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Inequality and Social Ties: Evidence from 15 U.S. Data sets

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Abstract: What is the relationship between inequality and social ties? Do personal networks, group memberships, and connections to social resources help level the playing field, or do they reinforce economic disparities? We examine two core empirical issues: the degree of inequality in social ties and their consolidation with income. Using 142,000 person-wave observations from 15 high-quality U.S. data sets, we measure the quantity and quality of social ties and examine their distribution. Our findings show that (1) the Gini coefficient for social ties often exceeds that of income and (2) social ties are concentrated among those with the highest incomes. We introduce an overall inequality–consolidation curve, demonstrating that social ties generally reinforce economic inequality. However, we identify one key exception: there is no class gradient in the use of social ties for job search. These findings contribute to debates about the role of social ties in perpetuating or mitigating inequality.

Keywords: social ties; inequality; networks; economy; job search

Reproducibility Package: All code, and all data that can be publicly shared, is available at OSF (https://osf.io/ky4ws/). The package also includes information about requesting access to confidential data sets, such as the Addhealth restricted-use data.

WHAT is the relationship between social ties and economic inequality? Social ties provide access to valuable resources—such as job opportunities, information, and social support—that can increase well-being and facilitate upward mobility (Bourdieu 1986; Coleman 1988; Putnam 2000). Yet, these same networks can also reinforce and perpetuate inequality when concentrated among the advantaged. Those with well-connected, high-status networks often enjoy greater access to exclusive opportunities, whereas individuals with weaker networks may face persistent barriers to advancement, further compounding inequality (DiMaggio and Garip 2011, 2012; Khan 2011; Lin 2001; McPherson, Smith-Lovin, and Cook 2001). Do personal connections, community interactions, and network resources help diffuse opportunity throughout society, or do they reinforce economic differences and build social closure among the well-off?

We focus on two key distributional dimensions of social ties: their quantity and their alignment with economic capital (Blau 1977; Blau and Schwartz 1997). First, to what extent do some individuals have an abundance of social ties, while others have very few? The Gini coefficient for social ties captures a distinct form of inequality, measuring the uneven distribution of social connectivity. Second, what is the relationship between social ties and income? Do high-income individuals also have larger and more advantageous social networks than low-income earners? A weak correlation would suggest that social and economic resources operate as distinct domains—some individuals may have high income, whereas others are

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rich in social connections. This is similar to Weber's idea that dimensions such as "class" and "status" represent separate axes of societal differentiation (Weber 1978). When social ties function as an independent axis of differentiation, they can broaden access to opportunity and counterbalance economic inequality. In contrast, a strong correlation would indicate that social and economic resources are consolidated (Blau 1977). When social and economic capital become consolidated, society polarizes into those who possess both income and social ties versus those who have neither. In such cases, social ties and economic advantage reinforce one another, amplifying inequality and further concentrating these scarce resources among the privileged.

We adopt a "big, diverse data" approach, drawing on a wide range of U.S. data sets to provide comprehensive evidence. We aggregate 15 independent data sets, including Add Health, the National Longitudinal Survey of Youth (NLSY), the General Social Survey (GSS), and the National Education Longitudinal Study (NELS), yielding more than 140,000 unique person-year observations. This approach combines the large-N statistical power of big data with the diversity of measurement strategies and sampling frames available in social tie research. By integrating multiple data sets, we pool across many potential forms of "total survey error" (Alwin 2007; Groves et al. 2009), enhancing reliability compared to single-source studies (Open Science Collaboration 2015; Workman, von Hippel, and Merry 2023; Young and Cumberworth 2025). This multi-source strategy strengthens the generalizability and robustness of our conclusions.

Our central thesis is that inequality in the distribution of social ties—and its consolidation with income—is a fundamental dimension of social stratification. We begin by examining the relationship between income and social ties, highlighting how economic advantage may shape the size and resources of personal networks. Next, we outline our data and methodological approach. Our findings reveal a striking pattern of inequality in social ties, while also uncovering contrasting results that call for deeper theoretical development and future research.

Social Ties and Inequality

Social ties influence many, if not most, outcomes of interest to social scientists (for reviews, see Cornwell and Eads 2013; Jackson 2020; Kwon and Adler 2014; Mouw 2006; Paxton 1999; Portes 1998; Portes and Vickstrom 2011). Social ties refer to the interactions individuals engage in and the relationships they maintain. The structure of these ties often shapes access to information and opportunities. Social ties have two key dimensions: (1) a relational component—the number of ties and one's position within social networks and (2) access to resources or support—such as connections to powerful others or help securing a job (Bourdieu 1986; Cornwell and Eads 2013; Lin 2001). A more general—many would say ill-defined—concept of social capital includes network ties and aggregate variables extending to the level of neighborhoods or even nation states, such as community trust (e.g., Coleman 1986; Putnam 2000). A key concern with this broader formulation is that individual access to macro-level social capital cannot be assumed (Smith 2005); even in communities rich in social capital—where information and resources flow freely—access to these benefits varies significantly among individuals (Bendeck and Hastings 2023). Those occupying more advantageous positions in their networks are often better equipped to mobilize resources through their ties, leading to an uneven distribution of network resources regardless of the overall community levels. This study focuses primarily on the individual and social tie level: personal networks, participation in groups where ties are often formed, and the socio-economic resources accessible through network connections.

Diffusing Opportunity or Compounding Inequality?

