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

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Abstract

Social capital is widely believed to impact a wide range of outcomes including subjective well-being, social mobility, and community health. We aggregate data on over 20 million Facebook users in the United Kingdom to construct several measures of social capital including cross-type connectedness, social network clustering, and civic engagement and volunteering. We find that social networks in the UK bridge class divides, with people below the median of the socioeconomic status distribution (low-SES people) having about half (47%) of their friendships with people above the median (high-SES people). Despite the presence of these cross-cutting friendships, we find evidence of homophily by class: high-SES people have a 28% higher share of high-SES friends. In part, this gap is due to the fact that high-SES individuals live in neighbourhoods, attend schools, and participate in groups that are wealthier on average. However, up to two thirds of the gap is due to the fact that high-SES people are more likely to befriend other high-SES peers, even within a given setting. Cross-class connections vary by region but are positively associated with upward income mobility: low-SES children who grew up in the top 10% most economically connected local authorities in England earn 38% more per year on average (£5,100) as adults relative to low-SES children in the bottom 10% local authorities. The relationship between upward mobility and connectedness is robust to controlling for other measures of social connection and neighbourhood measures of income, education, and health. We also connect measures of subjective well-being and related concepts with individual social capital measures. We find that individuals with more connections to high-SES people and more tightly-knit social networks report higher levels of happiness, trust, and lower feelings of isolation and social disconnection. We make our aggregated social capital metrics publicly available on the Humanitarian Data Exchange to support future research.

JEL classification code: D85

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1 Introduction

Social capital—the network of relationships and interactions in a society—is a central concept in the social sciences (Putnam (1995), Granovetter (1973)). A recent series of studies by Chetty et al. (2022a,b); Bourdieu (2018) used Facebook friendship data to map social capital across communities in the United States, revealing that certain aspects of social networks have powerful associations with economic outcomes. In particular, Chetty et al. (2022a) found that economic connectedness—the extent to which individuals with low socioeconomic status (SES) befriend those with high SES—is a strong predictor of intergenerational upward mobility. To date, such patterns have only been documented in the United States, leaving open the question of whether similar relationships hold in other contexts. In this paper, we build on and extend this prior research by examining the connection between social capital and intergenerational mobility in the United Kingdom and evaluate other classes of outcomes such as subjective well-being and trust.

We leverage individual-level data on over 20 million Facebook users in the UK to construct a detailed portrait of social capital across all regions of the country. Many of the social capital metrics that we measure parallel those in Chetty et al. (2022a)—including economic connectedness (a form of socio-economic bridging capital), network clustering (a form of bonding capital), and civic engagement. To relate these metrics to economic mobility, we leverage UK Longitudinal Educational Outcomes (LEO) data from the Office for National Statistics. Following the approach introduced by Carneiro et al. (2020), we use the LEO data to estimate the average income rank in adulthood of students who were eligible to receive free school meals as teenagers. To assess the impact of social capital on outcomes beyond economic mobility, we also survey Facebook users in the UK regarding several aspects of subjective well-being and related concepts, including happiness, trust, life satisfaction, feelings of social support, and feelings of isolation and disconnection.

Our analysis yields several key findings:

1. **Friendships in the United Kingdom bridge economic divides**: Although there is notable stratification of friendships by socioeconomic status, people with below-median socioeconomic status (SES) still form 47% of their friendships with people with above-median SES. This level of economic connectedness is higher than Chetty et al. (2022b) observed in the United States.

2. **Regions with higher economic connectedness exhibit higher economic mobility**: Low-SES children who grew up in the top 10% most economically connected local authorities in England earn 38% more per year on average (£5,100) as adults relative to low-SES children in the bottom 10% local authorities. The relationship between economic connectedness and economic mobility is robust to controlling for various other social-capital measures and to controlling for regional measures of average income, educational attainment, and physical health.

3. **Exposure to high-SES individuals and friending bias both contribute to the gap in economic connectedness between low-SES and high-SES individuals**: High-SES individuals have a 28% higher share of high-SES friends than low-SES individuals. Three factors can contribute to this difference: the communities in which low-SES and high-SES people form friendships ("friending share"), the rate at which they encounter high-SES people in those communities ("exposure"), and the rate at which they form friendships with high-SES people conditional on exposure ("friending bias"). We find that exposure and friending bias account for approximately one-third and two-thirds of the high-SES friending gap respectively, with friending shares playing a small role.

4. **Hobby and recreation groups promote cross-class interaction among their members**: Although a small percentage of friendships are formed in hobby and recreation groups, friending bias is lowest in these settings, meaning that members of these groups are relatively likely to form cross-class ties within the group.
5. **Social capital is associated with higher subjective well-being**: Individuals with more high-SES friends and more tightly-knit social circles (higher support ratio in their network) report higher levels of happiness, life satisfaction, trust, feelings of social support, and lower levels of feelings of isolation and disconnection. These relationships are robust to controlling for age, gender, and self-reported income in our survey.
6. **Data from Facebook can be used to measure economic mobility for the entire UK**: The LEO data only allows us to report economic mobility estimates for England only. By linking individuals on Facebook to their parents, we can construct estimates of economic mobility that line up well with the LEO data in England and extend to Northern Ireland, Scotland, and Wales.

2 Data

Our sample consists of 20.5 million Facebook users who, as of February 20th 2025, reside in the UK, have at least 100 Facebook friends, are aged between 25–64, 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 25–64 (Office for National Statistics, 2024a). We refer to this group of users as the analytic sample. Figure 1 shows that our analytic sample slightly overrepresents females and younger adults. This is consistent with known patterns of social media usage (Ofcom, 2023; Gottfried, 2024).

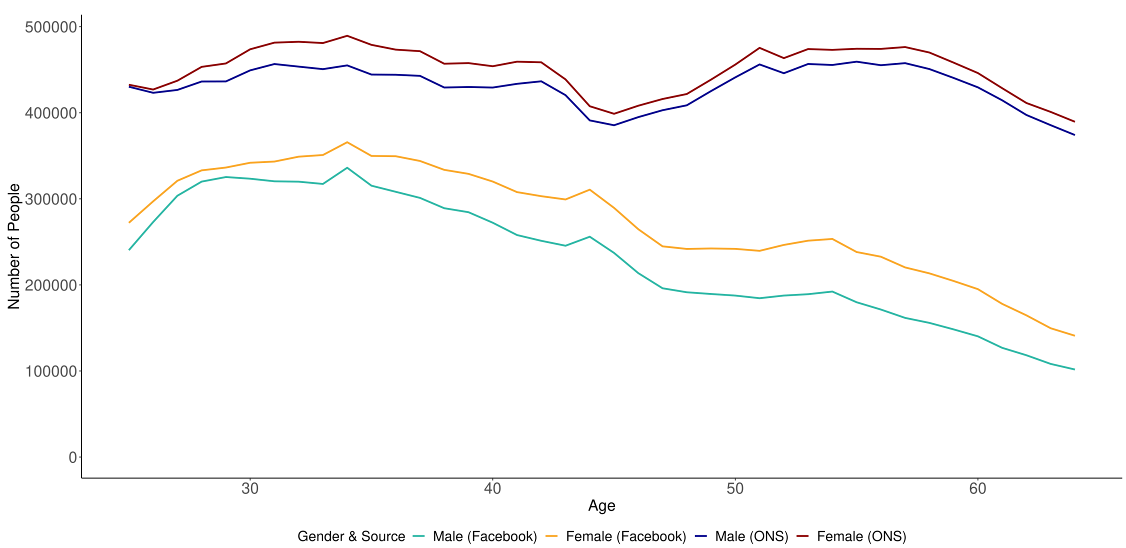


FIGURE 1: Age Distribution by Gender in the Analytic Sample.

Notes for Figure 1: The ONS series uses data from Office for National Statistics (2024a) on national mid-year population estimates for the UK and its constituent countries, by age and sex. We compare this the counts from our Facebook analytic sample for ages 25 to 64.

We determine a predicted home location for each user based on a combination of signals, including the city reported on Facebook profiles as well as their device and connection information, such as the IP addresses used to connect to Facebook. Figure 2 shows that the user counts by area in our analytic sample closely track population counts from UK administrative data for individuals aged 25–64, with a correlation of 0.93. Breaking user counts and population counts down by gender, we observe a correlation between the user counts in our analytic sample and administrative population counts for 25–64 year-olds of 0.93 for both males and females.

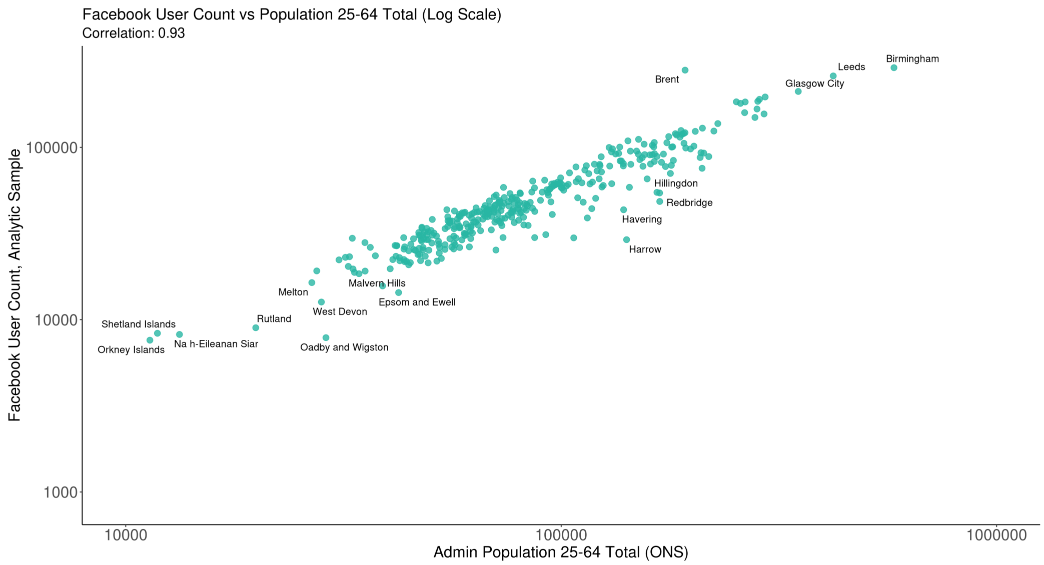


FIGURE 2: Correlation between user counts for our analytic sample administrative population counts for 25–64 year-olds by administrative area.

Notes for Figure 2: The ONS series uses data from Office for National Statistics (2024a) on national mid-year population estimates for the UK and its constituent countries, by age and sex. We compare this to the counts from our Facebook analytic sample for ages 25 to 64.

We assign each user a socioeconomic status (SES) using a machine learning model which predicts an SES index based on features observed for all users on the platform, including the price of devices used to connect to the platform, characteristics of the user's residential area (such as average income), and activity on Facebook platforms such as Marketplace. The model is a gradient-boosted tree that is trained to predict a composite index derived from the results of an on-platform survey of the finances, income, and wealth of 206,539 users in 64 countries. The model is being developed as part of a broader effort to map social capital around the world (Bailey et al., 2025). To assess the validity of our SES model, we elicited granular income responses in a sample of 5,472 UK Facebook users of whom 2,138 are in our analytic sample and reported their income in the survey. When ranked within this sample, SES predicted by our model and self-reported income are correlated with a coefficient of 0.44. Figure 3 shows a binned scatter plot comparing our SES predictions to the self-reported income of these survey respondents. To construct our final SES measure, we assign each user an SES score based on our SES model and then rank users on the basis of that score within birth cohorts.

We augment our user-level data with information on Facebook friendships. These are undirected connections between users, meaning all friendships are reciprocated. Users can have up to 5,000 friends, though most users do

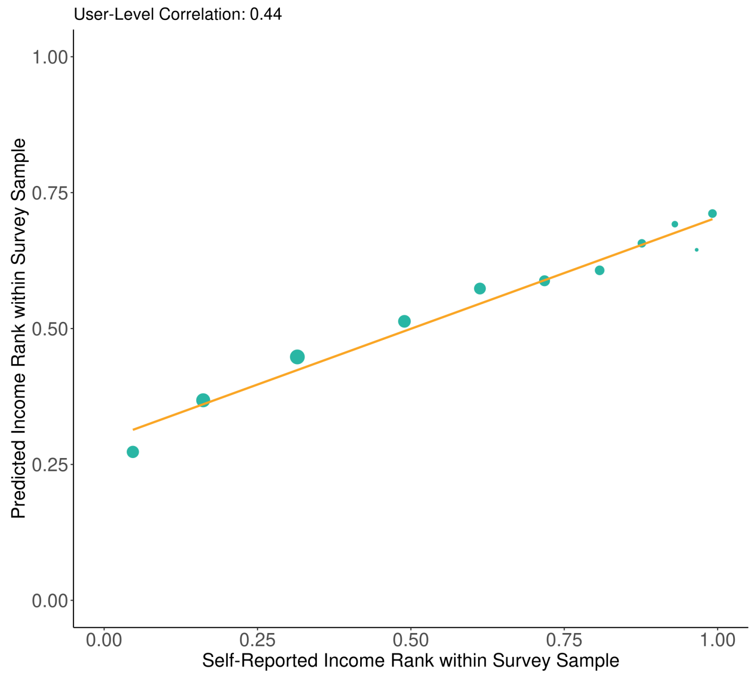


FIGURE 3: Binned scatter plot showing self-reported income vs predicted SES for 2,138 respondents to our well-being survey.

not come close to this limit. Recognising that users often maintain a larger number of Facebook friends than those they engage with frequently in person, we conduct additional analyses focused on users' closest friends, since the measures of interaction online we use (which are based on the frequency of interactions such as post reactions, photo tags, and comments) are strongly associated with the strength of the tie offline (Gilbert and Karahalios, 2009; Jones et al., 2013).

To understand the contexts in which social connections are formed and maintained, we assign users to various social and institutional groups, including secondary schools, universities, further education providers, workplaces, neighbourhoods, as well as faith-based communities and hobby and recreation groups. We describe our process for assigning users to groups, and assigning friendships to particular settings, in Appendix A.1.

In order to construct measures of the socioeconomic status of users in our sample while they were growing up, we link them, where possible, to their parents. Appendix A.2 provides details of the procedure we use to link users in our analytic sample to their parents, which relies on both self-reported information and imputed ties. In total, we are able to link 15% of the analytic sample to at least one parent. We find that our imputed ties are quite accurate: when users self-report a parent of a particular gender and our imputation methods specify a linked parent of the same gender even in the absence of the self-report, the self-report and our predicted linked parent of the same gender concur around 90% of the time. For users 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.

We show in Figure 25 that our university-level estimates of economic connectedness based on the SES of students' parents line up well with administrative data estimates from Britton et al. (2021), providing support for the validity of our approaches to imputing SES, linking users to parents, and assigning users to groups.

3 Measures of Social Capital

We operationalize social capital through three distinct yet interconnected categories: cross-type connectedness (bridging social capital), social cohesion (forms of bonding capital), and civic engagement.

3.1 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 (1973), which refers to bonds between acquaintances with less frequent social interaction, often connecting people who are not in the same immediate social circle. Putnam (1995) 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 Economic connectedness is defined as the proportion of high-socioeconomic status (SES) friends among individuals of low SES (Chetty et al., 2022a) and is a form of socio-economic bridging social capital. To compute the EC for a community c, we first define individual-level economic connectedness (IEC) for a person i as:

$$\text{IEC}_i = \frac{|\{j \in F_i : SES_j > p_{50}\}|}{|F_i|}$$

where F_i is the set of friends of i, SES_j is the socioeconomic status of friend j, and p_{50} is the median SES among our analytic sample in j's birth cohort. Then, the economic connectedness for community c is the average IEC among the set of low-SES individuals L_c in the community (i.e., $SES_i \leq p_{50}$ for $i \in L_c$):

$$\text{EC}_c = \frac{1}{|L|} \sum_{i \in L} \text{IEC}_i$$

Age Connectedness Other cross-type connectedness measures are calculated similarly. For age connectedness, we first calculate the individual-level fraction of person i's friends F_i who are between the ages of 35 and 44:

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

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 $i \in NE_c$):

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

3.2 Social Cohesion

Social cohesion reflects the structural characteristics of social networks. Bourdieu (1986) 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 (1973) 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 (1995) refers to as "bonding social capital".

We represent a set of friendships by the matrix $\mathbf{A} \in \{0, 1\}^{n \times n}$, where $A_{ij} = 1$ denotes the existence of a friendship between individuals i and j, and $A_{ij} = 0$ denotes the absence of a friendship. We focus on two key metrics to quantify this dimension.

Clustering Coefficient The clustering coefficient captures the tendency of an individual's friends to also be friends with each other. For an individual i, it is defined as:

$$\text{Clustering}_i(\mathbf{A}) = \frac{\sum_{j,k \in F_i, j<k} A_{jk}}{|F_i|(|F_i| - 1)/2}$$

where F_i denotes the set of i's friends.

We measure clustering in a community c as the average individual clustering coefficient across individuals in the community:

$$\text{Clustering}_c = \frac{1}{|N_c|} \sum_{i \in N_c} \text{Clustering}_i(\mathbf{A})$$

where N_c is the set of individuals in community c.

Support Ratio The support ratio (Jackson et al., 2012) assesses the proportion of an individual's friendships that are reinforced by mutual connections. For a community c, it is defined as:

$$\text{Support Ratio}_c = \frac{|\{(i, j) : i, j \in N_c, A^c_{ij} = 1, [(A^c)^2]_{ij} > 0\}|}{|\{(i, j) : i, j \in N_c, A^c_{ij} = 1\}|}$$

where A^c denotes the subset of friendships between individuals who are both members of community c.

3.3 Civic Engagement

Putnam (1995) 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.

3.4 Socioeconomic Diversity

Socioeconomic Status Entropy As a simple measure of the socioeconomic diversity of a community c, we consider the Shannon entropy of the distribution of low-SES and high-SES individuals. If $p_{H,c}$ is the fraction of high-SES individuals in the community, the entropy is:

$$\mathrm{ENT}_c = -p_{H,c} \log_2(p_{H,c}) - (1 - p_{H,c}) \log_2(1 - p_{H,c})$$

This entropy is equal to one if the community is perfectly balanced between low-SES and high-SES individuals, and is zero if everyone in the community falls into one of these categories.

