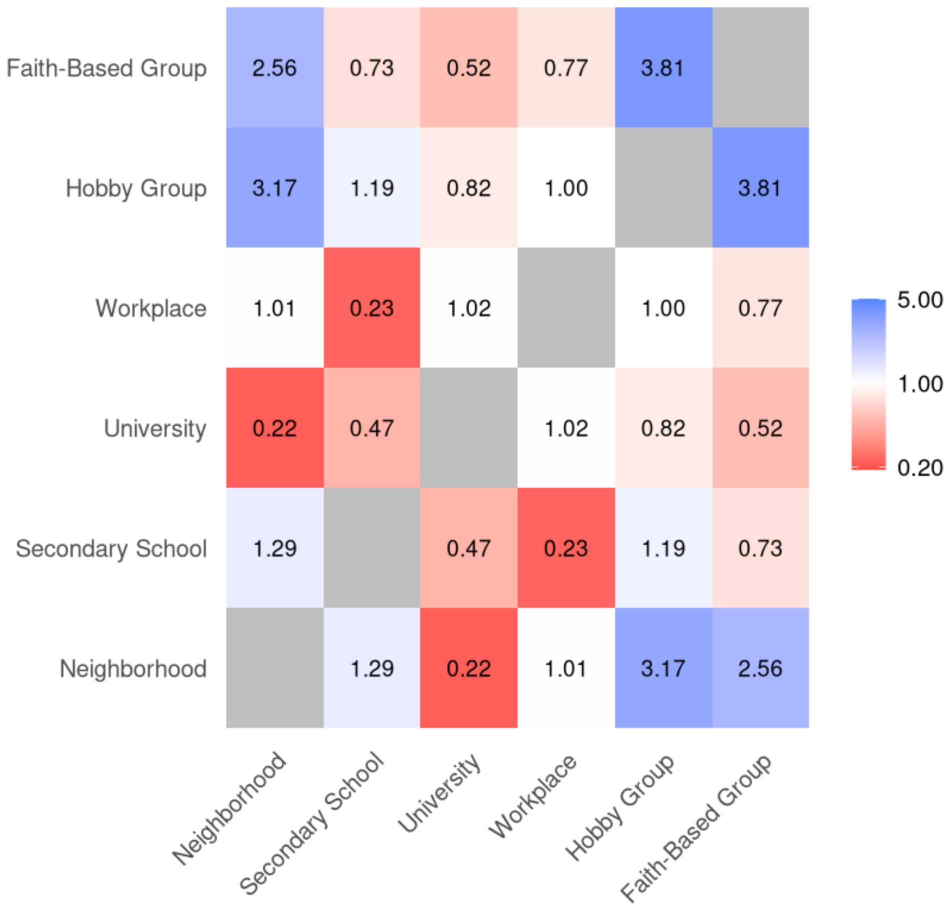


FIGURE S27: Relative probabilities of friendships spanning two settings.

Notes for Figure S27: 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.