Scholars have long emphasized the independence of social and economic forms of capital. Weber distinguished "class" and "status" as separate dimensions of stratification, each with unique pathways for accumulation and success. Bourdieu (1986) similarly argued that while social ties have some connection to material wealth, they operate on their own logic and remain "relatively irreducible to the economic." These perspectives frame social ties as a potentially autonomous axis of opportunity, capable of functioning independently of material resources. This autonomy opens the possibility that "networks can be used to reduce inequality" (Christakis and Fowler 2009:171). If social ties are diffuse in society and differentiated from economic status, they can serve to diversify opportunity.

At the same time, other perspectives complicate this view by emphasizing how social ties often reinforce economic inequality (DiMaggio and Garip 2011, 2012; Lin 2001; Loury 1977; Zhao and Garip 2021). Networks tend to exhibit closure and monopolization, consolidating resources within specific groups (Lin 2001). Class-based homophily—the tendency for individuals to connect with others of similar social standing—fosters a self-reinforcing cycle in which the wealthy share information and opportunities primarily with one another, whereas the poor remain confined to resource-scarce networks (McPherson, Smith-Lovin, and Cook 2001). Ethnographic research provides granular insights into these dynamics. Smith (2005) describes how low-income black workers hesitate to recommend peers for jobs, fearing it might jeopardize their own tenuous positions. Desmond (2012) highlights "disposable ties" among the urban poor, where dire need drives a cycle of forming, using, and burning temporary relationships, depleting long-term social connections. In contrast, research on affluent communities often reveals robust social networks that enable resource consolidation and mutual advantage. The wealthy leverage co-membership on corporate boards, elite nonprofit organizations, and ties with political leaders to sustain and expand their opportunities (Burris 2005; Mills 1956; Page, Bartels, and Seawright 2013). In business, high-end markets are characterized by strong relationships and networks, which enable cooperation and competition to coexist (Hochberg, Ljungqvist, and Lu 2007; Ingram and Roberts 2000; Uzzi 1999). High-tech hubs such as Silicon Valley exemplify the power of dense networks, where the circulation and recombination of ideas among knowledge workers drive innovation and maintain a competitive edge (Powell, Packalen, and Whittington 2012; Saxenian 1994; Sorenson 2017).

Yet, social ties clearly do not always amplify inequality. In certain contexts, it can serve as a counterbalance to material disadvantage—a phenomenon described as "inverted advantage" (DiMaggio and Garip 2012:109). For instance, in the Cuban immigrant economy of Miami, low-income migrants leveraged strong co-ethnic networks to access work and entrepreneurial opportunities, offsetting their lack of financial resources (Portes 1998). Similarly, Scott (1985) shows how tight-knit ties in low-income regions empowered collective resistance to exploitative labor practices and urban renewal projects, illustrating social ties as a "weapon of the weak." These cases demonstrate the potential of social networks to build resilience and mitigate inequality.

However, evidence from population-level data on the distribution and consolidation of social ties remains limited and equivocal. Using the GSS, York Cornwell and Cornwell (2008) found that high-income households have greater access to expertise within their social networks. Similarly, college graduates were shown to have larger and more stable networks, though the absolute differences were modest (Cornwell 2015; York Cornwell and Behler 2015). European surveys reveal that high-income earners participate much more in voluntary organizations, yet their informal social ties with friends show little disparity (Pichler and Wallace 2009). Among high school students, data from Add Health indicate that having a best friend with highly educated parents increases the likelihood of college completion, but such relationships are predominantly found among students with higher socio-economic status (Cherng, Calarco, and Kao 2013). Analysis of Facebook data highlights that while cross-class friendships are associated with greater social mobility, such connections are scarce in many communities and high-income individuals have substantially more social ties overall (Chetty et al. 2022a, 2022b).

Understanding the contribution of social ties to inequality ultimately requires examining two elements: the distribution of social ties and their interaction with economic resources. Social ties can be concentrated among a small subset of well-connected people, or broadly shared, a distribution measurable using the Gini coefficient. They may also "intersect" economic inequality or be "consolidated" alongside it (Blau 1977; Blau and Schwartz 1997). Strong correlations between social ties and economic resources compound inequality, whereas weak or inverse correlations suggest the potential for social ties to serve as an independent axis of differentiation and a mechanism for more diffuse opportunity (Weber 1978). This framework allows for a nuanced analysis of how the distribution of social ties interacts with income to shape patterns of inequality.

Data and Methods

Social ties have been measured across many U.S. data sets, yet most studies rely on a single source—missing opportunities to provide the most comprehensive and compelling evidence available. We pursue a big, diverse data approach, drawing on 15 independent, high-quality U.S. data sets that include measures of social ties. These include Add Health, the NLSY, the GSS, the Current Population Survey (CPS), the NELS, and the National Social Life, Health, and Aging Project (NSHAP), among others. We selected data sets based on relevance (containing social tie measures) and feasibility of access. A full list is provided in the online supplement A. Pooling these sources yields more than 142,000 unique person-wave observations.

These data sets reflect a range of data collection protocols, which we believe strengthens robustness beyond the large sample size. Real world data sets always contain both sampling and non-sampling errors, each of which can introduce bias, jointly making up the total survey error (Groves et al. 2009). Sampling errors result from random variation in sample selection. Non-sampling errors stem from the data collection process itself and occur independently of random sampling. These errors introduce systematic biases that cannot be reduced by increasing sample size. Differences in non-sampling error arise from: (a) how variables are defined and measured, including survey question wording and response categories, (b) the sampling frame and non-response rates, which affect representativeness, and (c) the method of survey administration (e.g., online, in-person, or telephone), which introduces mode effects and interviewer biases. We believe that all of the data sets in this study represent high-quality data collection efforts, albeit with different protocols and different degrees of (unknown) total survey error. Given the multiple credible ways of implementing the collection of sociological data, a key question is whether different data sources converge on similar answers. When relying on just one data set, it is always possible that unique survey errors may be driving the results (e.g., Paik and Sanchagrin 2013). Using multiple independent data sets offers more robust evidence than relying on a single data set with fixed measurement protocols (Alwin 2007; see also Mouw 2003; Reardon 2011; Song et al. 2020).