4 Patterns of Social Capital in the UK

4.1 SES Homophily

Figure 4 illustrates the relationship between an individual's SES rank and the mean SES rank of their friends. We observe homophily in individuals' friendship networks, with a one percentile point increase in an individual's SES rank associated with a 0.19 percentile point increase in their friends' average SES rank. This relationship is nearly linear between the 10th and 90th percentiles, with a steeper slope in the top and bottom deciles, indicating stronger SES homophily in the tails of the SES distribution. When restricting the analysis to an individual's ten closest friends, we find a stronger relationship with a slope of 0.25. This indicates that, on average, homophily is approximately 30% stronger among an individual's closest friends compared to their entire network.

Figure 5 illustrates the socioeconomic segregation in UK social networks, revealing homophily across all socioeconomic status (SES) deciles. This homophily is most pronounced at the distribution's extremes. Individuals in the bottom decile have nearly 20% of their friends from the same decile, with about 5% from the top decile. Conversely, those in the top decile have nearly 20% of friends from their own decile and about 5% from the bottom. Despite the strong homophily at both ends, it is noteworthy that even the most disadvantaged individuals maintain some connections, albeit limited, to those in the highest socioeconomic group.

As well as having a greater proportion of high-SES friends, high-SES individuals also have a greater total number of friends than low-SES individuals, as shown in Figure 6. In combination with the greater *proportion* of high-SES

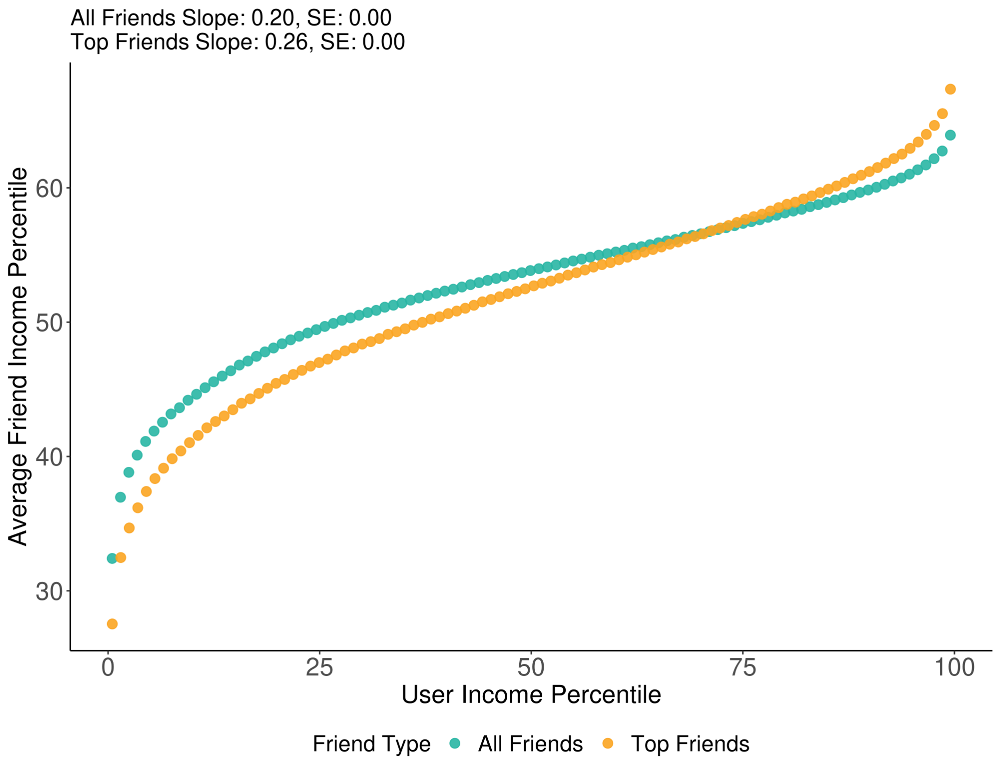


FIGURE 4: SES Homophily in the UK

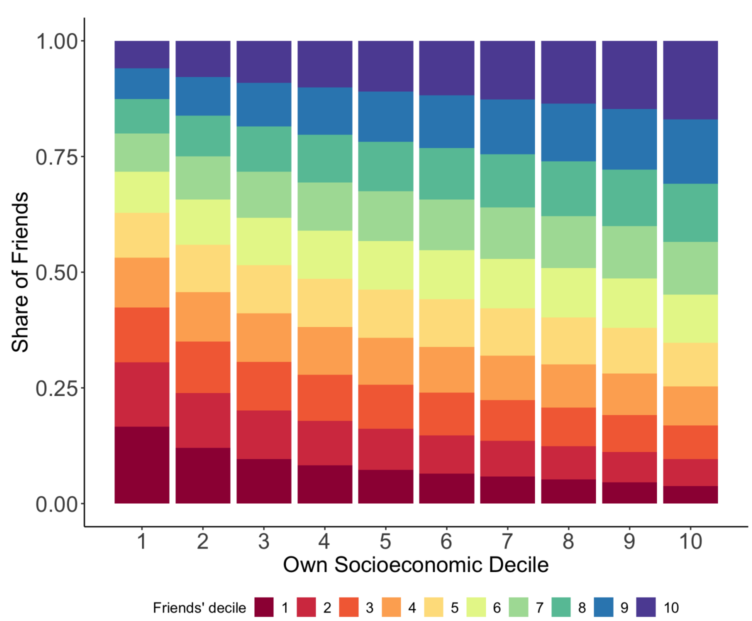


FIGURE 5: Share of friends in each socioeconomic decile, by own decile

friends that high-SES individuals have, this leads to a marked difference across the SES distribution in the *total* number of high-SES friends that individuals have, also shown in Figure 6. To the extent that friends matter because they are conduits of information and provide access to new opportunities, the absolute number of high-SES friends is an important factor beyond just an individual's proportion of friendships that extend to high-SES alters.

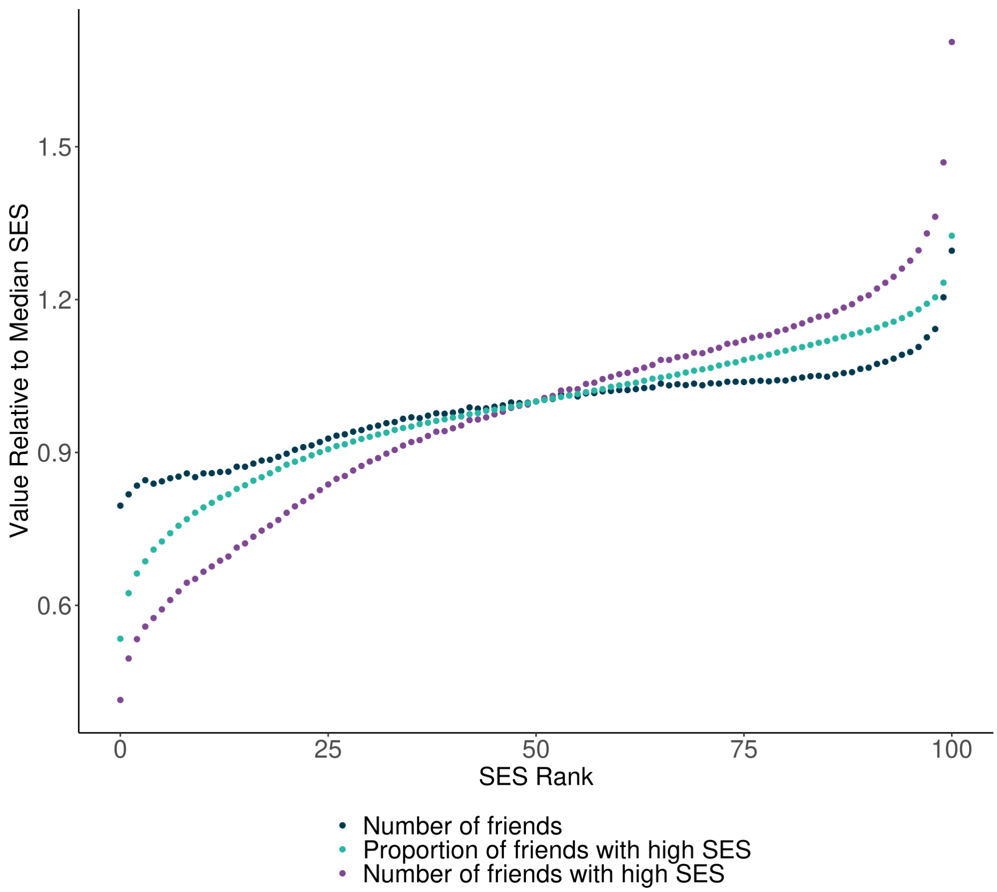


FIGURE 6: Number of friends, proportion of high-SES friends, and number of high-SES friends by own SES rank.

When we divide the individuals in our analytic sample into below-median (low) and above-median (high) SES groups on the basis of their within-cohort SES rank, we find that friendship patterns show less pronounced homophily than might be expected. On average, 47% of the friends of low-SES individuals have high SES. This figure is notably higher than the approximately 39% observed in comparable US data[1]. Meanwhile, 60% of the friends of high-SES individuals have high SES. These percentages sum to more than 100% since high-SES individuals have more friends on average than low-SES individuals as shown in Figure 6.

The geographical distribution of EC (that is, the average share of a low-SES individual's friends who are themselves high-SES) across the UK reveals significant regional variation. This variation is depicted in Figure 7. EC is

[1]These two estimates were calculated at different times and used different methodologies to assign SES estimates to individuals, and as such the magnitude should be interpreted with caution.

highest in the South of England, particularly in the Home Counties surrounding London, and lowest in more deprived areas such as South Wales, the North East of England, the Scottish Central Belt, and Northern Ireland. Figure 8 shows that EC also varies substantially within London, with neighbourhoods in the South West of the city showing the highest levels of EC and areas in the North East showing the lowest levels.

To further understand geographic patterns in social capital, we examine variation across ONS Area Classifications (Gale et al., 2016). These classifications group UK local authorities based on demographic, household, housing, socio-economic, and employment characteristics derived from the 2011 Census. The classification methodology employs hierarchical K-means clustering on 59 key variables selected from an initial set of 167 census statistics (Office for National Statistics, 2015).

Figure 9 reveals distinct patterns in three dimensions of social capital across these area classifications. Economic connectedness (EC) shows substantial variation, with the highest levels observed in Rural-Urban Fringe (0.59), Rural Growth Areas (0.58), and Affluent Rural areas (0.61). In contrast, Industrial and Multi-ethnic areas show the lowest EC (0.40), followed by Mining Legacy and Scottish Industrial Legacy areas (both 0.42). This pattern suggests a notable urban-rural divide in economic connectedness, consistent with previous research on geographic segregation in the UK (Dorling, 2012). Although areas with more high-SES residents generally have greater EC, a high concentration of affluent individuals does not always result in more cross-class friendships. For example, Kingston upon Thames and Canterbury have similar levels of affluence, yet the share of high-SES friends among low-SES residents is 10% higher in Kingston upon Thames. These geographic patterns of economic connectedness also align with political divisions. EC is negatively correlated with an area's Brexit vote share (with a coefficient of -0.33) and positively correlated with referendum turnout (with a coefficient of 0.72), echoing findings that areas with stronger social fabric showed markedly different voting patterns in the 2016 EU referendum (Tanner et al., 2020). Notably, this relationship persists when controlling for the local share of high-SES residents.

Clustering coefficients show less variation across area types, ranging from 0.08 to 0.11. The highest clustering is observed in Scottish Countryside and Northern Ireland Countryside (both 0.11), while most urban and suburban areas show slightly lower levels of clustering (0.08-0.09).

Volunteering rates also display meaningful variation across area types. Prosperous Semi-rural areas show the highest volunteering rate (0.10), while London Cosmopolitan and Ethnically Diverse Metropolitan Living areas show the lowest (0.04).

These patterns suggest that social capital metrics vary systematically with area characteristics, with rural and affluent areas generally showing higher levels of economic connectedness and volunteering, while urban and industrial areas typically show lower levels.

4.2 Cohesiveness

We construct two measures of network cohesiveness: clustering and the support ratio. Clustering, which measures the rate at which friends of a given individual are also friends with each other, exhibits distinct patterns across the UK (Figure 7), as does the support ratio (Appendix Figure A1). Areas with high clustering coefficients often have lower economic connectedness, particularly evident in regions such as South Wales and the North East of England.

The urban-rural divide is apparent in the clustering data, with rural areas, particularly in Scotland and Wales, showing higher clustering coefficients. The ONS Area Classification data supports this observation, with "Scottish Countryside" and "Northern Ireland Countryside" areas exhibiting high clustering values (0.45 and 0.44 respectively).

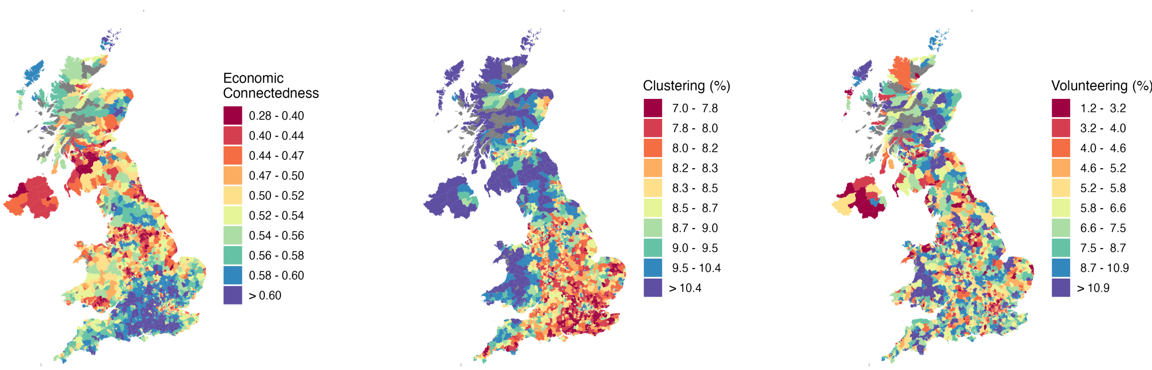


FIGURE 7: Geographic distribution of social capital measures by postcode district across the UK.

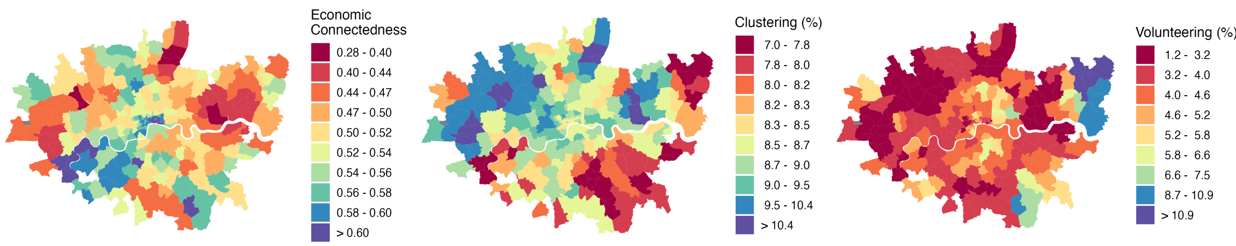


FIGURE 8: Geographic distribution of social capital measures by postcode district in London.

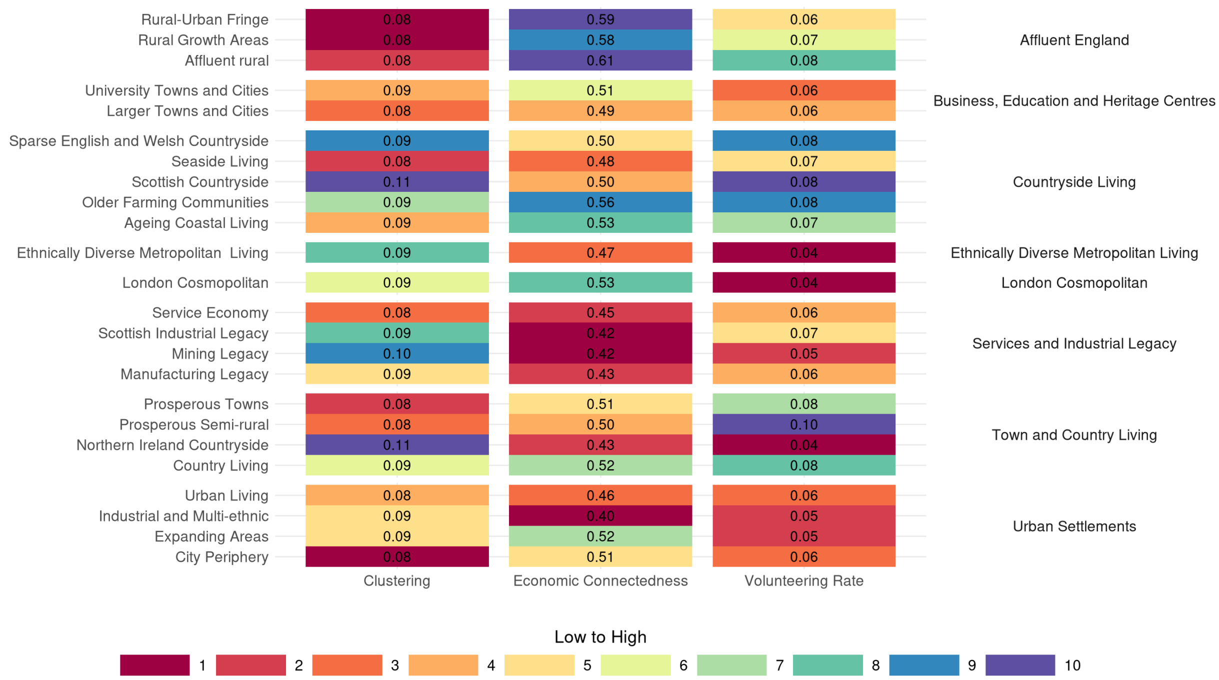


FIGURE 9: Social Capital by ONS Area Classifications.

4.3 Civic Engagement

Figure 7 reveals that volunteering fractions are generally higher in more remote and rural areas, such as the Scottish Highlands and parts of Wales. Some urban areas also show high rates of volunteering, particularly in and around major cities like London, Manchester, and Edinburgh. Appendix Figure A1 shows that a similar pattern holds for another measure of civic participation: the regional density of civic organizations.

The ONS Area Classification data shows that "Prosperous Semi-rural" areas have the highest volunteering rates (8%), while "Ethnically Diverse Metropolitan Living" and "Northern Ireland Countryside" show the lowest rates (3%).