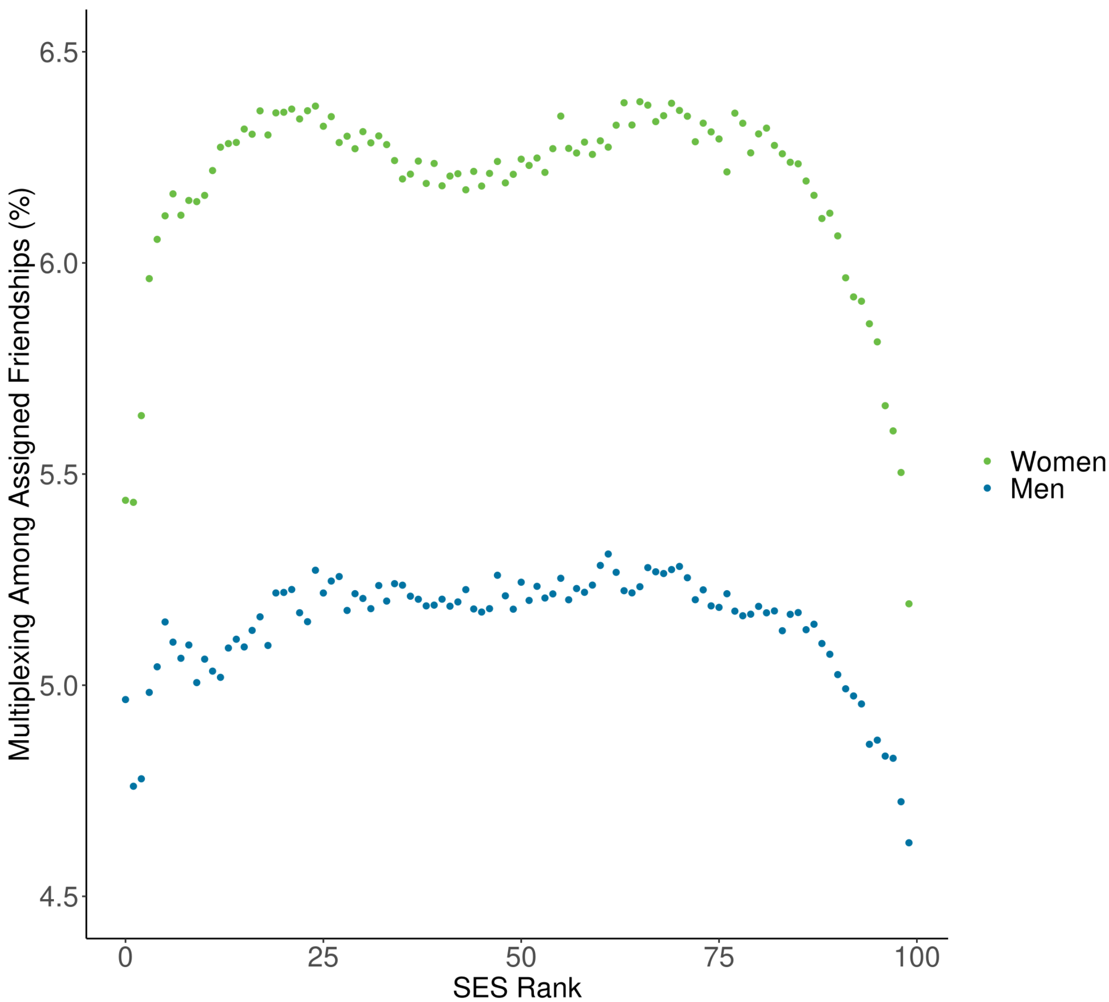


Figure S28: Multiplexing by SES rank and gender.

Notes for Figure S28: 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.

Table S1: Bivariate associations between social capital and outcomes

	Economic mobility		Educational attainment	Preventable mortality	Crime
	LA-level	PCD-level			
Economic connectedness	0.57	0.50	0.53	-0.87	-0.28
	(0.05)	(0.02)	(0.05)	(0.03)	(0.05)
Language connectedness	-0.15	-	0.10	-0.22	-0.22
	(0.06)	(-)	(0.06)	(0.06)	(0.06)
Age connectedness	-0.48	-0.41	-0.50	0.07	-0.30
	(0.05)	(0.02)	(0.05)	(0.06)	(0.05)
Clustering	0.12	0.07	-0.09	0.22	0.22
	(0.06)	(0.02)	(0.06)	(0.06)	(0.06)
Long-tie ratio	0.70	0.58	0.52	-0.17	0.20
	(0.04)	(0.02)	(0.05)	(0.06)	(0.06)
Volunteering rate	-0.08	0.01	-0.01	-0.30	-0.29
	(0.06)	(0.02)	(0.06)	(0.05)	(0.05)
Activism rate	0.00	-0.01	-0.03	0.27	0.19
	(0.06)	(0.02)	(0.06)	(0.05)	(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 S2: Multivariate associations between social capital and outcomes

	Economic mobility		Educational attainment	Preventable mortality	Crime
	LA-level	PCD-level			
Economic connectedness	0.73	0.57	0.41	-1.00	-0.17
	(0.07)	(0.04)	(0.06)	(0.05)	(0.07)
Language connectedness	-0.03	-	0.09	0.08	-0.07
	(0.06)	(-)	(0.05)	(0.03)	(0.04)
Age connectedness	0.20	0.11	-0.17	-0.24	-0.22
	(0.07)	(0.06)	(0.06)	(0.05)	(0.09)
Clustering	0.31	0.20	0.13	-0.21	0.04
	(0.06)	(0.03)	(0.05)	(0.04)	(0.05)
Long-tie ratio	0.61	0.41	0.34	-0.16	-0.02
	(0.06)	(0.04)	(0.06)	(0.04)	(0.04)
Volunteering rate	-0.06	-0.06	-0.05	-0.01	-0.06
	(0.07)	(0.04)	(0.07)	(0.03)	(0.05)
Activism rate	0.05	0.02	-0.05	0.03	0.03
	(0.03)	(0.03)	(0.05)	(0.02)	(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 S3: Multivariate regressions with other area-level covariates

(A) Economic mobility

Economic connectedness	0.24 (0.09)
Long-tie ratio	0.34 (0.06)
Median weekly pay	0.33 (0.07)
Residential stability	0.09 (0.05)
High-growth enterprises	-0.12 (0.04)
GCSE English & Maths	0.11 (0.06)
Share Asian	0.20 (0.06)
Children at expected level for literacy at EYFS	-0.06 (0.06)
Preventable cardiovascular mortality	-0.21 (0.08)
Adjusted R^2	0.82
Observations	288

(B) Educational attainment

Long-tie ratio	0.19 (0.07)
Age connectedness	-0.01 (0.07)
Gross disposable household income per head	0.06 (0.06)
Child obesity (Year 6)	-0.22 (0.08)
Share in professional occupations	0.35 (0.12)
Share Asian	0.25 (0.06)
High-growth enterprises	0.03 (0.03)
Cigarette smokers	-0.10 (0.05)
Adjusted R^2	0.59
Observations	288

(C) Preventable mortality

Economic connectedness	-0.24 (0.07)
Long-tie ratio	-0.26 (0.03)
Activism rate	0.10 (0.02)
Share in professional occupations	-0.14 (0.05)
Children at expected level for maths at EYFS	-0.20 (0.08)
Single-parent households	0.24 (0.08)
GCSE English & Maths	-0.06 (0.04)
Urban population share	0.05 (0.05)
Travel time to employment centre by public transport and walking	-0.29 (0.05)
Adjusted R^2	0.88
Observations	288

(D) Crime

Language connectedness	-0.10 (0.07)
Volunteering rate	-0.12 (0.08)
Share in professional occupations	-0.01 (0.09)
Net housing additions	-0.08 (0.06)
Modelled unemployment rate	0.00 (0.08)
Residential stability	-0.17 (0.09)
Gigabit-capable broadband	-0.01 (0.08)
Child obesity (Year 6)	0.20 (0.12)
High-growth enterprises	0.30 (0.20)
Adjusted R^2	0.38
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 (*37*, *38*) (full variable list in A.7; LASSO paths in Figs. 3c, S14c, S15c, and S16c). 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.

Table S4: 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 − EC/Exposure; *higher values indicate less cross-SES mixing (worse).*

Table S5: 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 − EC/Exposure.