The types of social ties examined in this study fall into three broad categories: (1) core personal networks and their structure (Coleman 1988; Burt 1992), (2) participation in social groups (Feld 1981; Small 2009), and (3) access to tangible resources through social ties (Granovetter 1995; Lin 2001). Our 15 data sets include 22 unique social tie variables, many of which offer alternative approaches for operationalizing these concepts. The concrete measurement of each variable is available in the online supplement B; here, we provide an overview of the variables we analyze.

Network size is our first measure, for which we primarily draw on "important matters" networks measured in national surveys. This item asks respondents to name up to five people with whom they discuss things that are important to them.[1] Despite the heterogeneity in what counts as an "important matter" to different respondents (Bearman and Parigi 2004), it is widely agreed that this name-generator battery captures the core networks for most individuals in the United States (Burt 1984; McPherson, Smith-Lovin, and Brashears 2006). Having someone to talk about important matters, however defined, can be thought as an important social resource in itself (Small 2017), and the size of these ego networks is associated with multiple benefits (Cornwell and Laumann 2015; McClurg 2003; Umberson and Montez 2010). We supplement this measure of core network size with questions that ask for the number of close friends—a simpler way to access the same concept. We also examine network closure (Coleman 1988, 1990), which refers to the degree to which one's associates are connected with one another, forming a tight-knit network. Using school-based data, we measure the tight knitness of networks among both high school students and their parents.

Next, we examine individuals' connections to and participation in community groups and religious organizations. These groups often serve as primary settings for interaction, providing structured opportunities for social engagement through which additional social ties are formed (Feld 1981; Small 2009). Participation in these groups can extend beyond immediate personal networks, fostering connections that bridge different social circles. As such, group involvement can serve as a proxy for broader network ties—particularly weak ties that might otherwise go unreported in measures focused on close friendships.

Finally, beyond the quantity or configuration of ties to individuals and groups, a core element of social ties lies in the resources embedded within social networks (Lin 2001). From this perspective, social ties are most valuable when they connect individuals to more powerful others—those with greater capacity to act or exert influence on their behalf. The income, education, and social status of friends serve as proxies for the potential advantages of these ties, reflecting their ability to provide support, resources, or opportunities. As Nan Lin wrote, "Embedded resources are indicated by the wealth, status, and power of social ties" (Lin 2001:43). We examine network resources—including friends' income, education, and occupational prestige—across nine data sets. In addition, we analyze job search as a key form of network support and a classic mechanism through which social ties may contribute to inequality (Granovetter 1995; Mouw 2003).

A Standardized Approach to Reduce Researcher Degrees of Freedom

Applied research involves a complex array of analytical decisions, often leading to a "garden of forking paths" where each choice can lead to a different set of final results. *Researcher degrees of freedom* refer to the flexibility scholars have in selecting data and analysis strategies—a flexibility that, if unchecked, can yield biased or misleading results. Just as there are many data sets measuring social ties, there are also many credible ways of analyzing those data, including different choices of control variables, functional form assumptions, and estimation methods (Young and Cumberworth 2024; Young and Holsteen 2017). Researchers studying the same question—even with the same data—rarely use the same models (Breznau et al. 2022; Silberzahn et al. 2018). The selection of data and statistical models represents two key researcher degrees of freedom that become particularly problematic when used in combination. If each data set is analyzed with a different statistical model, none of the results are strictly comparable and there are no real guardrails against inadvertent p-hacking.

A widely recognized problem in social science is that null results are difficult to publish, while achieving statistical significance is often equated with high-quality data and analysis—potentially leading to literatures suffused with false positives (Christensen, Freese, and Miguel 2019; Gerber and Malhotra 2008; Ioannidis 2005; Simmons, Nelson, and Simonsohn 2011). As DiMaggio and Garip (2012:99) observe, "researchers who find network effects are more likely to publish their results than those who do not." If a research community collectively explores the landscape of available data and statistical models in pursuit of significant results—much like a school of fish probing their environment for nutrients—false positives can quickly emerge. For instance, testing 10 data sets with 10 possible models yields 100 empirical findings. Even in the absence of true associations, some of these findings will, in expectation, achieve statistical significance (Freedman 1983). If publication success is tied to statistical significance, the resulting literature will be misleading (Stanley and Doucouliagos 2012).

To mitigate these risks, we apply a standardized statistical model across all data sets and report all results transparently. Specifically, we estimate two regression models for each data set—one unadjusted and one adjusted for a standard set of demographic controls. Our analysis spans 15 data sets and 22 outcome variables, incorporating one descriptive statistic (the Gini coefficient) and two regression models per outcome. By standardizing both data selection and model specification, we eliminate data set-specific specification searches, enhancing the robustness, credibility, and comparability of our findings.