Overall, we show that there are distinct geographical patterns for different forms of social capital across the UK, highlighting the need for nuanced and context-specific approaches when assessing community-level social capital. This study underscores the importance of clearly defining and differentiating between various dimensions of social capital in future research and policy interventions.

5 Measuring Upward Mobility in the UK

5.1 Constructing Mobility Estimates using Eligibility for Free School Meals

We utilize the Longitudinal Education Outcomes (LEO) dataset—an administrative dataset from the Department for Education that links individuals' educational records with employment and earnings data. Using this data, we estimate economic mobility across 326 local authorities and 1,618 postcode districts in England.

As the LEO data currently does not include data on individuals' parents' earnings during childhood, we first adopt the approach used in Carneiro et al. (2020) by using free school meals (FSM) eligibility at age 16 to indicate childhood economic disadvantage. In order for children to be eligible for FSM, their families need to be on means-tested benefits, such as income support or jobseeker's allowance. As a result, FSM serves as a good proxy for economic disadvantage. Around 15% of the children in our sample were eligible for FSM at age 16. Although we do not observe the FSM-eligibility of private school students (who constitute around 7% of UK school students), considering these students usually come from the top 10% of the parent income distribution (Henseke et al., 2021), we are unlikely to be excluding a substantial proportion of FSM-eligible students in our sample.

We measure adult economic outcomes using both HMRC Pay As You Earn (PAYE) records (earnings from standard employment) and self-assessment earnings (income from self-employment and other sources) contained in the LEO dataset. We assign earning ranks to FSM-eligible pupils based on their national income position at age 28 compared to all other individuals in their birth cohort in the LEO data. For each geographic area, we define its upward mobility level as the average adult income rank achieved by all pupils who were eligible for FSM and lived in that area at age 16.

Our analysis extends previous work in two ways. First, while Carneiro et al. (2020) initially estimated mobility using FSM-eligible pupils from the 1986-1988 birth cohorts, we expand this to cover the 1986-1992 birth cohorts using more recent LEO data. This increase in sample size improves the precision of the mobility estimates. This improvement is non-trivial given that the previous local authority-level estimates often relied on fewer than 100 children's outcomes. Our expanded estimates correlate well with Carneiro et al.'s original estimates, showing a weighted correlation of 0.89 at the local authority level.

Second, the expanded set of birth cohorts we make use of in LEO's latest release enable us to publish novel economic mobility estimates for postcode districts—a geographical area more granular than local authorities. We are able to release FSM-based mobility statistics for about 80% of postcode districts in England.

5.2 Patterns of FSM-Based Economic Mobility in England

Our analysis reveals substantial earnings gaps between FSM-eligible and non-FSM individuals at age 28. FSM-eligible men earn a median annual income of £13,753—37% less than their non-FSM peers (£21,771). For women, this disparity is even more pronounced: FSM-eligible women earn £6,644, which is about 59% less than the average annual earnings of non-FSM women (£16,187).

Examining earnings trajectories between ages 28 and 32 reveals important patterns. While median incomes increase for both FSM and non-FSM men during this period, the relative position of FSM-eligible men improves only marginally (1.6 percentile ranks). For FSM-eligible women, the improvement in relative position is even smaller. These patterns suggest that aggregate early-career earnings differences become entrenched by the early 30s.

For women, interpretation requires particular care due to two key data limitations. First, the LEO dataset lacks information on working hours, making it impossible to distinguish between wage differences and variations in labor force participation. Second, the absence of data on non-earned income, including benefits, may particularly affect our understanding of living standards for women from disadvantaged backgrounds who are more likely to work part-time or have caring responsibilities.

There are substantial differences across England's 326 local authorities in terms of FSM-based mobility, with differences of 17 percentile ranks between the local authorities with the highest and lowest mobility for both men and women.

One key drawback of our FSM-based metrics is that the average income of FSM-eligible students across areas will vary with the income composition of the area. As a result, FSM-eligible children may not be comparable across areas. This drawback motivates our next approach, which facilitates comparison of the adult outcomes across areas of children who grew up at a *given point* in the income distribution.

5.3 PCA-Based Mobility Measures

We next follow Carneiro et al. (2020) in constructing a childhood SES index using several indicators of childhood socioeconomic status available within LEO. Those indicators consist of whether the child was on FSM and several variables from the 2001 census available at the (granular) output area level (we observe the output area in which the child grew up):

- the percentage of individuals who owned their own home.
- the percentage of those in work in higher professional and managerial occupations.
- the percentage of those in work in lower professional and managerial occupations.
- the percentage of those with at least level 3 qualifications in the national qualifications framework.

We also use the 2004 index of multiple deprivation score for the LSOA in which the child grew up. The left panel of Figure 10 shows the national level rank-rank slope of adult SES against childhood SES. Our slopes line up closely with those presented in Van Der Erve et al. (2024), which are constructed using the 1986–88 cohorts.

Our ability to use an expanded set of cohorts gives us enough precision to release mobility indices based on the average adult earnings of people who were children in each postcode district, who grew up at the 25th percentile of the national parental SES distribution. These indices have the advantage versus the FSM measures that they are not as vulnerable to contamination by differences in the parental SES distribution across areas. However, they are only available for England due to the limited coverage of the LEO data. This motivates our third approach, using the Facebook data directly to calculate mobility statistics.

5.4 Estimating Upward Mobility in the UK using Facebook Data

To complement and extend these insights, we introduce a novel approach using internal Facebook data to estimate intergenerational mobility across the entire United Kingdom. Unlike the LEO dataset, which tracks individuals longitudinally, our Facebook approach relies on constructing parent-child links in contemporary data. In order to construct measures of the socioeconomic status of users in our sample while they were growing up, we link them to their parents, as detailed in A.2. This approach is supported by research from Chetty et al. (2014), which demonstrates strong correlations between parent and child income ranks across generations. Their findings suggest that parental socioeconomic status remains relatively stable during adulthood, making parents' current SES a reasonable proxy for the economic environment experienced during a child's upbringing.

Mirroring the time series of the LEO data, we use children born between 1986 and 1992. Children's SES ranks are based on their ranks within their birth cohort among children linked to parents, while parents' SES ranks are based on their ranks relative to other parents in the same group of parents linked to children born between 1986 to 1992.

For each parent-child pair identified through our linkage process, we estimate a rank-rank regression of the form:

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

where R_i^{child} represents the child's SES rank in adulthood and R_i^{parent} represents their parents' SES rank, both measured contemporaneously. The slope coefficient β provides a measure of relative mobility, with higher values indicating stronger intergenerational persistence of socioeconomic status.

The validity of this approach is supported by previous research comparing Facebook-based mobility estimates to administrative tax records in the United States (Chetty et al., 2022a). That study found remarkably similar rank-rank slopes between Facebook data (0.32) and IRS tax data (0.34), suggesting that Facebook-based parent-child linkages and SES measures can reliably approximate intergenerational mobility patterns found in administrative data.

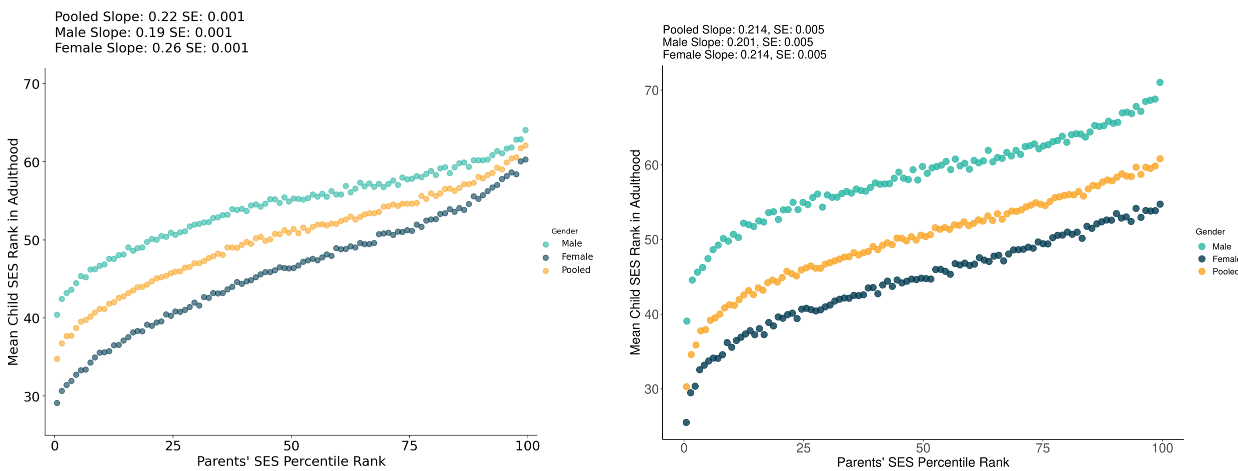


FIGURE 10: Comparison of Rank-Rank Intergenerational Mobility Curves. Left: LEO Data. Right: Facebook Data.

Figure 10 presents our rank-rank intergenerational mobility estimates derived from both LEO and Facebook data. The rank-rank curves derived from Facebook data closely mirror those obtained from the LEO data, with similar slopes for both men (0.20 vs. 0.19) and women (0.22 vs. 0.26), although there is a level shift in child SES ranks which are higher in the Facebook-based data. This alignment between two independent data sources—comprehensive administrative records and social network data—validates our Facebook-based approach and demonstrates its potential as a complementary tool in mobility research.

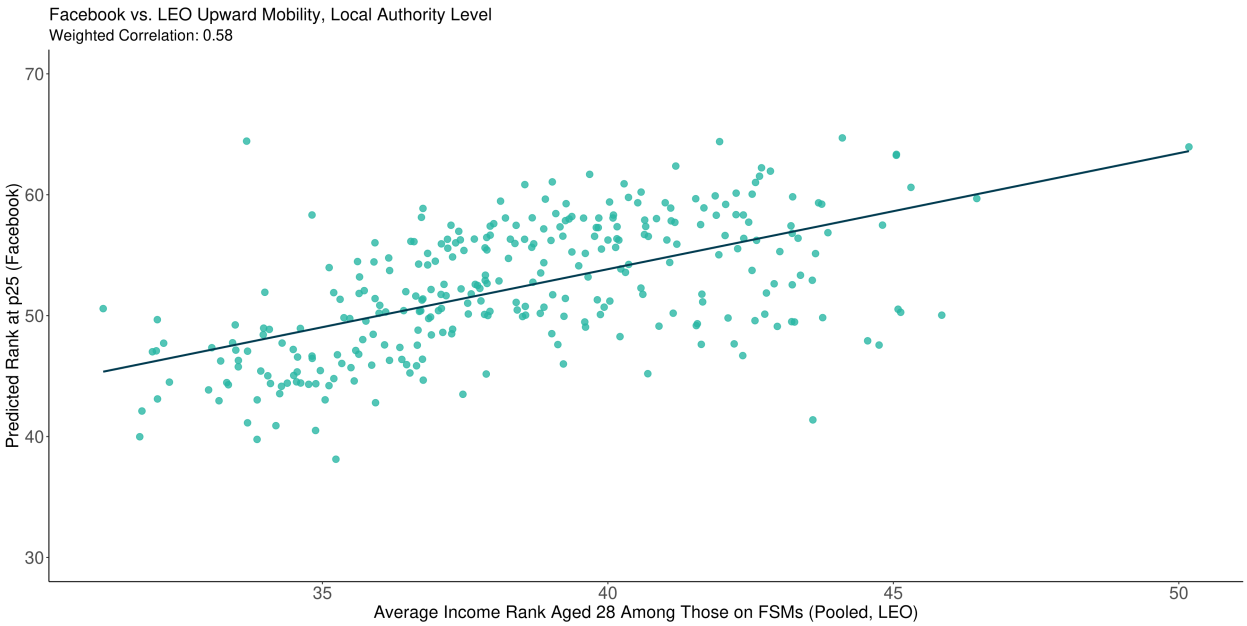


Figure 11: Correlation between Facebook and LEO Upward Mobility Estimates at Local Authority Level

At an area-level, in Figure 11, we also see that our Facebook-based measure of intergenerational mobility correlates strongly with our FSM-based measure of upward mobility in English Local Authorities where we have data from both series.

The Facebook data enables us to overcome two key limitations of the LEO dataset. First, it provides coverage beyond England to include Scotland, Wales, and Northern Ireland. Second, it allows for more granular geographical analysis. Figure 12 presents the first comprehensive map of upward mobility for the entire UK at a fine geographical level.

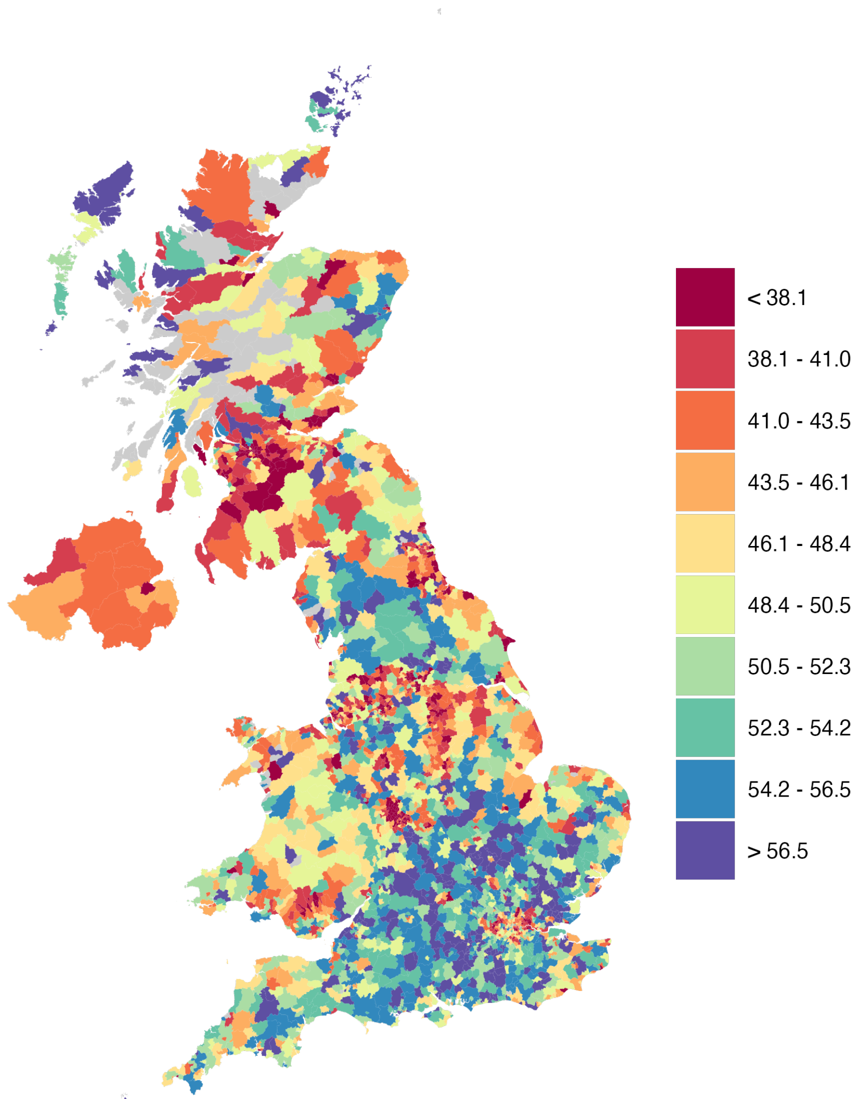


FIGURE 12: Geographic Distribution of Upward Mobility in the UK by Postcode District, constructed from Facebook data.

Notes for Figure 12: This map shows predicted income ranks in adulthood for children whose parents are at the 25th percentile of the national parent income distribution, estimated using Facebook data. Child income ranks are measured based on their current socioeconomic status within their birth cohort (1986-1992), while parent income ranks are measured relative to other parents with children in these birth cohorts. The predictions are derived from rank-rank regressions of children's ranks on parents' ranks within each postcode district.

6 Social Capital and Upward Mobility

Regional differences in upward mobility—the likelihood of children from disadvantaged backgrounds achieving higher earnings as adults—persist across the UK. Although research has examined how childhood conditions and educational opportunities drive these inequalities, the role of social capital in shaping mobility outcomes remains poorly understood in the UK (Social Mobility Commission, 2023). In this section, we examine the role that the measures of social capital that we constructed above play in explaining regional variation in upward mobility.

Here, we explore the relationship between different forms of social capital and upward mobility in England, using our new set of LEO-based estimates.

Figure 13 presents both univariate correlations and multivariate regression results at the local authority level. The univariate correlations (Panel A) reveal that economic connectedness shows the strongest positive relationship with upward mobility among our set of social capital metrics (with a correlation coefficient of 0.6). This finding aligns with previous research using UK telecommunications data showing that communities with more diverse social networks tend to have better economic outcomes (Eagle et al., 2010).

To benchmark the importance of economic connectedness for economic mobility, consider two children eligible for FSM, one of whom grows up in a local authority at the 10th percentile of the distribution of economic connectedness, and another who grows up in a local authority at the 90th percentile of the economic connectedness distribution. The child growing up in the local authority at the 10th percentile can expect 44% of their friends to have high SES, while the child growing up in the 90th percentile local authority can expect 66% of their friends to have high SES. That is a difference of 22 percentage points. A 10 percentage point increase in economic connectedness for a local authority is associated with an increase of the average adult earnings of a child eligible for FSM of 3.24 centiles in the national income distribution. As a result, the difference in connectedness between a 10th percentile and a 90th percentile local authority is associated with an increase of 7.13 centiles in the national income distribution, which translates to an increase of roughly £5,100 above the adult earnings of the average child eligible for FSM.

This relationship remains robust and significant in the multivariate analysis (Panel B), where we control for other forms of social capital simultaneously. The magnitude of the standardized coefficient suggests that a one standard deviation increase in economic connectedness is associated with a 0.7 standard deviation increase in upward mobility, holding other factors constant.

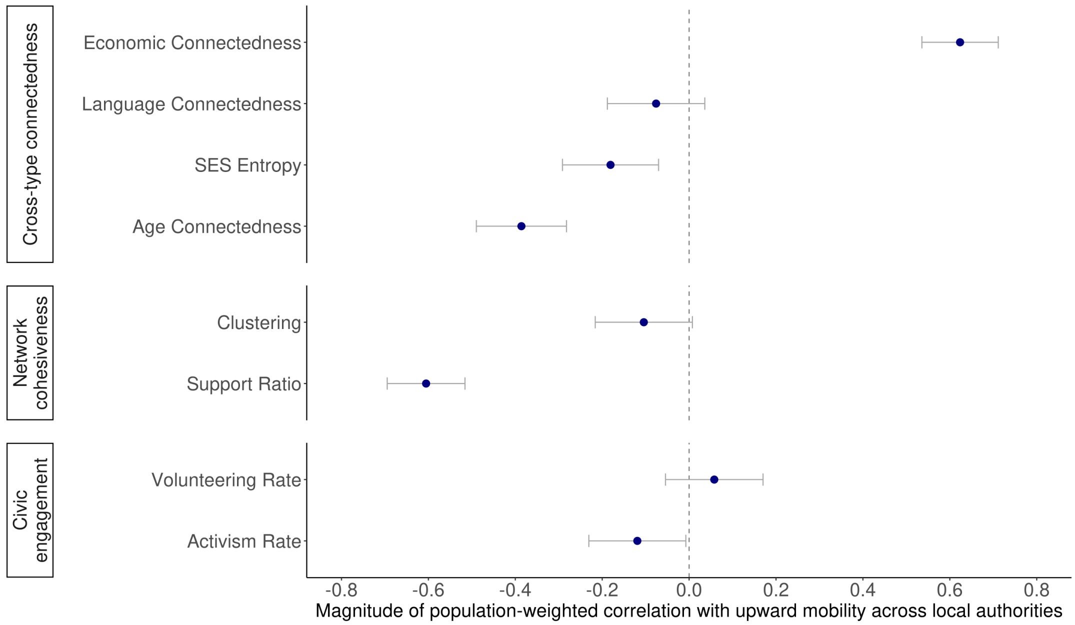
Other measures of social capital show more modest or negative relationships. Clustering (the tendency for friends to be friends with each other) shows a positive correlation, while the support ratio (the share of friendships with mutual connections) exhibits a negative relationship. This pattern suggests that while dense local networks might support mobility, excessive clustering within a small set of groups could be detrimental. Age connectedness and measures of civic engagement (volunteering and activism fractions) show weaker associations with mobility outcomes.

Figure 14 presents bivariate correlations between our upward mobility estimates and various area-level characteristics, including measures of social capital, ONS subnational indicators (Office for National Statistics, 2024b), and metrics from the Social Fabric Index (Tanner et al., 2020). Economic connectedness emerges as one of the strongest predictors of upward mobility among all characteristics analysed, supporting the similar findings from Chetty et al. (2022a) in the United States.

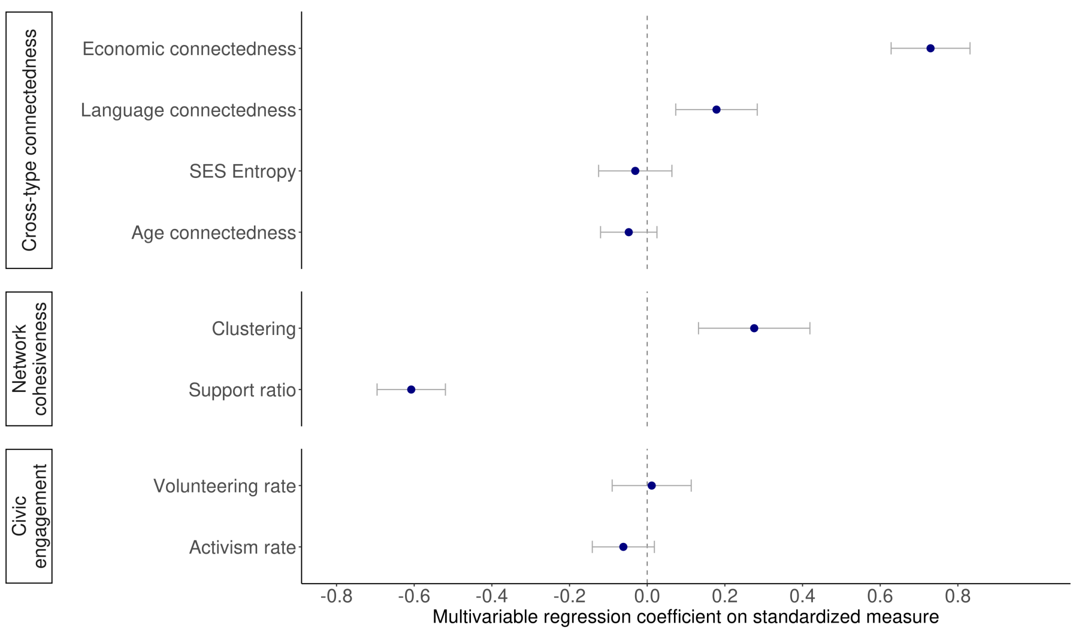
The correlations reveal several patterns. First, economic indicators—including median weekly pay, disposable income per head, and the deprivation gap ranking—show strong positive associations with mobility. Second, educational metrics across different stages (primary school, secondary school, and 5 year achievements) demonstrate consistently positive correlations, suggesting the crucial role of educational institutions in fostering mobility. Third, health-related measures such as male and female healthy life expectancy and early cancer diagnosis rates also show notable positive correlations.

Components of the Social Fabric Index also show strong positive correlations with upward mobility. The "Positive Social Norms" domain, which measures factors including educational attainment, healthy behaviors, and family stability, shows a particularly strong association. Similarly, the "Civic Institutions" domain, which captures the health of local democracy and governance through measures such as electoral turnout, trust in institutions, and quality of public services, demonstrates a robust positive correlation with mobility outcomes. These traditional measures of social capital complement our network-based measures, suggesting that both strong civic institutions and cross-class social connections play important roles in facilitating economic mobility.

To test the strength of the relationship between economic connectedness and upward mobility, Figure 15 presents results from a multivariate regression, including the seven strongest predictors identified from the bivariate correlations exercise (see Figure 14 notes for more detail). Even after controlling for other key factors such as median weekly pay, income deprivation, health indicators (preventable cardiovascular mortality rate and child obesity prevalence), and educational quality (GCSE achievement), economic connectedness remains a strong predictor of upward mobility. Its significance persists even when accounting for the Social Fabric Index Score, which encompasses various aspects of community cohesion, demonstrating that cross-class social connections capture critical elements not fully represented by traditional measures of social capital.



(A)



(B)

FIGURE 13: Local authority-level relationships between upward mobility and measures of social capital. **a**, Univariate correlations between local authority upward mobility and various social capital measures. **b**, Coefficient estimates from a multivariable regression of upward mobility on all social capital measures, with both outcome and independent variables standardized to mean zero and standard deviation one. Upward mobility is measured as the mean income rank at age 28 of children who were eligible for Free School Meals at age 16. All correlations and regressions are weighted by the number of FSM-eligible children in each local authority. Error bars represent 95% confidence intervals calculated using heteroskedasticity-robust standard errors.

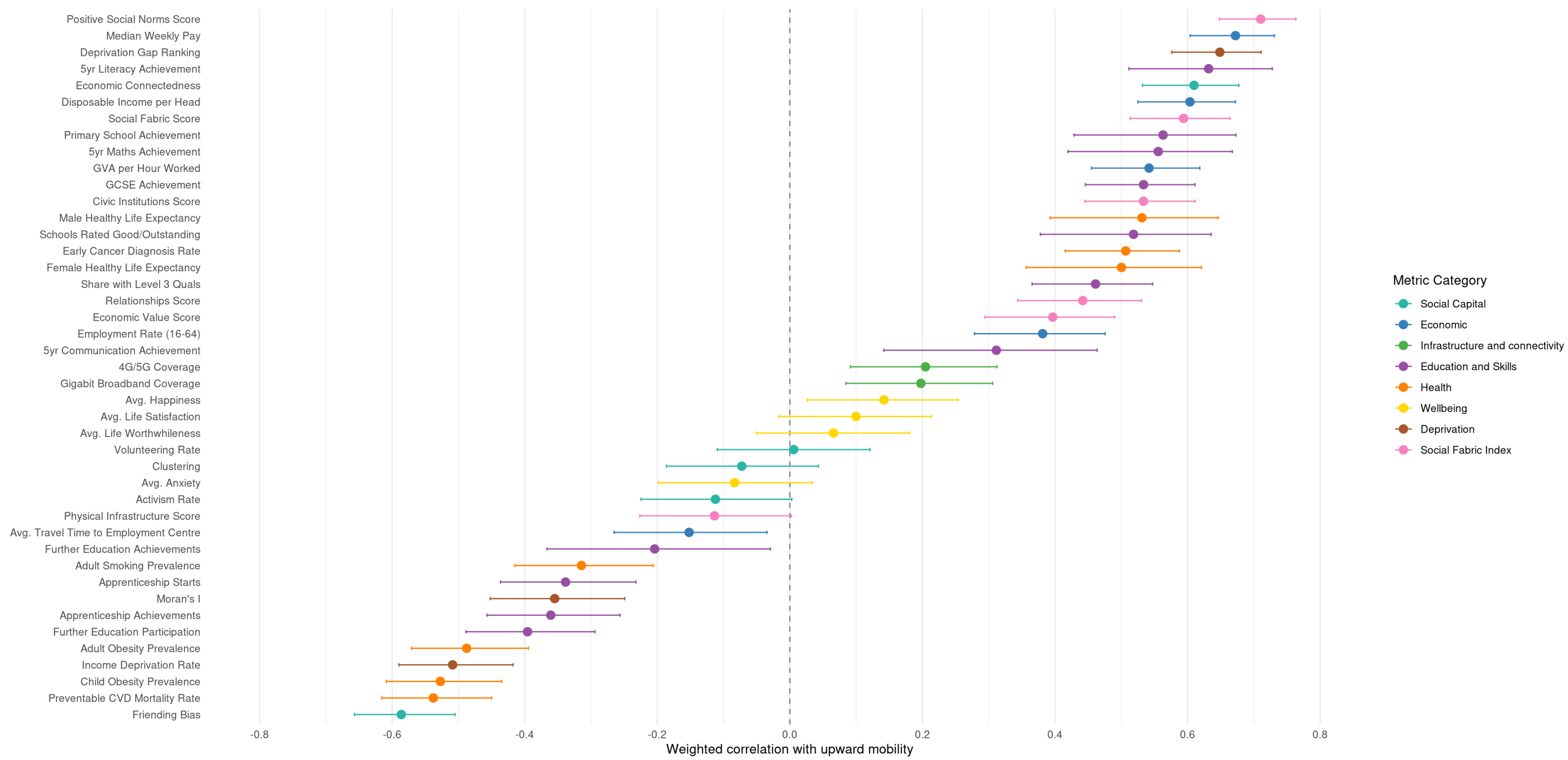


FIGURE 14: Local-authority-level bivariate correlations between upward income mobility and area characteristics. *Notes:* Subnational statistics are sourced from the Office for National Statistics (2024b), while the Social Fabric Index is provided by Tanner et al. (2020).

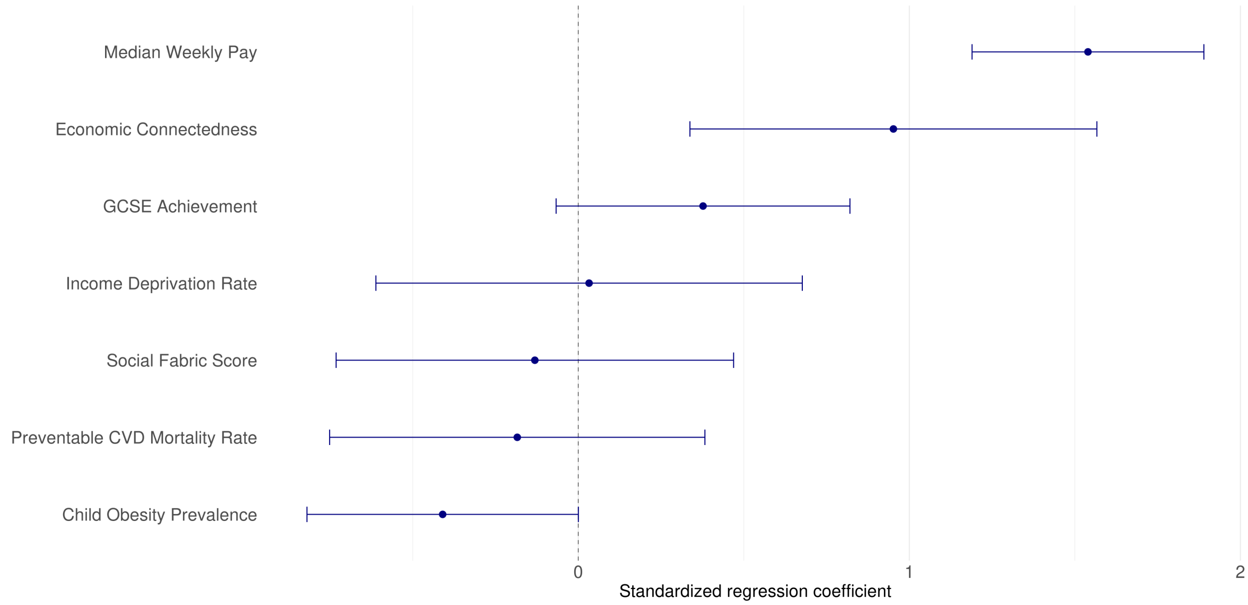


FIGURE 15: Multivariate regression of upward mobility on top 7 neighbourhood characteristics. *Notes:* The variables used here are the top 7 predictors from the bivariate correlations in Figure 14, which exhibit the largest correlations with upward mobility, excluding variables with substantial missing data or high collinearity (e.g., average bias, gross value added per hour worked, gross disposable household income per head, sub-component indices of the Social Fabric Index, and deprivation gap ranking). This approach ensures the inclusion of all strong predictors identified in previous research. All correlations and regressions are weighted by the 2022 local authority population, with intervals representing 95% confidence calculated using standard errors.

The extended birth cohorts we are able to make use of in LEO enable us to publish novel upward mobility estimates for postcode districts—a more granular geography than local authorities. Similarly, we construct our Facebook-based measures of mobility at the postcode district level. Figures 16 and Figure 17 present the relationship between economic connectedness, household income, and mobility, first using our FSM-based mobility measure and then using our Facebook-based mobility metric.

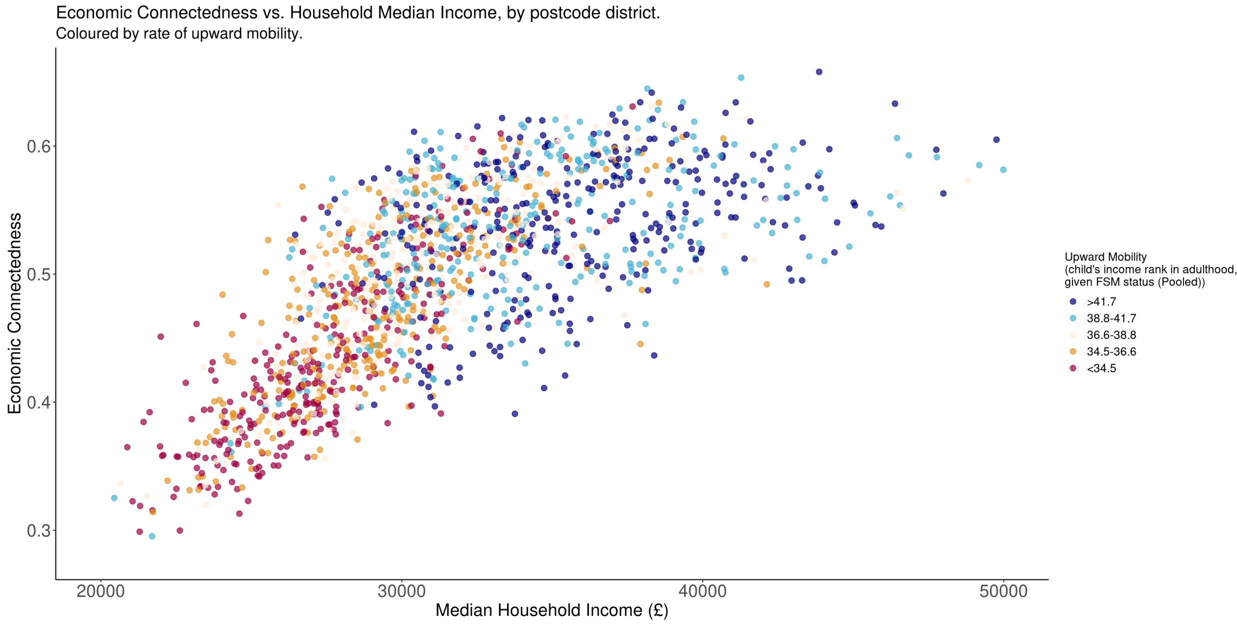


FIGURE 16: Economic connectedness, median household income, and FSM-based mobility.

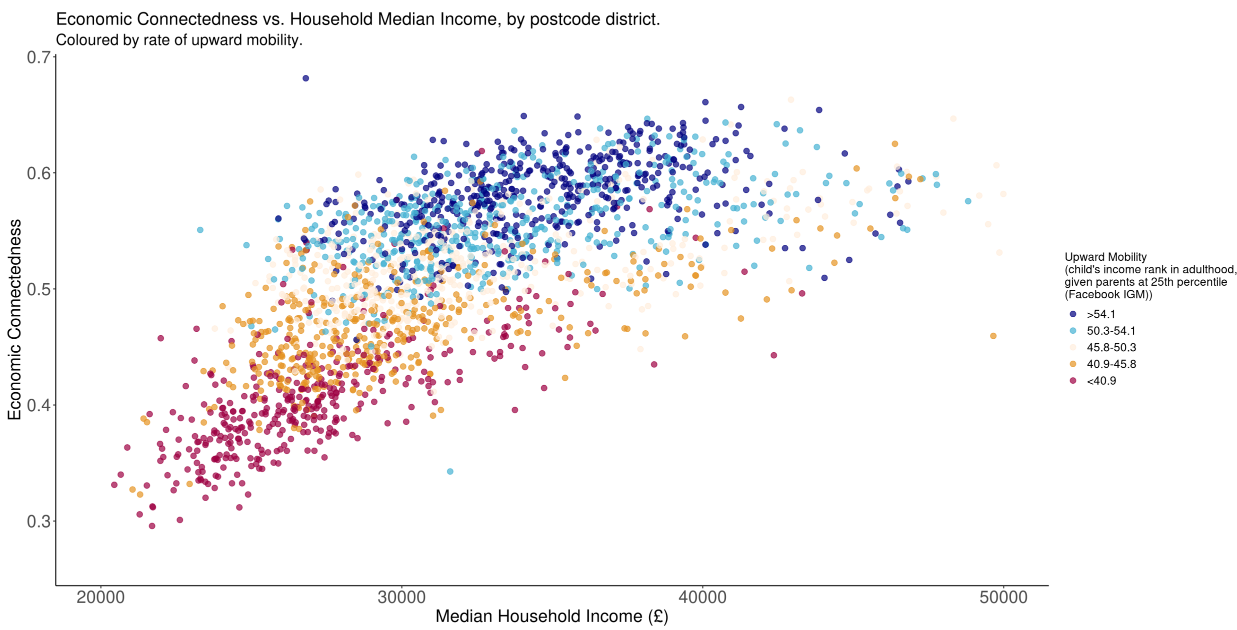


FIGURE 17: Economic connectedness, median household income, and Facebook-based mobility.