Measuring Inequality in Social Ties

Are social ties a resource that most people have in broadly similar amounts, or are they distributed more like income, with some individuals having abundant connections while others have very few? We measure inequality in social ties using the Gini index, which quantifies the dispersion of social ties in a population. If y is a measurement of a social tie, then for sets of individuals i, j, the Gini coefficient is computed as

$$G = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} \left| y_i - y_j \right|}{2\bar{y}n^2}, \tag{1}$$

where n is the sample size and $\overline{y}$ is the sample mean. The Gini coefficient was originally developed to analyze income inequality, but it has since been applied across numerous social dimensions. It is used to measure health inequality, capturing disparities in individual longevity or disease burden (Steinbeis et al. 2019); education inequality, reflecting the distribution of completed years of schooling (Thomas, Wang, and Fan 2001); and even climate emissions inequality, quantifying dispersion in household carbon footprints (Chancel 2022). This broad applicability highlights several key properties that make the Gini coefficient particularly useful for measuring inequality in social ties: (1) unit invariance—the Gini coefficient does not depend on the scale or units of y, making it comparable across different types of social connections; (2) binary compatibility—it remains well-defined even when social ties are measured as a simple binary outcome (e.g., the presence or absence of a connection); and (3) sample-size independence—the Gini coefficient is unaffected by population or sample size, allowing for meaningful comparisons across data sets of varying scales.

A Gini coefficient of 0 indicates perfect equality in social ties, where all individuals have the same level of connection. A Gini of 1 indicates maximum inequality, so higher Gini values reflect greater disparities in social connectivity. We also visualize these distributions using the Lorenz curve, which graphically represents the Gini index. As a reference point, we compare the Gini coefficient of social ties to the Gini coefficient of family income in the United States, using estimates from the 2019 CPS. In all data sets, income is inflation adjusted and expressed in 2020 constant dollars.

Measuring Consolidation: The Top–Bottom Ratio

To quantify the consolidation of social ties with income, we use the top–bottom ratio (TBR), a simple and intuitive measure that compares social ties at the highest and lowest income deciles. For any y metric of social ties,

$$\text{Top bottom ratio} = \frac{\mathrm{E}\left[y_i \,\middle|\, income_i^{(10)} = 1\right]}{\mathrm{E}\left[y_i \,\middle|\, income_i^{(1)} = 1\right]}, \tag{2}$$

where $income_i^{(10)}$ is a variable indicating whether individual i is in the 10th income decile. Similar to the Gini, the TBR is unit invariant, meaning it does not depend on the measurement scale of the social tie variable—whether it is the number of social connections or the average income of friends—making it comparable across different types of social ties in this study. This is a key advantage over regression coefficients (marginal effects), which are defined in the units of the social tie variable and are not directly comparable across different outcomes. Moreover, the TBR offers an intuitive interpretation[2]: it measures the extent to which the rich hold more social ties than the poor. Broadly:

- TBR > 1 indicates that individuals in the highest income decile have more social ties than those in the lowest decile, reflecting consolidation of social ties with income and reinforcing inequality.
- TBR $= 1$ indicates no systematic difference in social ties across income levels, implying that social ties and income function as independent axes of differentiation.
- TBR < 1 indicates an inverted advantage, where lower-income individuals hold more social ties than their high-income counterparts.

We estimate social ties at different income deciles using two semi-parametric regression models. The first model provides unadjusted estimates of the level of social ties in each income decile:

$$y_i = \beta_1 x_i^{(1)} + \beta_2 x_i^{(2)} + \cdots + \beta_{10} x_i^{(10)} + \epsilon_i, \tag{3}$$

where $x_i^{(q)}$ is an indicator variable that is equal to 1 if individual i belongs to the qth income decile and zero otherwise, and where ϵ_i is the error term. The semi-parametric specification of income can flexibly capture nonlinear associations, which we illustrate with graphical results. The second model adjusts for a set of demographic characteristics to account for potential confounding factors:

$$y_i = \gamma_1 x_i^{(1)} + \gamma_2 x_i^{(2)} + \cdots + \gamma_{10} x_i^{(10)} + \delta^T \mathbf{Z} + \nu_i, \tag{4}$$

where $\mathbf{Z}$ is a vector of variables measuring basic demographic attributes of respondents: age, gender, and race/ethnicity.[3] We selected a minimal set of controls that are both consistently available across all our data sets and credibly non-endogenous (i.e., not a downstream consequence of social ties) (Cinelli, Forney, and Pearl 2022).

Whenever available, we use survey weights when calculating the Gini coefficient and fitting the regression models. When aggregating results across data sets, we normalized the survey weights to the sample size of each survey, so that data sources with larger sample sizes contribute more to the aggregated results than those with smaller sample sizes.

Results

We begin our analysis at the most microscopic level, focusing on an individual's network size and network closure. We then examine connections to groups and ties to social resources.

Network Size and Connectedness

Personal networks and close associations are the basic building blocks of connectivity. Figure 1 shows the degree of inequality in close network size: the number of people with whom one discusses "important matters" (Panel A), pooled across 10 data sets with a combined N of more than 14,000. The Gini for network size (solid line) is 0.36. This indicates relatively modest inequality. In comparison, our estimate of the Gini for family income in the United States in 2019 is 0.47 (dashed line).[4] There are clearly disparities in network size—for example, 15 percent of the population report zero close confidants—but there is less inequality in network size than there is in family income. Panel B shows the consolidation of network size with income. In the top-income decile, respondents have nearly 2.6 close confidants, whereas at the bottom, network size is closer to 2. The adjusted top-bottom ratio is 1.31, meaning that the highest income earners have 31 percent larger networks than those in the bottom 10 percent of the income distribution after adjustments for age, race, and gender. This example illustrates how we conduct the analysis for all social tie variables.

Our full evidence on personal networks is reported in Panel C. We supplement the analysis of network size by three additional data sets that measure the number of "close friends." As shown in first two rows in Panel C, both measures of core network size yield a TBR of approximately 1.3. The next two rows focus on measures of network closure: one among high school students (from Add Health data) and the other on parental network closure (from Add Health and NELS data). Although there is minimal class gradient in network closure among adolescents themselves, *parental network* closure rises significantly with income, reflecting how well parents within adolescent social networks know one another (Coleman 1988). The adjusted TBR shows that parents in the highest income decile have more than 50 percent denser networks than those in the bottom decile even after adjustments for race, age, and gender. Among personal network metrics, parental network closure showed the strongest consolidation with income.