7 Determinants of Economic Connectedness

Figure 6 shows that the proportion of high-SES friends an individual has varies dramatically as a function of the individual's own SES. In this section, we break down that difference.

7.1 Exposure and Friending Bias

As in Chetty et al. (2022b), we decompose EC into two components: exposure and friending bias. Exposure refers to the share of high-SES individuals within groups like schools and workplaces, and measures the SES composition of the pool of people that individuals in these groups could potentially befriend. For example, if an individual is in a hobby group, and 70% of the members of that hobby group have high SES, then their exposure in that hobby group would be 0.7.

Since our settings represent real-world locations (such as a particular school, university, or church), our measure of exposure is conceptually related to measures of co-location and experienced segregation derived from mobile phone GPS pings (Athey et al., 2021; Moro et al., 2021; Nilforoshan et al., 2023; Iyer et al., 2023). One drawback of these GPS-based estimates is that it is difficult to determine which co-locations were genuine interactions. Two individuals who co-locate at a particular restaurant, for example, may be two friends dining at the same table, separate individuals dining on different tables, or one individual dining and a waiter. To the extent that connections matter because they facilitate, for example, the sharing of norms or information, the actual interaction is key as opposed to the co-location. An advantage of our data from Facebook is that we are able to see when individuals who inhabit the same social setting end up forming a friendship. Low-SES individuals in a given setting may still form a relatively greater proportion of their friendships to other low-SES individuals than you would see if they had the same probability of forming a friendship with any alter in the setting regardless of the alter's SES. We denote this gap as "friending bias". Formally we define friending bias in a community c as:

$$\text{Friending Bias}_c = 1 - \frac{\text{Economic Connectedness}_c}{\text{Exposure}_c}$$

Positive values of friending bias indicate that low-SES individuals in community c have fewer high-SES friends in that community than they would have if they formed friendships randomly within the community. For example, if half of the within-groups friends of below-median members of a hobby and recreation group are above-median alters (so that economic connectedness is equal to 0.5), and 70% of the members of the group have high SES (so that exposure is equal to 0.7) then friending bias would be $1 - \frac{0.5}{0.7} \approx 0.29$.

Since friending bias and exposure can only be calculated in reference to a particular community, we focus in the rest of this section 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.1 provides a detailed description about how we assign users to particular groups within each settings. We assign a friendship to a particular setting if both individuals involved in the friendship are members of the same group within a setting, with the additional requirement for high-school, sixth-form, and university friendships that both members of the friendship must also be within three birth cohorts of each other. Using these criteria, we are able to assign just under one half of the friendships between users in our analytic sample to one of these settings. These assigned friendships therefore constitute around 3 billion friendships. Figure 18 shows that these friendships are representative of overall friendships in terms of the degree of SES homophily.

We begin by examining how the share of friends that an individual makes in each setting varies with their socioeconomic status (SES). In Figure 19, we present the average share of high- and low-SES users friends that are made in each context. We see that individuals with lower SES make a substantially larger share of their friends within their neighbourhoods compared to individuals with higher SES. Conversely, high-SES individuals form a

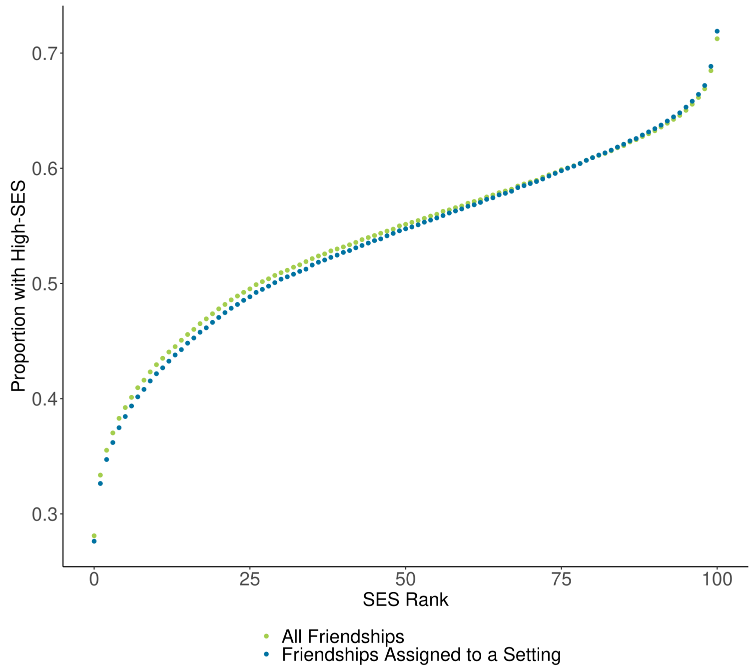


FIGURE 18: The proportion of all friendships to high-SES alters and the proportion of friendships assigned to a setting to high-SES alters, by ego SES.

much greater proportion of their friendships in universities. Other contexts are responsible for a relatively low share of friendships. In Figure 20, we display further disaggregated information on friendship formation, showing the normalized share of friendships made in each context by individuals in each ventile of the SES distribution.

In Figure 21, we show economic connectedness, exposure, and friending bias for each of our settings. Exposure is especially high for both below-median and above-median SES individuals in universities, reflecting the fact that individuals who occupy this setting tend to be richer. Additionally, note that the gap between exposure for low-SES and high-SES individuals in this setting is small. This means that if you are a low-SES individual attending university in the UK, the SES distribution of your peers is likely to be similar on average to that of a high-SES individual attending university. The share of high-SES friends that low-SES students have at university is over 40% greater than the share of the friends they make in their home neighbourhoods that are high SES.

Of course, the lower-SES individual is less likely to be attending university and making friends there in the first place, as shown in Figure 19. On the other hand, note that exposure in hobby and recreation groups is markedly different between low-SES and high-SES individuals. While exposure for low-SES individuals in hobby and recreation groups is close to 1, suggesting that they participate in hobby and recreation groups whose SES composition matches the national distribution, exposure for high-SES individuals in hobby and recreation groups is much higher. The average high-SES individual is participating in hobby and recreation groups whose members are generally better-off compared to the national distribution.

For friending bias, we see that above-median SES individuals tend to display greater *absolute* levels of friending bias than below-median SES individuals. Since our networks are undirected, there are the same number of cross-class friendships going from below-median SES to above-median SES individuals as there are going from above-median to below-median SES individuals. However, as shown in Figure 6, high-SES individuals also tend to have

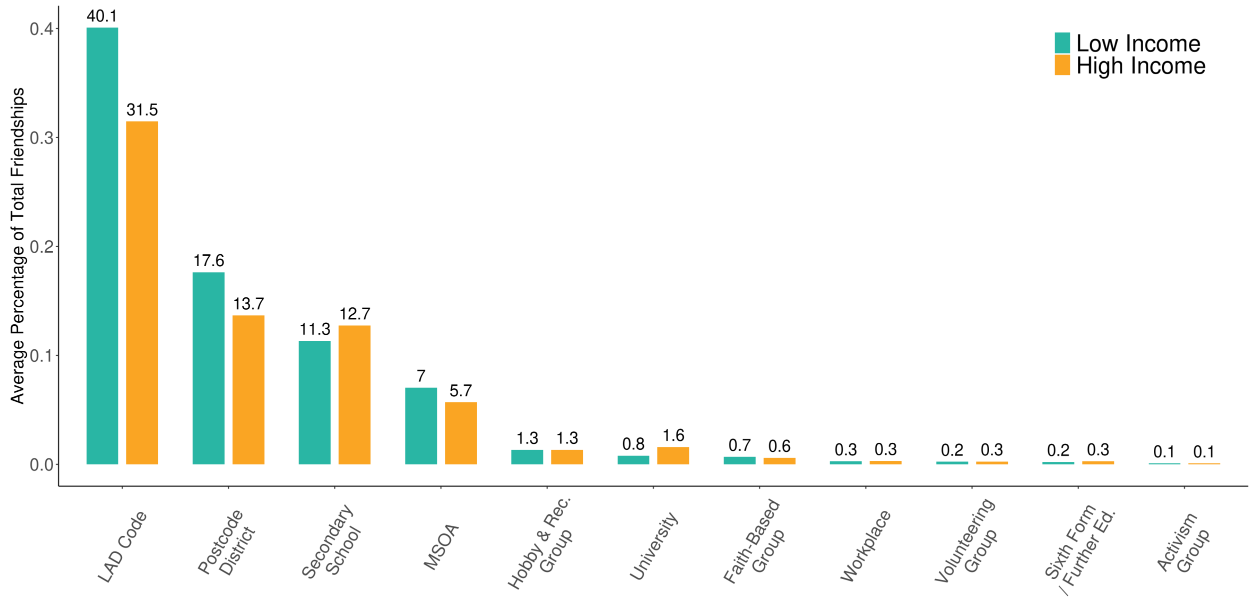


FIGURE 19: Proportions of Friendships by Setting in the UK

Notes for Figure 19: This figure captures the average share of users' total friendships made in each context, separately for above- and below-median SES users in our sample.

more friends in total, so the fraction of their friendships extending to low-SES individuals will be lower than the fraction of friendships from low-SES individuals that extend to high-SES individuals. We see that absolute friending bias is especially high in neighbourhoods, which likely reflects residential segregation even within fairly granular geographic areas and the hyper-local nature of many within-neighbourhood friendships. Note that friending bias for low-SES individuals in hobby and recreation groups is *negative*, indicating that low-SES individuals in hobby and recation groups tend to form a greater proportion of their friendships to high-SES individuals than would be expected if they extended friendships randomly within the group. Additionally note that friending bias for low-SES individuals in hobby and recreation groups is in fact lower (more negative) than friending bias for high-SES individuals. While this may seem paradoxical at first, it is consistent with the fact demonstrated by the exposure statistics that the average low-SES individual and the average high-SES individual inhabit different hobby and recreation groups and we may expect the characteristics of friending within those groups to be different as well. We provide further analysis of social capital in hobby and recreation groups in Appendix Section C.

7.2 Decomposition of Differences in Economic Connectedness by SES

We construct economic connectedness for a representative low-SES individual by taking the weighted average of economic connectedness within each of our seven 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 0.46. A similar procedure for a representative high-SES individual yields yields a value of economic connectedness of 0.60. These values closely match the values of economic connectedness for low- and high-SES individuals calculated using all friendships reported in Section 4.1. We now

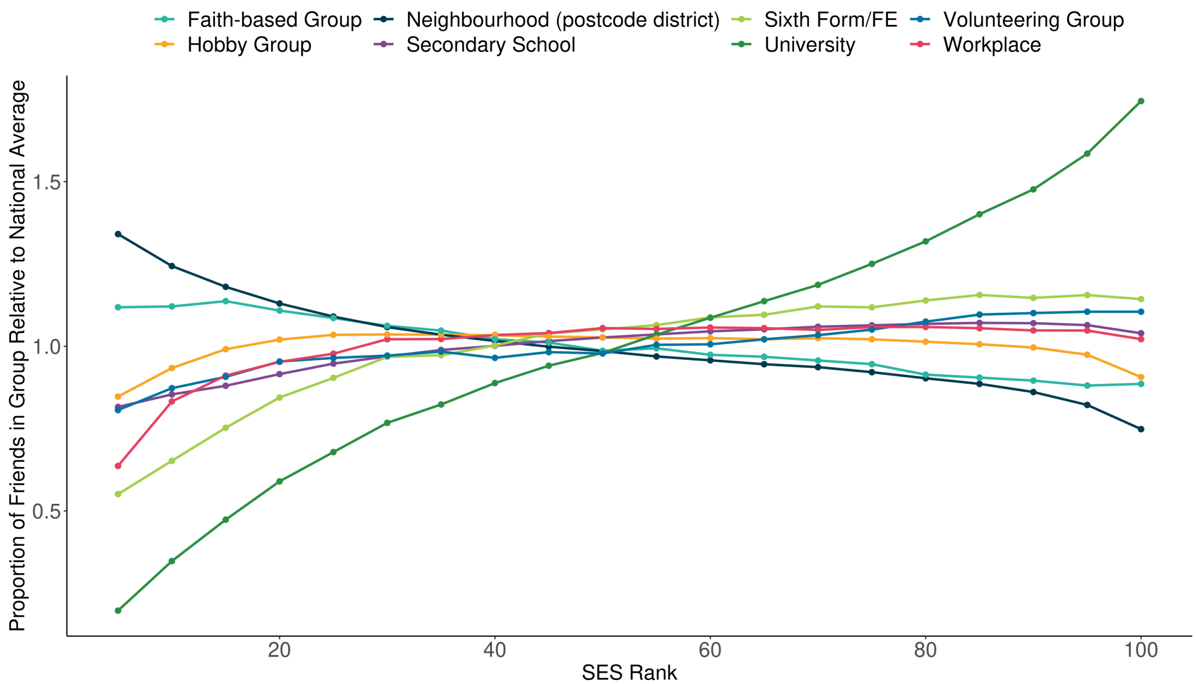
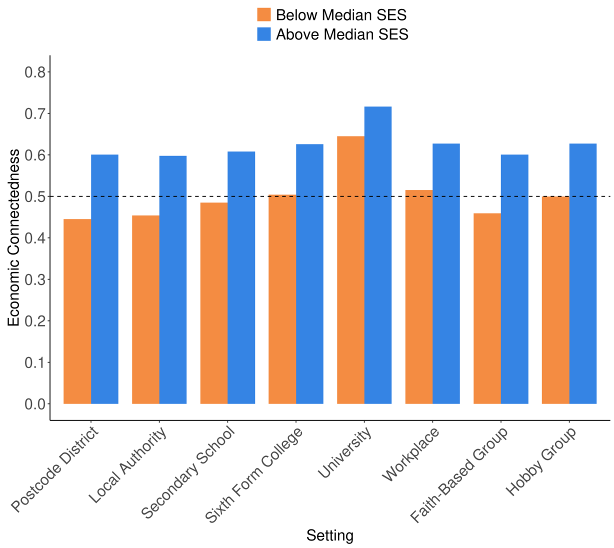
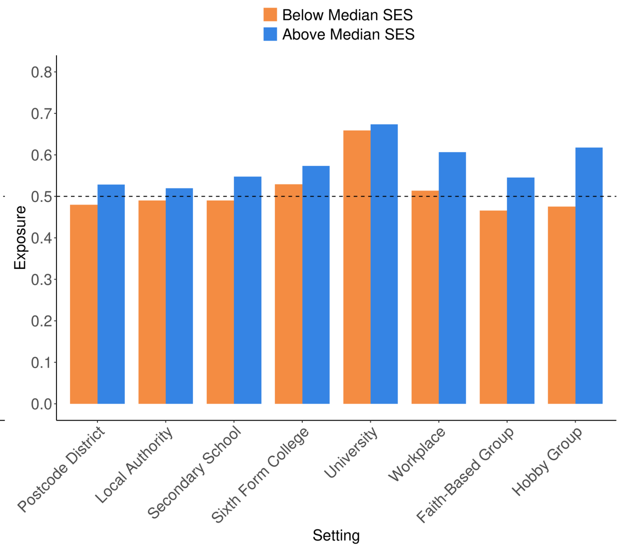


FIGURE 20: Relative Friendship Proportions by Setting and SES in the UK

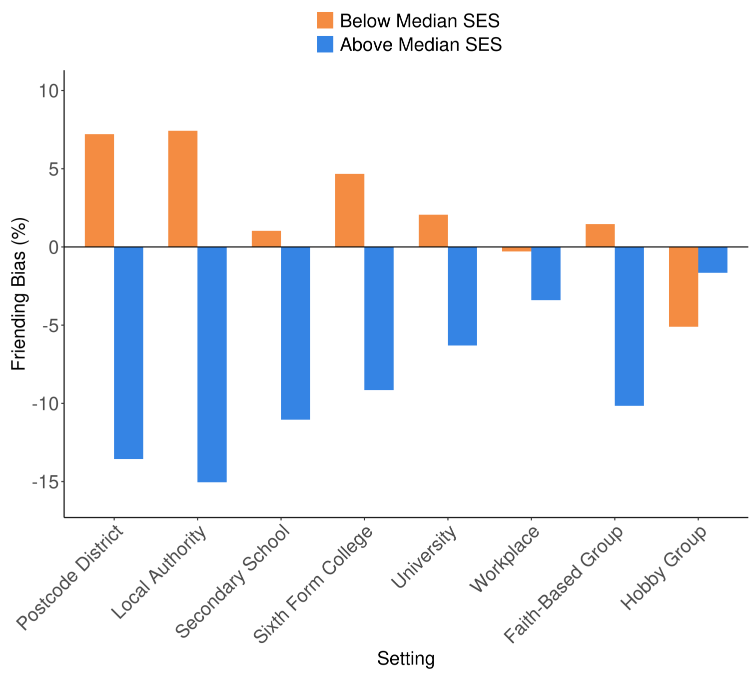
Notes for Figure 20: These series are calculated in a multistep process. First, for each user in our analytic sample, we calculate the proportion of their total friends we can assign to each setting (allowing friendships to be assigned to more than one setting if say, both friends are members of the same hobby and recreation group and the same faith-based community). We then calculate the average share of friends we can assign to each setting over all users. We also calculate this average for each setting restricting to users in each ventile of the SES distribution. Each dot on the chart represents the average share of friends for users in that particular ventile that can be assigned to the relevant setting, divided by the average share of friends over all users that can be assigned to each setting.



(A) Economic Connectedness



(B) Exposure



(C) Friending Bias

FIGURE 21: Economic Connectedness, Exposure, and Friending Bias by Setting and SES.