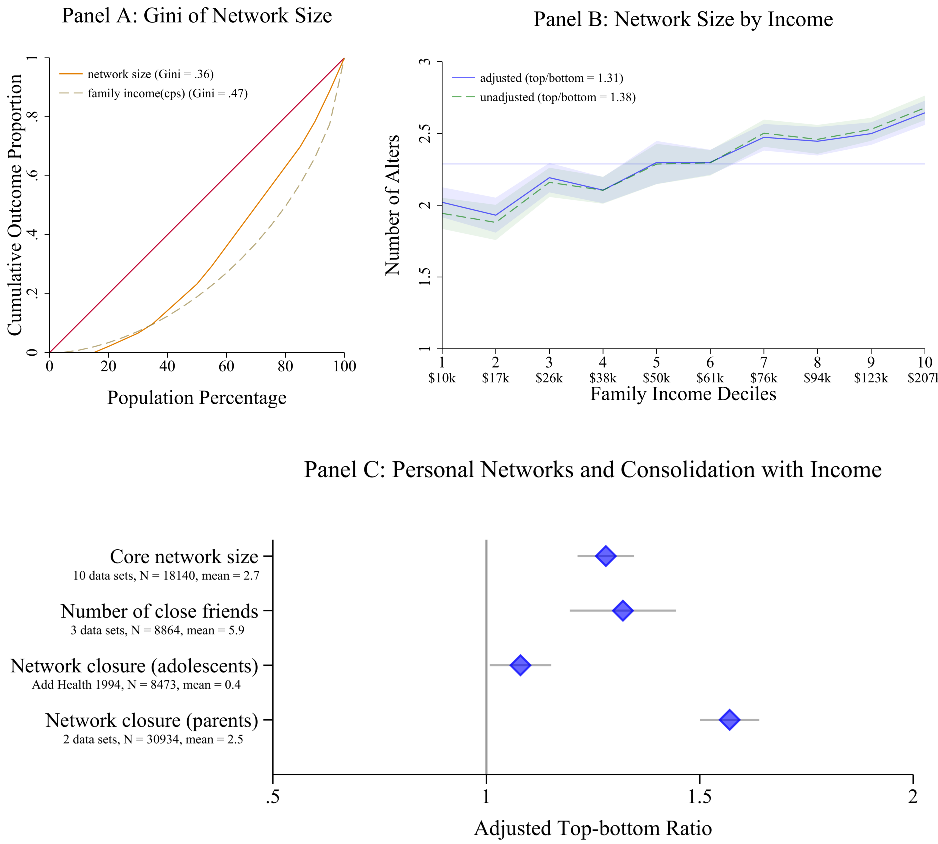

Figure 1: Personal networks and consolidation with income. *Note:* Panel A shows the Lorenz curve and Gini index of the number of alters with whom the respondent discusses “important matters” and Panel B shows the average number of alters by family income decile ($n = 14,126$, pooled across GSS1985, GSS1987, CNES1992, MCSUI1992, GSS2004, ANES2006, GSS2010, TESS2010, and TESS2016). For all data sets, the network size is capped at 5 for consistency. Shaded area shows the 95 percent confidence interval. Panel C shows TBRs of network size and closure. Estimates from linear regression models of income deciles on the social tie metric, conditioning on age, gender, and race/ethnicity (see Eq. [2]). The 10 data sets for important-matter network size are GSS 1985, GSS 1987, CNES 1992, MCSUI 1992, GSS 2004, NSHAP 2005 and 2015, ANES 2006, GSS 2010, TESS 2010, and TESS 2016. The number of close friends uses CPS 2008, PROSPER 2003, and SCBS 2000. Network closure of parents uses Add Health 1994–95 and NELS 1988. Mean TBR is 1.39 ($sd = 0.20$). The mean Gini (not shown) is 0.38. Combined $n = 57,938$. 95 percent confidence intervals based on 600 bootstrap resamples.

Connectedness to Social Groups

Individuals are connected to others through voluntary groups and organizations, which can be a central nexus of tie formation. Indeed, voluntary groups dedicated to sports, hobbies, neighborhood initiatives, or religious communities play a crucial role in establishing and sustaining both strong and weak social ties—and thus fruitfully augment our evidence on close contacts (McPherson and Smith-Lovin 1982; Putnam 2000; Small 2009). An illustrative measure of group participation comes from GSS data on the number of different types of social groups in which