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 0.46 to 0.47. As a result, even though the share of friendships made in each setting varies dramatically by SES, as shown in Figure 19, 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 0.46 to 0.51.

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 68% of the gap by moving the EC of the representative low-SES agent from 0.46 to 0.56.[2]

8 Multiplexing

Using our assignments of friendships to settings, we are able to analyze 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* (Verbrugge, 1979; Kivelä et al., 2014). Understanding multiplexity is important because multiplexed relationships, by virtue of their value in multiple settings, may enable greater levels of cooperation in relationships (Cheng et al., 2021) and experimental evidence shows that the degree of multiplexity in relationships affects the speed with which new information spreads through a society (Chandrasekhar et al., 2024).

Figure 22 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. (2024) 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 to setting s (with entries a_{ij}^s), and $\mathcal{S}$ denote the set of settings to which we assign friendships (neighbourhoods, secondary schools,

[2]Our finding in this portion is somewhat sensitive to the granularities at which neighbourhoods are defined. If neighbourhoods are defined in a more granular way, the level of bias tends to decrease, while the average difference in exposure between high- and low-SES individuals increases. As a result, when we run our decomposition exercise, exposure accounts for less of the gap in EC between low- and high-SES individuals (and bias more) when we define neighbourhoods in a broader sense.

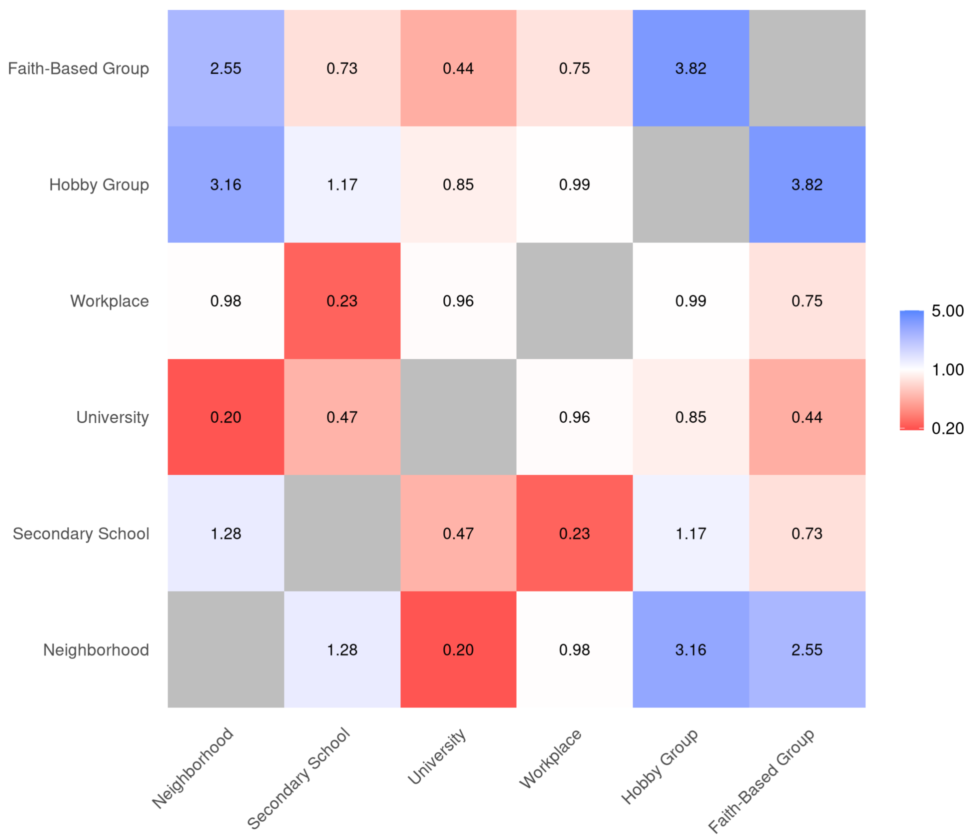


FIGURE 22: Relative probabilities of friendships spanning two settings.

Notes for Figure 22: 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.

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 where the cardinality of $S = \#(\mathcal{S})$ is the number of settings to which we assign friendships (in our case, six) and $\mathbf{1}$ 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 23, we plot the average multiplexing index over individuals by SES and gender. As in Chandrasekhar et al. (2024), we see that multiplexity is a more common feature of friendships for women than men. 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.

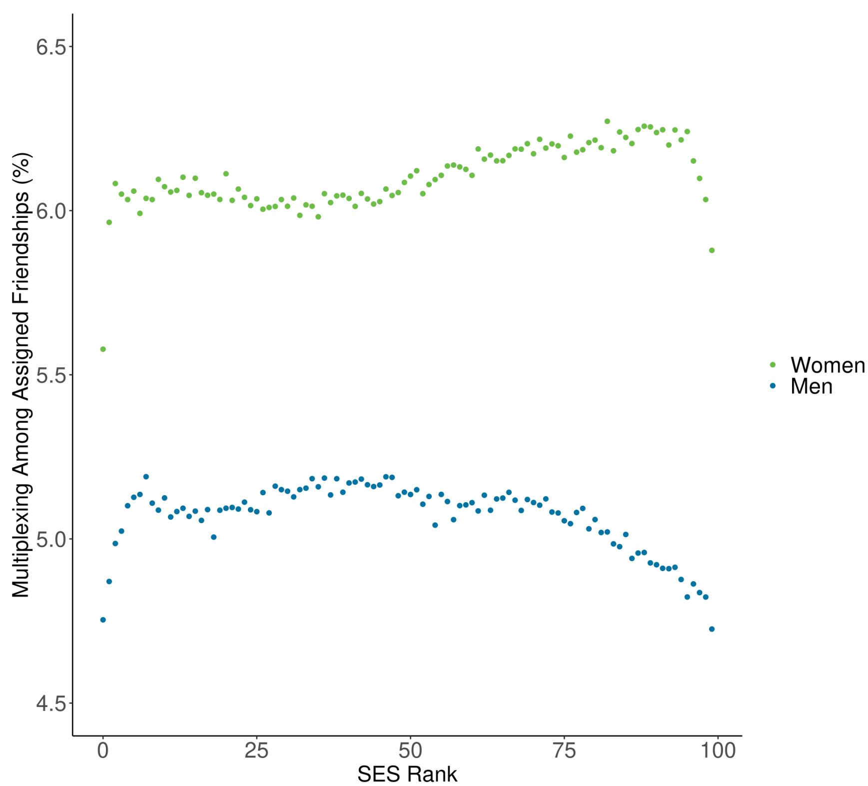


FIGURE 23: Multiplexing by SES rank and gender.

Notes for Figure 23: 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.

9 Social Capital in Universities

Figure 21 shows that universities are unique in terms of the level of exposure to high-SES individuals they provide to both low- and high-SES students. In this section, we examine how UK universities vary in their capacity to foster cross-class interactions by analyzing patterns of economic connectedness and exposure among their alumni. In this section, we use the SES of *parents* of university attendees to construct our measures of EC, exposure, and friending bias[3]. We term this index of exposure based on the SES of users' parents "parental exposure", and argue that it represents a better index of the availability of cross-class ties in a context in which most individuals are young and not yet in the workforce.

Table 1 presents the highest and lowest-ranking universities in our sample across three key metrics: economic connectedness (EC), exposure to high-SES individuals, and friending bias. The rankings reveal substantial variation across institutions. The University of Cambridge leads in economic connectedness (0.78), indicating that its lower-SES students form a high proportion of friendships with higher-SES peers. However, this high EC partly reflects Cambridge's high exposure rate (0.75)—the share of potential friends who are high-SES. In contrast, universities like Bolton and Wolverhampton show lower EC (0.48 and 0.54 respectively), largely reflecting their lower exposure rate as well.

Figure 24 plots our measure of exposure to peers whose parents are high-income ("parental exposure") for each university against the share of students at the university who were eligible for free school meals (FSM) while in school provided by Britton et al. (2021). (Those authors refer to this measure as the "access rate".) We would not expect these measures to line up perfectly (or even linearly) since most students whose parents have below-median SES would not have been eligible for FSM. But the strong correlation (with a coefficient of -0.60) between our measure of parental exposure and the share of students attending who were eligible for FSM helps to validate our SES imputations, our procedure to match students to the universities they attended, and our method to link users to their parents.

Figure 25 plots economic connectedness against universities' success rates—the proportion of students who were eligible for FSM in school who are in the top 20% of the earnings distribution at age 30, taken from Britton et al. (2021). We see an extremely strong relationship between the two measures, with a correlation coefficient of 0.82. That is, low-SES students attending universities where low-SES students have greater shares of high-SES students in their friendship networks are more likely to earn well as adults. Put another way, universities that foster more cross-class friendships for their disadvantaged students tend to be more effective at promoting upward mobility among those same students.

These findings highlight both the potential and limitations of universities as engines of social mobility. While some institutions successfully foster cross-class interactions that may aid mobility, there is a tension between providing opportunities for such interactions (which requires a diverse student body) and maintaining high access rates for disadvantaged students.

[3]We provide details on how we link users to their parents in Appendix A.2.

Table 1: Top and Bottom Universities by Social Connection Metrics

Rank	Economic Connectedness	Exposure	Friending Bias
Top 1	U of Cambridge (0.78)	U of Bath (0.76)	U of Bolton (0.08)
Top 2	U of Bath (0.76)	U of Cambridge (0.75)	U of Westminster (0.08)
Top 3	U of Bristol (0.75)	U of Bristol (0.75)	U of Central Lancashire (0.07)
Top 4	U of Exeter (0.74)	Oxford U (0.75)	U of Wolverhampton (0.04)
Top 5	Oxford U (0.74)	U of Exeter (0.74)	U of Warwick (0.03)
Bottom 1	U of Bolton (0.48)	U of Bolton (0.53)	U of Salford (-0.05)
Bottom 2	U of Wolverhampton (0.54)	U Of Teesside (0.55)	Kingston U (-0.04)
Bottom 3	U Of Teesside (0.55)	U of Wolverhampton (0.56)	U of East London (-0.04)
Bottom 4	U of Sunderland (0.57)	London Metropolitan U (0.57)	U of Cambridge (-0.03)
Bottom 5	U of Central Lancashire (0.57)	U of East London (0.57)	U of Reading (-0.03)

Notes for Table 1: All metrics are calculated using parental socioeconomic status. Economic connectedness represents the share of above-median-SES friends among below-median-SES individuals. Exposure is the share of individuals who are high-SES. Friending bias measures the tendency to form friendships with high-SES individuals relative to their presence in the university.

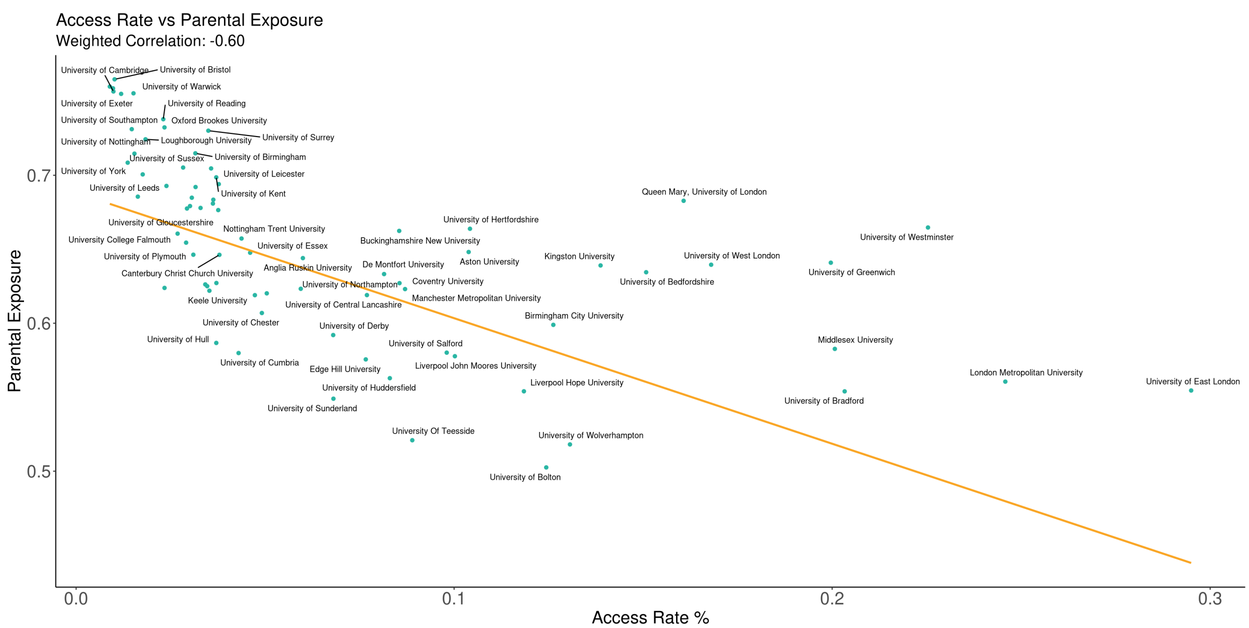


Figure 24: Exposure and access rates for universities.

Notes for Figure 24: In this figure, we validate our estimates of economic status by school, by comparing statistics about the users who attended each school in the Facebook data against administrative data. To do so, we compare parental exposure (that is, the share of students with above-median SES parents, as a share of those we can match to their parents) in each school in the Facebook data against the access rate, which is the share of students attending each institution who received free school meals before attending university, which we use following Britton et al. (2021). We find a strong correlation between the two measures of economic status by school, despite the differences in definition between the two measures.

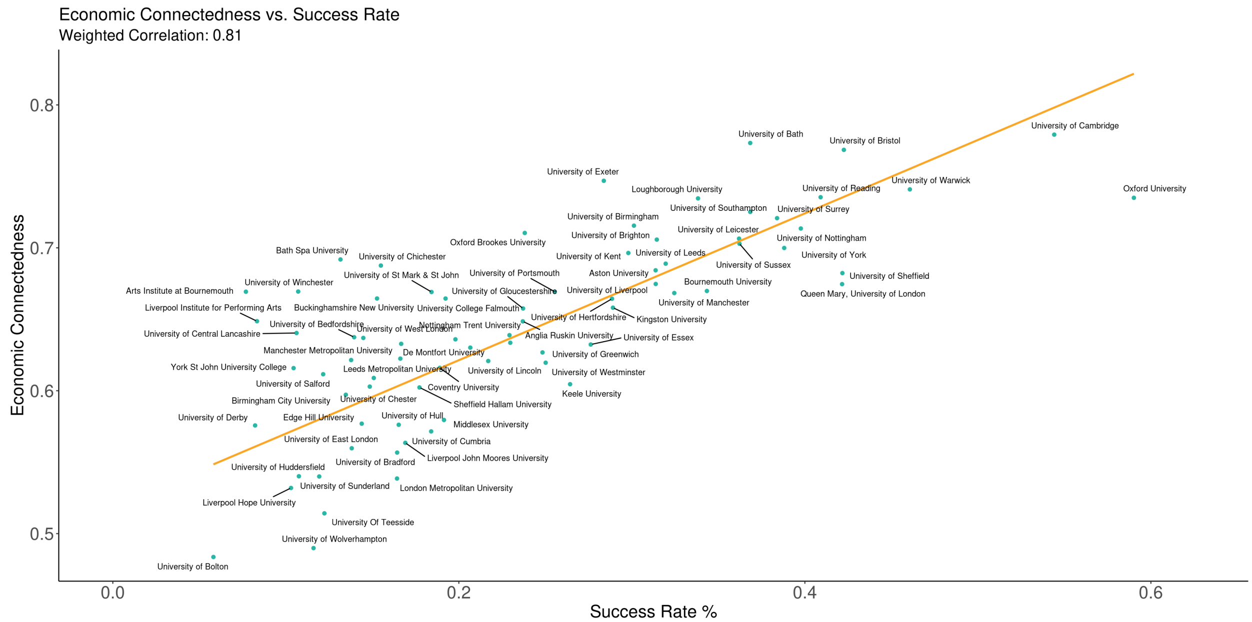


Figure 25: Economic Connectedness based on parental SES and success rates for universities.

Notes for Figure 25: We calculate economic connectedness on the basis of parental SES for the sample of users we are able to link to a parent. The success rate statistic is the fraction of students attending the university who were eligible for free school meals who made it to the top 20% of the earnings distribution at age 30, and is taken from Britton et al. (2021).

10 Social Capital and Subjective Well-being

There are several studies that indicate having positive social connections can improve subjective well-being (Halpern (2005), Rohrer et al. (2018), Blanchflower and Oswald (2004), Diener et al. (2018)), but the types of relationships and social capital that influence subjective well-being has been difficult to study due to the lack of availability of social networks data tied to outcomes. To study the relationship between social capital, subjective well-being, and related outcomes (trust, feelings of social support, and feelings of social disconnection), we administered a survey to 5,472 Facebook users in the UK between June and July of 2024. Of these respondents, 3,770 are in our analytic sample allowing us to link their survey responses to our individual-level measures of social capital.

Our survey consisted of 14 questions, covering the following four categories and household income:

1. Life Satisfaction: Four questions about happiness, life satisfaction, and worry including “how happy did you feel yesterday?” , “how satisfied are you with your life nowadays?”, and “how worried are you about the current state of the world?” adapted from the ONS well-being surveys (Office for National Statistics, 2023).

2. Trust: Three questions about trust including “would you say that most people can be trusted?” derived from the OECD trust surveys (OECD, 2017), the World Values Survey (Inglehart et al., 2020), and the European Social Survey (European Social Survey, 2020).

3. Feeling Disconnected: Three questions about feeling disconnected and isolated, including "how often do you feel left out?" and "how often do you feel isolated from others?" adapted from the UCLA loneliness scale (Hughes et al., 2004).

4. Social Support: Five questions on perceived social support, including "[do you have] someone who shows you love and affection?" and "[do you have] someone who can lend you money if you fall on hard times?" adapted from the MOS Social Support Survey and the State of Connections Survey (Sherbourne and Stewart, 1991).

5. Income: One question on household income (choosing from options such as "Below £10,000", "£10,001 to £20,000", "£20,001 to £30,000", and so on).

The life satisfaction questions were asked on a 10 point scale, while the trust, feelings of disconnection, and social support questions were on a 5 point scale. We report the full details of our survey in Appendix D.