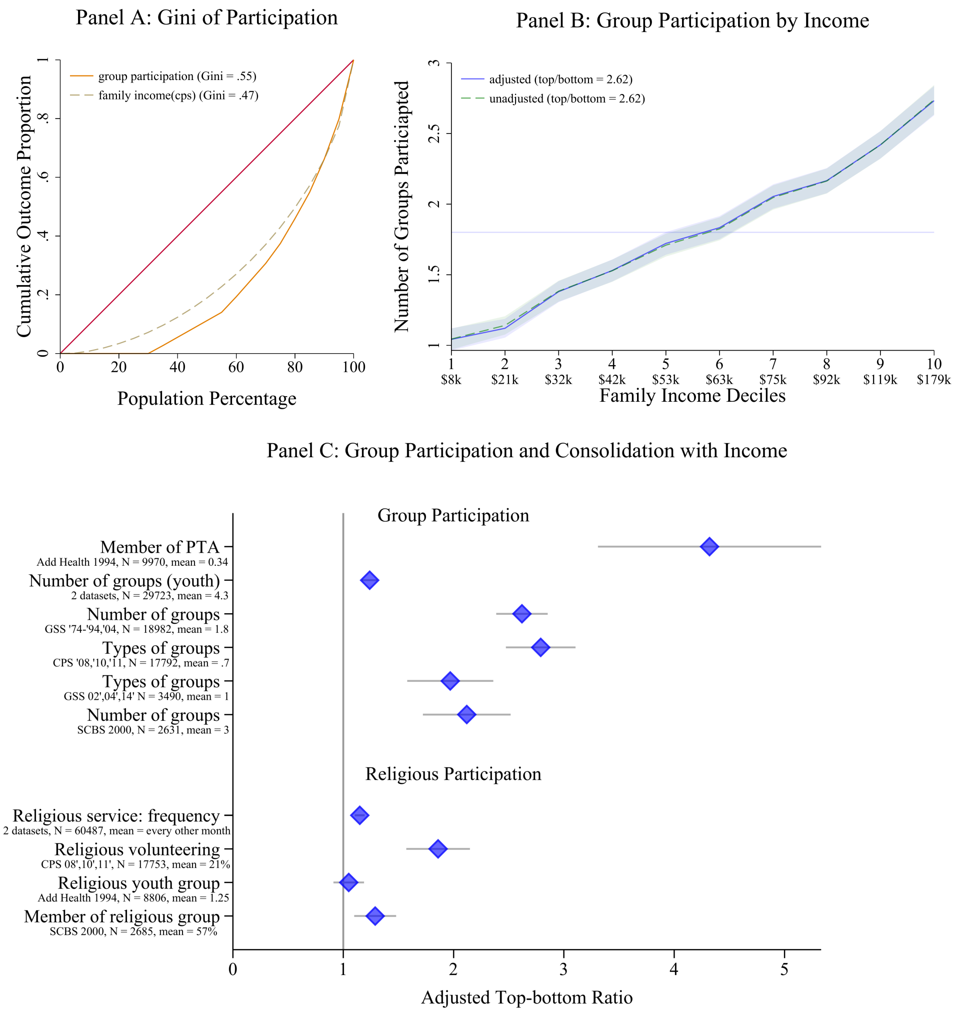

Figure 2: Group participation and consolidation with income. *Note:* Panel A shows the Lorenz curve and Gini index for group participation and Panel B shows the average number of social groups participated by family income decile ($n = 18,982$, pooled across the data sets GSS1974–1994 and GSS 2004). Shaded area shows the 95 percent confidence interval. Panel C shows TBRs of group participation. Estimates from linear regression models of income deciles on the social tie metric, conditioning on age, gender, and race/ethnicity (see Eq. [2]). Row two (number of groups) draws on youth from Add Health 1994–1995 and NELS 1988. Row seven "religious service: frequency" uses SCBS 2000 and GSS 1972–2018. The mean Gini for group participation is 0.57 and for religious participation is 0.51. The mean TBR for group participation is 2.32 and for religious participation is 1.28. All means are weighted by sample sizes. 95 percent confidence intervals based on 600 bootstrap resamples. Pooled $N = 108,002$.

people participate (Fig. 2, Panel A). Ties to groups are highly uneven, with a Gini index of 0.55; this is larger than the Gini for family income (0.47). Moreover, top-decile earners participate in 2.6 times as many groups as bottom-decile earners, and the relationship is strongly linear (Panel B).

These results generalize to other data sources and measurements. In Panel C, we report evidence from nine data sources on various measures of group participation.

This includes parent–teacher association membership in Add Health—which shows a dramatic class gradient; youth participation in extracurricular clubs (e.g., sport teams, yearbook, and other groups) from Add Health and NELS data; another variable from the GSS assessing active participation in five types of voluntary groups (e.g., professional associations or neighborhood groups); the CPS data on participation in any of five different types of organizations; and the Social Capital Community Benchmark Survey data on the number of clubs or organizations in which one participates. Across all these measures, the weighted-average Gini is 0.57. Participation in voluntary groups varies widely; numerous individuals are not engaged in any, whereas others are active in many. The average top-bottom ratio is approximately 2.3, indicating that top earners participate in twice as many groups and twice as many types of groups as low-income earners. PTA membership shows the largest degree of unevenness and consolidation with income of any social variable in this study, showing an organizational foundation for the high social closure among rich parents that we reported earlier.

A key element of group involvement is participation in religious groups, as highlighted by Wuthnow (2002) and Putnam (2000), among others. The bottom half of Panel C provides a detailed analysis, offering separate metrics specifically focused on religious involvement. The GSS and the SCBS data measure the frequency of attendance at religious services. CPS data measure the rate of volunteering in one's religious group, separately from attending service. SCBS also asks whether people personally identify as a member of one's local church, synagogue, or other religious/spiritual community. Engagement in religious groups rises with income, though much less so than with general group participation. Participation in youth religious groups shows no income-based difference. Overall, top-decile earners have a 28 percent higher rate of religious participation than those in the bottom decile, mostly driven by the strong class gradient in religious volunteering.

Embedded Network Resources

Network ties are more valuable when they link individuals to greater resources. This section delves into the income, educational background, and occupational prestige of one's personal connections, examining how these factors enhance the potential value of networks.

This analysis begins by exploring the income levels of an individual's friends. The Add Health data set offers comprehensive network data on students within a school, where students identify their school-based friends and parents report household incomes. We compute network income for each student based on their named friends. For example, if a student lists four friends, each from a family earning \$50,000, the combined network income of the student's friends totals \$200,000.[5] How much inequality is there in network income, and how strongly does network income correlate with one's own income?