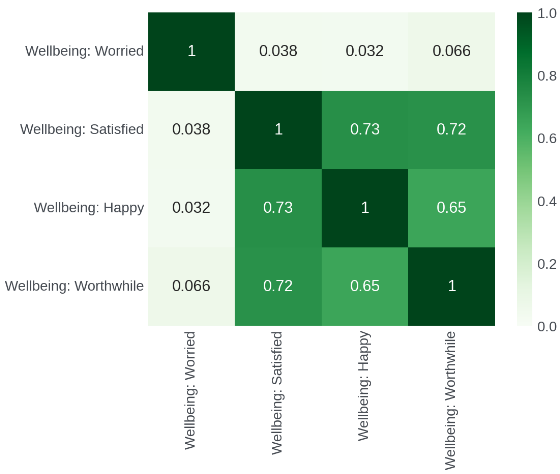
Several of the questions were highly correlated, especially within each survey category (Figure 26). We average responses for each individual and in each category to create a category response measure to simplify exposition (we omit the *worried about the world* question for the subjective well-being category and average the three questions about happiness, life satisfaction, and *things I do in my life are worthwhile*). While the concepts of happiness and life satisfaction are distinct and have different underlying mechanisms, we combine them into a singular *life satisfaction* category measure due to their high correlation in our study.

Figure 27 shows the relationships between our individual-level social capital metrics and survey responses (using the category averages), after controlling for age, gender, and self-reported income from the survey. Since many of our sample respondents said they preferred not to report their income, or did not check anything for the income box, this leaves us with a sample of 2,138 respondents.

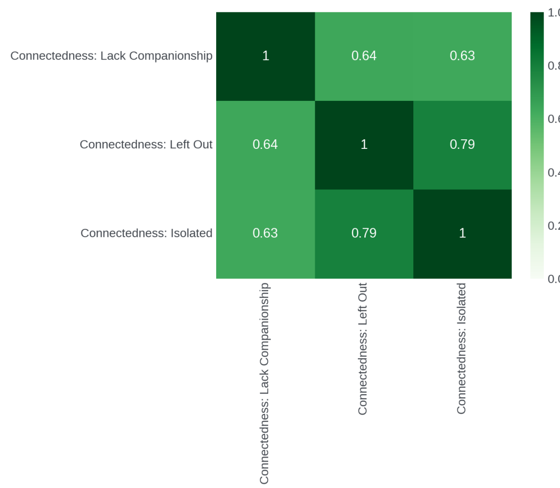
After controlling for income, age, and gender, respondents with more friends on the platform, more close friends, a greater proportion of friendships to high-SES individuals, and higher support ratios tended to report higher levels of life satisfaction, lower levels of disconnection, greater levels of trust, and greater levels of social support. Comparing individuals in the top 10% of share of friends that are very high-SES (top decile of the SES distribution) with those in the bottom 10% of share of very high-SES firends reveals the most economically connected individuals report 16.8% higher happiness (6.89 compared to 5.90 on a 10 point scale) and 42.3% higher trust (3.33 vs. 2.34 on a 5 point scale). Controlling for household income (comparing survey predictions holding household income constant at the average survey response level) shows increases of 4.6% in reported happiness and 23% in reported trust between the most and least economically connected individuals.

Although we find positive associations between our social capital measures and survey responses, the effect sizes are relatively small. An additional 100 friends is only associated with a 0.2 point increase in life satisfaction (on a 10 point scale), a 0.1 point increase in trust, a 0.1 point decrease in feelings of disconnectedness, and a 0.1 point increase in feelings of social support (on a 5 point scale). This is one of the first studies to combine individual social capital measurements from social networks data with subjective well-being measures and [other] survey outcomes, and our findings corroborate similar studies (Diener et al. (2018)) that find positive associations with social connections and subjective well-being. Even though individual social capital metrics are statistically significant predictors of subjective well-being, they do not explain a large amount of the variance between individuals.

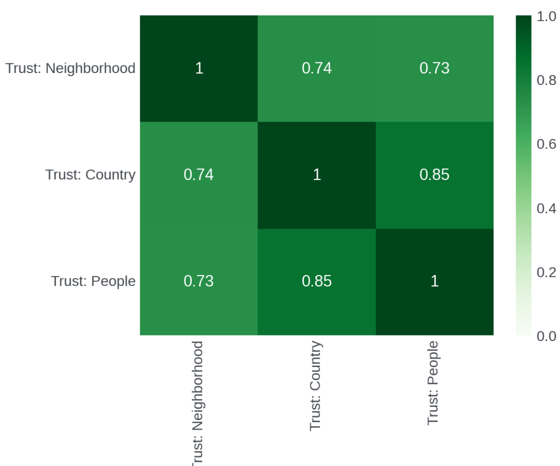
Figure 28 shows that our results are quantitatively and qualitatively similar when we just consider the bivariate relationship between our social capital metrics and our aggregated survey response indices. For context, the bivariate



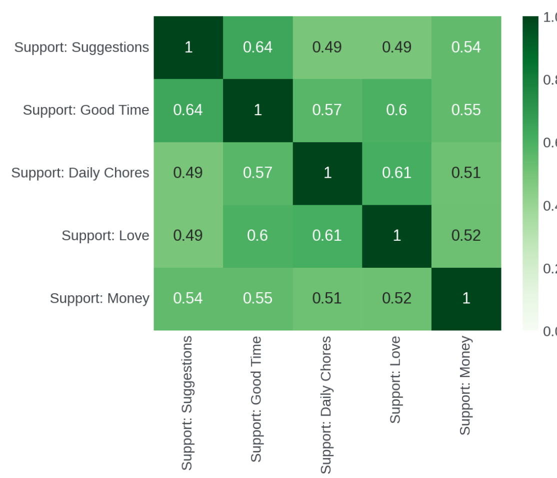
(A) Wellbeing.



(B) Connectedness.



(C) Trust.



(D) Support.

FIGURE 26: Correlations between survey responses.

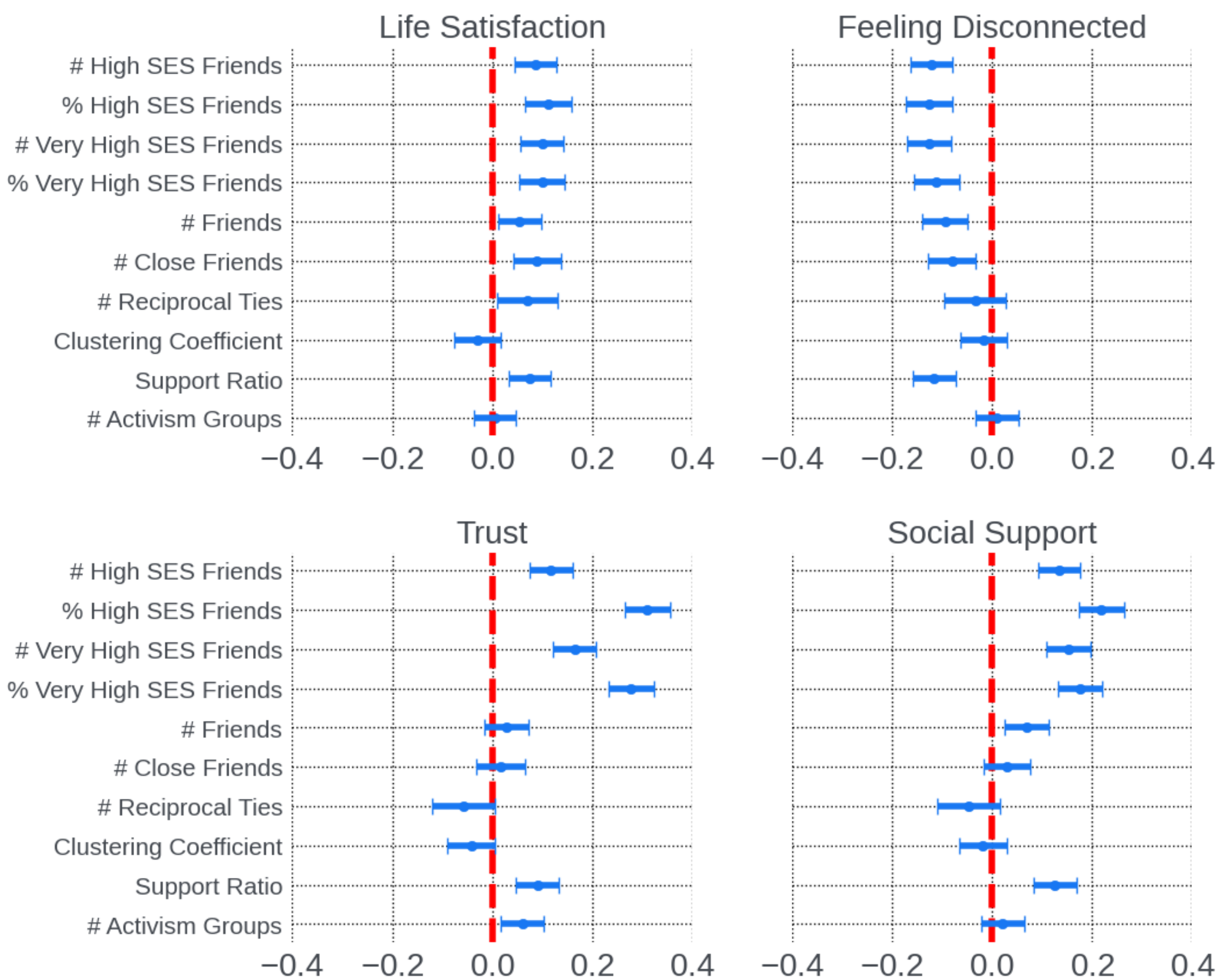


FIGURE 27: Correlations between our individual-level social capital measures and our survey measures, controlling for age, income, and gender.

Notes for Figure 27: We define a high SES friend as a friend with above-median SES, and a very high SES friend as a friend with SES in the top 10% of the distribution. We standardize our aggregated survey measure, features, income, age and gender to be mean 0 with standard deviation 1. Each dot represents the coefficient on the standardized feature listed on the y-axis from an individual-level regression of the survey response on the feature, income, age, and gender (with all variables standardized). The bar represents the 95% confidence interval constructed using the standard error on the feature's coefficient from the above regression. Our measure of income is the self-reported income bucket respondents mark in the survey.

correlations between our aggregated survey responses and our measures of connections to high-SES individuals are similar to the bivariate correlations between our aggregated survey responses and the income users self-reported as part of the survey. Controlling for income, as we do in Figure 27, does not change our results substantially since most of the variation in our measures of connections to high-SES individuals is orthogonal to income. (The correlation between self-reported income and the proportion of high-SES friends in our survey sample is 0.26.)

11 Conclusion

Social capital is a key concept throughout the social sciences, but only recently has data become available to researchers that allow social capital to be measured at scale. The findings of this study point to a few key areas where public policy could make a difference in tackling social issues:

- **Encouraging cross-class interaction could benefit social mobility and subjective well-being.** While our findings do not establish causality, they suggest that bringing people from different socioeconomic backgrounds together—through more inclusive schools, workplaces, and community initiatives—may help to grow the cross-class friendships associated with better economic and social outcomes.
- **Reducing friending bias in local neighbourhoods could significantly contribute to increasing cross-class friendships.** Since lower income individuals form a large share of their friendships in the areas in which they live, both residential segregation and in-group preferences within neighbourhoods can significantly limit the total number cross-class ties. Interventions aimed at creating more mixed-income housing and shared community spaces may increase meaningful interactions between people of different backgrounds.
- **Leveraging low-bias settings, such as hobby groups, offers promise.** Our data indicate high participation levels in hobby and interest-based groups across both low- income and high-income people. Policies that support the creation of local clubs that promote cross-class interactions for sports, arts, or volunteering can capitalise on these existing settings to foster socioeconomic mixing.

We are releasing our social capital metrics publicly on the Humanitarian Data Exchange to accelerate research in this space and help policymakers develop new approaches to solving social issues. There are several important outcomes we didn't have a chance to explore in this work including health, mobility, education, and urban studies and we hope our social capital metrics further the development of research on social capital and important life outcomes.

Acknowledgements

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This work contains statistical data from the Office for National Statistics (ONS), which is Crown Copyright. Its use here does not imply endorsement of our analysis or conclusions. This work also uses research datasets that may not exactly reproduce National Statistics aggregates. Construction of the LEO-derived mobility statistics was conducted in the ONS Secure Research Service.

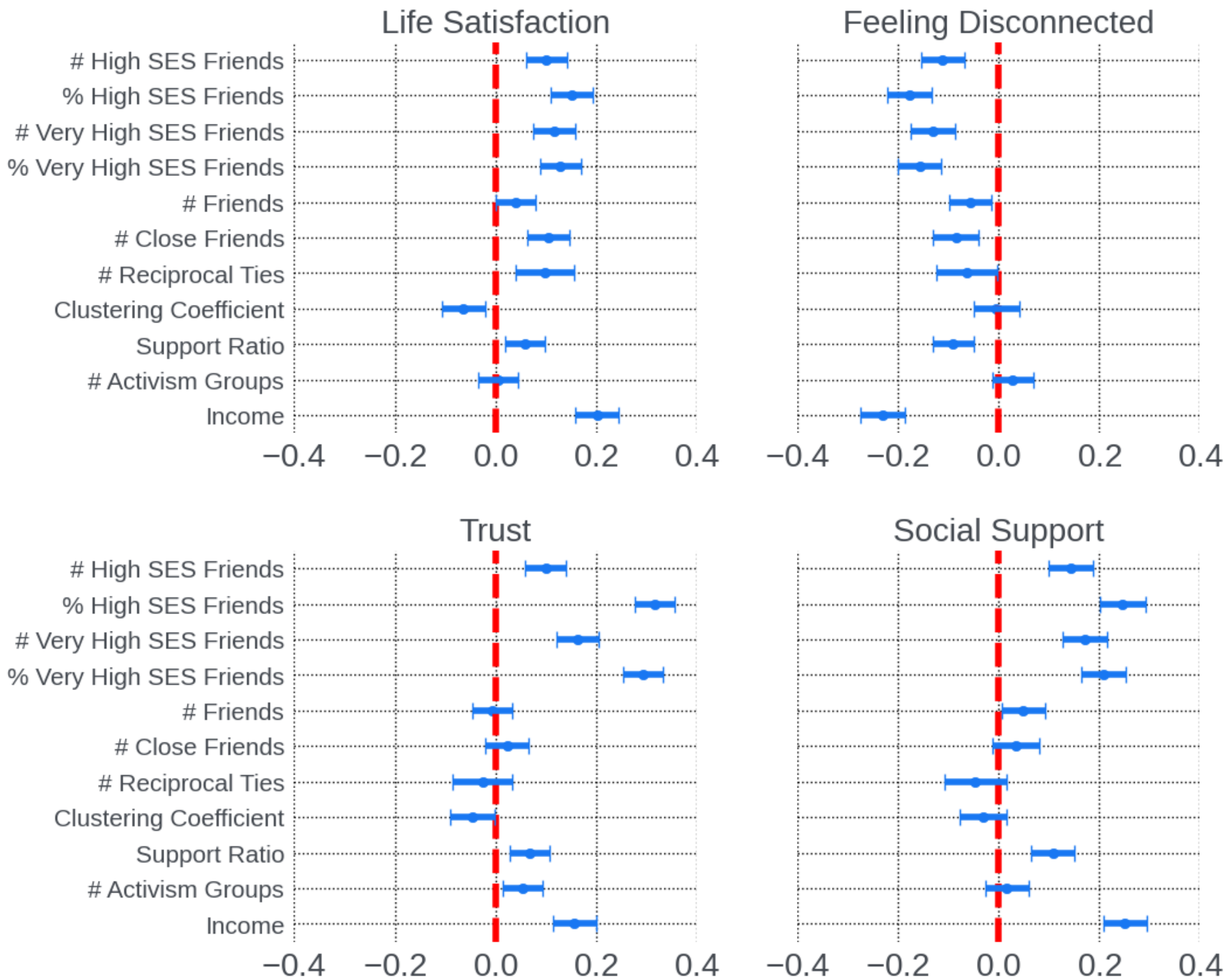

FIGURE 28: Bivariate correlations between our individual-level social capital measures and our survey measures.

Notes for Figure 28: We define a high SES friend as a friend with above-median SES, and a very high SES friend as a friend with SES in the top 10% of the distribution. We standardize our aggregated survey measure, features, income, age and gender to be mean 0 with standard deviation 1. Each dot represents the coefficient on the standardized feature listed on the y-axis from an individual-level regression of the survey response on the feature (with both variables standardized). The bar represents the 95% confidence interval constructed using the standard error on the feature's coefficient from the above regression. Our measure of income is the self-reported income bucket respondents mark in the survey.

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A Methods

A.1 Group Assignments

To understand the contexts in which social connections are formed and maintained, we assign users to various social and institutional groups, including secondary schools, universities, further education providers, workplaces, neighbourhoods, faith-based communities, and hobby and recreation groups.

For secondary school assignment, we employ a multi-step process. As a first pass, we construct secondary school to user matches for the analytic sample on the basis of the secondary school self-reported by users on their Facebook profile. If a user reports more than one secondary school, we match them to the school in which they have the most friends. We exclude virtual schools and schools with fewer than 25 students. We then merge reported schools with different listed names that are actually the same school (for example, the two names use different punctuation, or one name contains "school" at the end while the other does not), checking that these schools are listed in the same city and that the names are not too different based on string distance. When self-reported data is unavailable or invalid, we use a network-based imputation method, assigning individuals to schools based on their friendship networks. We attempt to impute a school for each user not assigned to a school in the first pass. To do this, we compute the number of friends each unassigned user has in each school, then ranking these schools for the user by number of friends. If a user has at least five friends at the highest-ranked school, and at least twice as many friends at the highest-ranked school vs the second-ranked school, we assign the user to that school.

University assignment and sixth-form college assignment are on the basis of self-reported information on the user's Facebook profile. We do not assign users to either colleges or sixth forms on the basis of their friends, since while the vast majority of users in our analytic sample will have attended a secondary school, many users will not have attended sixth form college or university.

For workplace assignments, we also utilize self-reported employment information from users' Facebook profiles.

Assignments to hobby and recreation groups are done on the basis of connection to relevant Facebook groups and pages. Assignments to faith-based communities is based on likes and follows on relevant Facebook pages.

A.2 Linking Users in the Analytic Sample to Their Parents

First, we link individuals to their partners, using self-reported relationships with each other on Facebook and individuals who tag another person in certain public life events[4]. We restrict to opposite gender pairs and exclude tags involving other family members.