First, we compare the Lorenz curve for friends' income in Add Health (solid line) with the same curve for family income in the United States (dashed line) in Figure 3 (Panel A). There is greater inequality in network income than in family income. The Gini for friends' income is 0.57, whereas the Gini for family income in

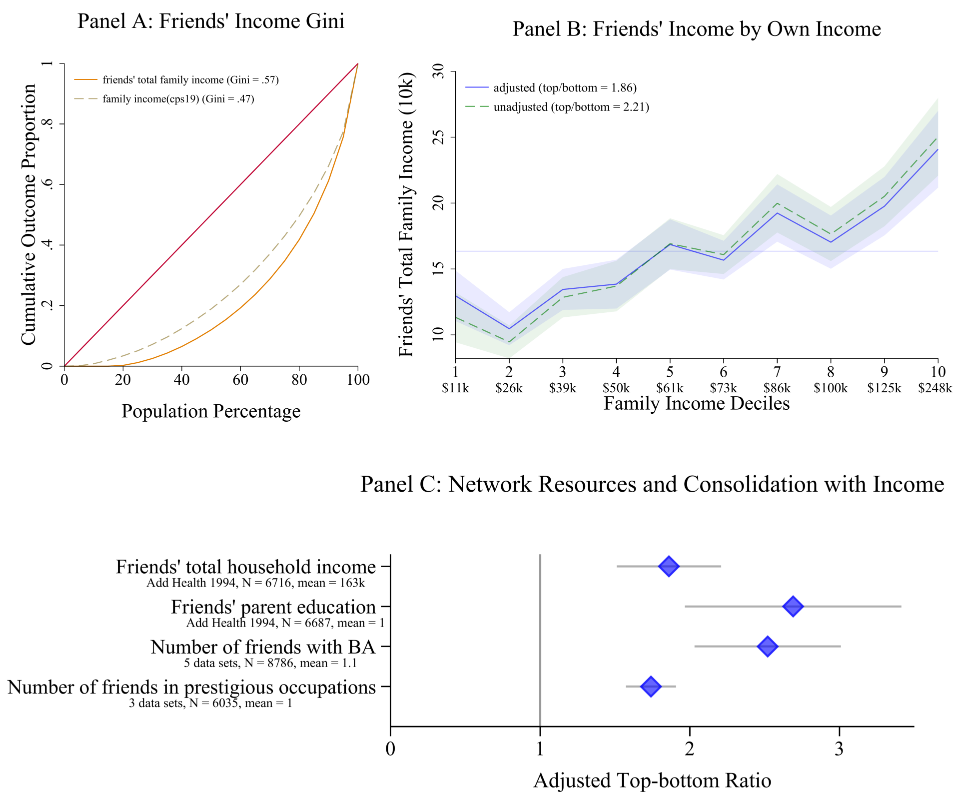

Figure 3: Network resources and consolidation with income. *Note:* Panel A shows the Lorenz curve and Gini index of friends' family income and Panel B shows the sum of friends' family income by family income decile ($n = 6,716$, from Add Health 1994–1995). Shaded area shows the pointwise 95 percent confidence interval. Panel C shows TBRs of social network resources. Estimates from linear regression models of income deciles on the social metric, conditioning on age, gender, and race/ethnicity (see Eq. [2]). Data for college graduates in network use ANES 2008, GSS 1985 and 2004, CNES1992, and MCSUI 1992. Prestigious occupations use Social Capital USA 2004, Pew 2008, and GSS 2018. The weighted average Gini (not shown) is 0.58. The weighted-average TB ratio for all estimates is 2.24. Pooled $N = 21,537$.

the United States is 0.47. Some students have very high-income social networks, whereas others have much lower-income networks. Students at the 50th percentile of family income hold 19 percent of aggregate family income, whereas those at the 50th percentile of friends' income have in network only 12 percent of aggregate friends' income. Consolidation is shown in Panel B. For bottom-decile students, the combined family income of their friends is roughly $130,000; for top-decile students, that figure is $241,000. The top-bottom ratio is 1.86, showing that the social networks of the richest students have nearly twice as much money embedded within them as do the networks of the poorest students. The richer a student is, the richer their social network.

Panel C pools together multiple data sources and metrics to provide overall summaries of consolidation in social resources, with evidence pooled across nine data sets and a combined sample size of 21,537 respondents. The metrics include network income (as detailed in Panel B), along with the educational levels of friends' parents in the Add Health data. For adults, we use five data sets to evaluate the number of college graduates in one's friend network. We measure ties to high-prestige occupations, such as lawyers, professors, and CEOs, in three data sets to assess the prevalence of prestigious occupations within these networks. Across these measures of network resources, the weighted average TBR is 2.24, indicating that top-decile earners have access to more than twice the social resources as those at the bottom. People with the highest incomes have better access to others with money, higher education, and positions in top occupations.

Social ties in the job market. The labor market is a common focal point for thinking about inequality in social ties. A large portion of jobs are found through informal social contacts and employee referrals (Fernandez 2021; Fernandez, Castilla, and Moore 2000; Granovetter 1995; Holzer 1996; Pedulla and Pager 2019). The importance of ties in job search and career attainment has been called "the invisible hand of social capital," in which "embeddedness in resource-rich networks" provides access to better jobs (Lin 2001:791). As Granovetter (1995: 22) argued, "better jobs are found through contacts, and the best jobs, the ones with the highest pay and prestige... are most apt to be filled in this way."