Second, we link siblings and step-siblings based on self-reports within Facebook. We require both members of the match to be within 14 years of age of each other.

With those matches in place, we begin to link users in our analytic sample to their parents. First, we make use of self-reported parents on the platform. We impose that parents must be between 18 and 45 years older than their matched child.

Second, we make use of name-based matches. We exclude users with last names among the 100 most common last names in our analytic sample when matching based on last name. We then match users to parents on the basis

[4]We include in this category the life events corresponding to marriage, engagement, having a child, expecting a baby, and pregnancy.

of last name, imposing again that parents must be between 18 and 45 years older than their matched child. We also look for matches with the last name of the spouse of a potential mother, to look for cases where the child is not Facebook friends with their father, with whom they nevertheless share a last name. We do not perform name-based matching for women who took their spouse's last name in order to avoid matching them to in-laws. If we produce multiple matches, we prioritize as follows: (1) If both a female and male parent are identified through methods other than last name matching, we prefer the female parent. (2) For matches based solely on last names, we prioritize the father, as this tends to be more accurate. (3) Finally, we consider matches to a mother based on a spouse's last name. This prioritization aims to balance the reliability of different types of matches while maximizing the number of successful parent-child links.

Third, we make use of wall posts. We look for public wall posts to another profile that occur on Father's Day or Mother's Day that contain words such as "father" or "dad", "mother" or "mum".

We then use sibling links to assign parents to all siblings if a parent was assigned to at least one of the siblings.

We prioritize matches in the following order, which is informed by the reliability of the matches: self-reports; wall posts; name-based matches to a father; name-based matches to a mother on the basis of a spousal name; and finally name-based matches to a mother's name.

We match 15% of our analytic sample to parents. When both our wall-post-based imputation and a self-report assign a male parent to a user, those two candidate parents are the same person 92% of the time. For male name-based imputation, that number is 92%. When assigning a female parent based on a wall post to a user with a self-report parent, the assignment matches the self-report 85% of the time. When assigning a female parent based on name, the assignment matches the self-report 70% of the time.

B Extended Figures

B.1 Geographical Variation in Other Social Capital Measures.

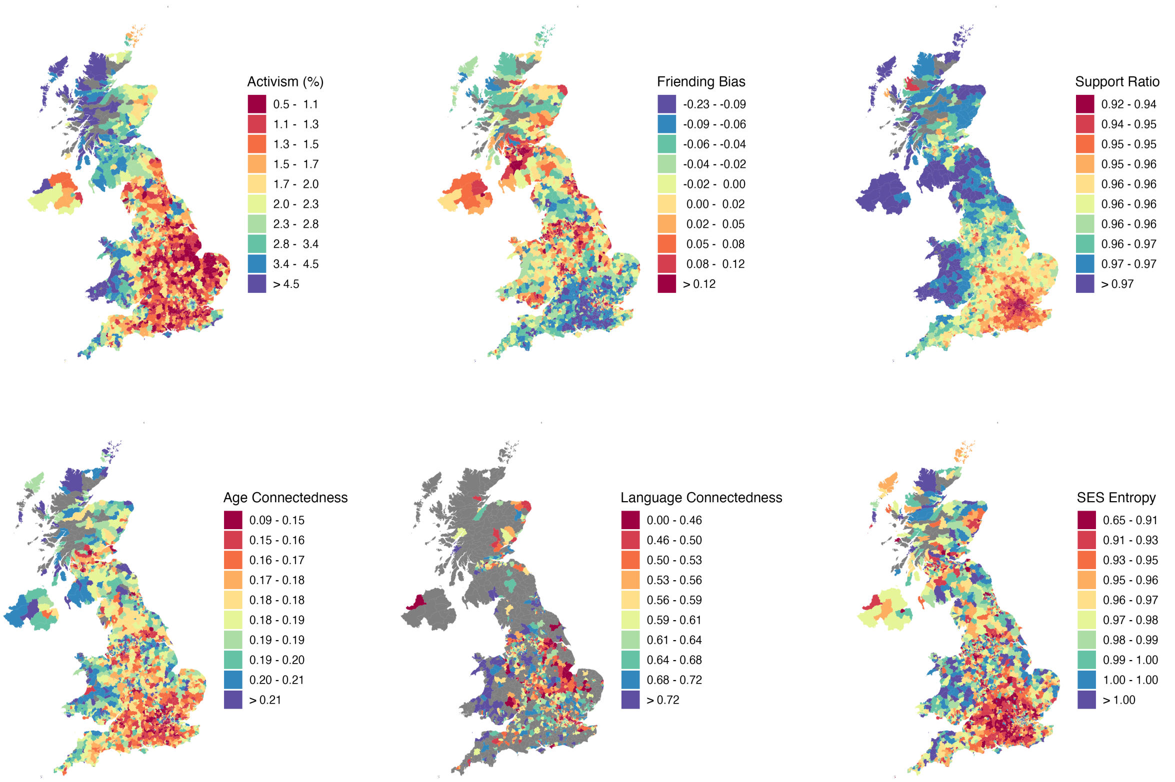


FIGURE A1: Geographical Variation in Other Social Capital Measures.

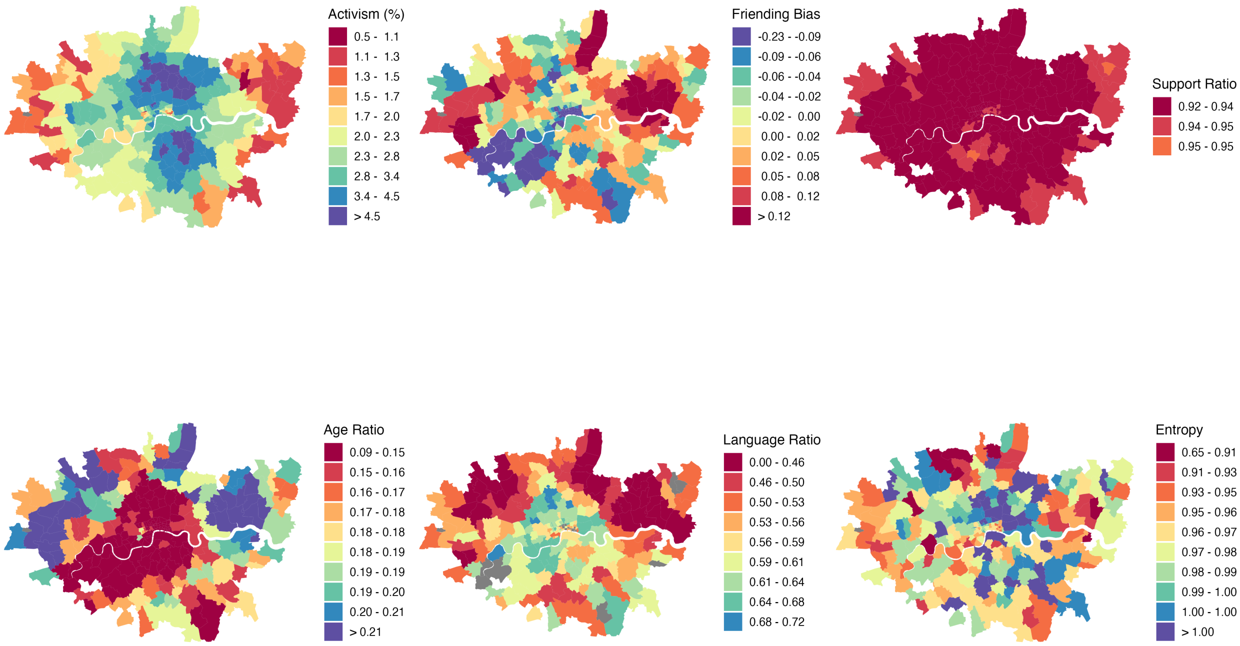
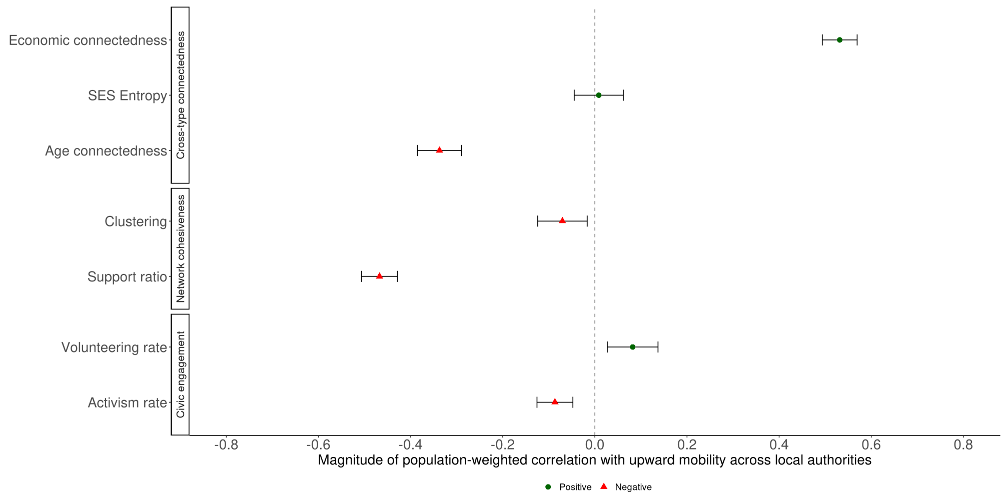
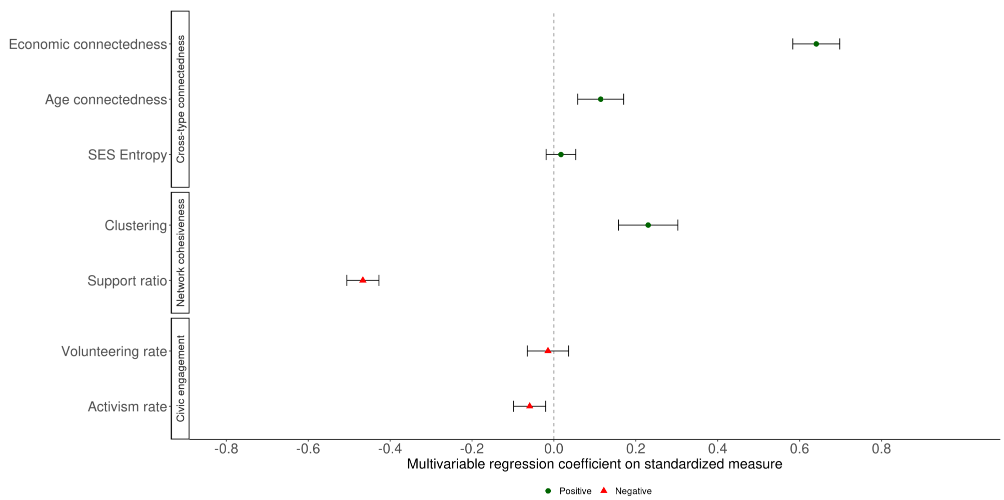


Figure A2: Geographical Variation in Other Social Capital Measures.

B.2 Postcode district-level analysis of social capital and upward mobility



(A)



(B)

FIGURE A3: Postcode district-level relationships between upward mobility and measures of social capital. **a**, Univariate correlations between local authority upward mobility and various social capital measures. **b**, Coefficient estimates from a multivariable regression of upward mobility on all social capital measures, with both outcome and independent variables standardized to mean zero and standard deviation one. Upward mobility is measured as the mean income rank at age 28 of children who were eligible for Free School Meals at age 16. All correlations and regressions are weighted by the number of FSM-eligible children in each postcode district. Error bars represent 95% confidence intervals calculated using heteroskedasticity-robust standard errors.

C Supplemental Analysis of Hobby and Recreation Groups

Of the social contexts that we examine in Figure 21, hobby and recreation groups exhibit the lowest friending bias for low-SES individuals. In fact, for low-SES individuals in our analytic sample, friendships formed in hobby and recreation groups are approximately 4.9% more likely to be with high-SES individuals than would be expected if friendships were formed randomly in these communities.

Figure A4 shows the friending bias in hobby and recreation groups by local authority district. Light and dark blue local authorities are those in which the friending bias in hobby and recreation groups is negative (i.e., low-SES people make more high-SES friends than we would expect from random chance), with the dark blue local authorities being those where the friending bias in hobby and recreation groups is even lower than the aforementioned average over all participants in these communities (approximately -4.9%). This map shows that the surplus of economically cross-cutting friendships in hobby and recreation groups is not geographically localised, but in fact holds across most of the UK. Since our hobby and recreation groups are local, this suggests that our finding of negative friending bias in hobby and recreation groups is not driven by a small number of groups either—the unique friending bias pattern holds across a large swathe of groups in the UK.

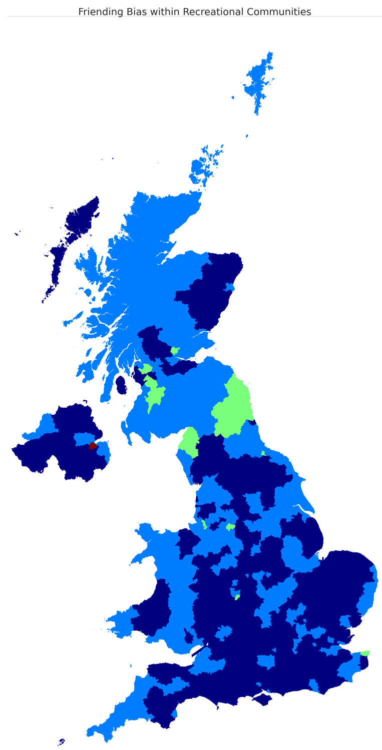


Figure A4: Friending Bias in hobby and recreation groups by Local Authority District.

Notes for Figure A4: Dark blue local authorities are those where the friending bias for participants in hobby and recreation groups is less than 4.9%, the average friending bias for all participants in these communities in the analytics sample. Light blue local authorities are those where the friending bias is still negative, but greater than 4.9%. Thus, in dark and light blue local authorities, low-SES people make more high-SES friends than we would expect based on random chance. Light green local authorities exhibit positive friendship bias in hobby and recreation groups, but less than the overall friendship bias across all friendships (3.7%). Dark red local authorities exhibit higher friending bias in hobby and recreation groups than 3.7%.

Furthermore, *participation* in hobby and recreation groups is widespread across the UK. Several conditions need to be met for us to be able to match a person to a hobby and recreation groups:

- the community must be represented by a Facebook group, for which the “secret" group setting has not been enabled
- that group must be classified to fall within the hobby and recreation category
- the group must be “locally relevant" to the person, meaning that the modal local authority district or modal city in the community must be the same as the person’s local authority district or city
- the person must have at least one “local friend" in the community, meaning that the person must have a friend who shares their home local authority district or home city

Even with all of these conditions in place, we match over 31% of individuals in our analytic sample to at least one hobby and recreation group.

Notably, we observe substantial levels of participation in hobby and recreation groups amongst both low and high-SES individuals. In those postal districts in which we have sufficient data (i.e., where we can average over at least 100 individuals), at least 20% of high-SES individuals can be matched to hobby and recreation groups in approximately 95% of districts. For low-SES individuals, that rate is only slightly lower: at least 20% of low-SES individuals can be matched to hobby and recreation groups in approximately 91% of postal districts.

D Social Capital and well-being

To better understand the relationship between social capital and subjective well-being, we surveyed Facebook users in the UK between June and July 2024 to ask questions about well-being, trust, and related topics. [5].

D.1 Participants

Participants (N = 5,472, 51.3% female) were recruited via an invitation to take a survey that was shown as a story in Facebook News Feeds on web and mobile interfaces with the text: "Today we're interested in your opinions about people's feelings on social connection. Your responses, together with information we have about you and how you use Meta Products, may be used for purposes such as to personalize and improve our Products, support research and innovation for social good, and for other purposes described in our Privacy Policy. To learn more, see our Privacy Policy." Once participants clicked "Continue" they were taken to the survey with a header containing the following text: "The following questions are about your overall well-being. There are no right or wrong answers. you can choose to skip any question that you'd prefer not to answer or exit the survey at any time."

The survey was targeted at a random sample of adults aged 18-64 on Facebook with a predicted home country of the United Kingdom. Participants saw the survey translated into their local language. The survey was voluntary and no additional consent text was included. Participants could quit the survey at any point. Participants were not compensated. On average, participants took 9 minutes to complete the survey. The survey response rate was approximately 3.5% (approximately 272k people saw the survey recruitment in News Feed to which approximately 10k people clicked through and 5,472 ended up completing the survey) .

D.2 Survey Content

Subjective well-being (4 questions): The survey contained four questions about subjective well-being adapted from the four ONS personal well-being questions (Office for National Statistics, 2023). The four questions we asked were:

1. Overall, how happy did you feel yesterday?
2. Overall, how satisfied are you with your life nowadays?
3. Overall, to what extent do you feel the things you do in your life are worthwhile?

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

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

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

Trust (3 items): The survey contained 3 trust questions adapted from the from the OECD trust surveys (OECD, 2017), the World Values Survey (Inglehart et al., 2020), and the European Social Survey (European Social Survey, 2020). This section started with the prompt "The next questions are about your feelings of social connection. There are no right or wrong answers. For the following groups, would you say that most people can be trusted?".

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

We asked participants to select one of five options:

1. No one can be trusted
2. A few can be trusted
3. About half can be trusted
4. Many can be trusted
5. Most can be trusted

Questions were shown in random order.

Feelings of Social Disconnectedness (3 items): The survey included 3 questions on feelings of social connection, adapted from the UCLA loneliness scale (Hughes et al., 2004). This section began "The following statements describe how people sometimes feel. For each statement, please indicate how often you feel the way described."

- How often do you feel that you lack companionship?
- How often do you feel left out?
- How often do you feel isolated from others?

We asked participants to choose from five options for each question:

1. None of the time.
2. A little of the time.
3. Some of the time.
4. Most of the time.
5. All of the time.

Questions were shown in a random order.

Social Support (5 items): We included 5 questions on social support. One question was taken from each of the subscales in The MOS social support survey (Sherbourne and Stewart, 1991), and we used an additional question on financial support. The text prompt for this section was "People sometimes look to others for companionship, assistance, or other types of support. How often is each of the following kinds of support available to you if you need it?"

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

Similar to the preceding section, participants could select from five options for each of the five items:

1. None of the time.
2. A little of the time.
3. Some of the time.
4. Most of the time.
5. All of the time.

Questions were shown in a random order.

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

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