We have documented that high-income earners have larger social networks composed of higher-status connections, both of which are considered critical facilitators of job opportunities (Granovetter 1995; Lin 2001). Larger networks, all else being equal, function like applying to more jobs, providing access to a broader range of employers and job leads. Meanwhile, higher-status contacts wield greater influence and can advocate more effectively for a candidate. Together, these advantages mean that having a large, high-status network not only increases the likelihood of discovering job opportunities but also improves the chances of securing a position once an opportunity is identified. In Mouw's (2003) job search model, individuals use both formal search methods (such as applying to job advertisements) and social networking to identify employment opportunities, ultimately choosing the best job offer they receive from any source. The model suggests that if social connections provide a strong advantage in the labor market, individuals with well-connected networks should be more likely to secure jobs through those networks.[6] This framework underscores the expectation that high-income earners—with their advantageous social networks as outlined above—would be more likely to secure jobs through their connections. In the following section, we investigate whether there is a significant class gradient in the use of social networks for job placement.

How often did people use their social networks to find their current job? According to NLSY97 data, some 36 percent of people contacted friends and relatives to find their current job (as shown by the intercept in Fig. 4, Panel A). In the GSS data, about half say they found out about their job from friends, family, or acquaintances. These results confirm the importance of social ties and network connections in the labor market: between a third to a half of all workers attribute finding their current job at least in part to their social network. However, there is no income gradient in either data: people at the bottom, middle, and top of the income distribution all used their social networks at about the same rate.

The absence of a class gradient in networked job search and job acquisition is well-established. Panel B shows the top-bottom ratios for eight different metrics

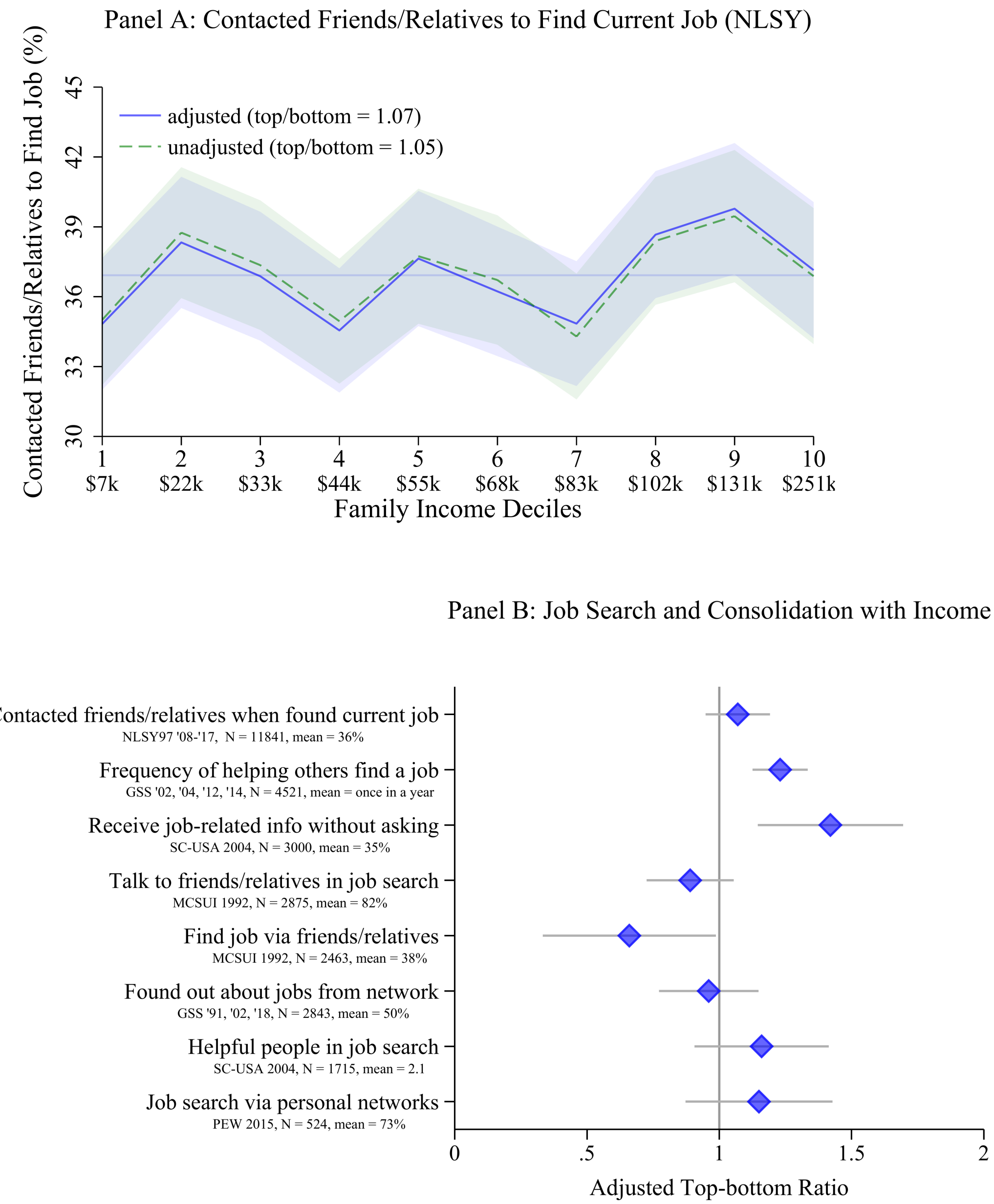

Figure 4: Job search and consolidation with income. *Note:* The data source for Panel A is NLSY97, 2008–2017. $N = 11,841$. Shaded area shows the pointwise 95 percent confidence interval. In Panel B, TBRs of social ties in job search, comparing top-decile earners to bottom-decile earners, in a linear regression model of income deciles on the social tie metric, conditioning on age, gender, and race/ethnicity (see Eq. [2]). Mean Gini = 0.50. Mean TB ratio = 1.1. Both the mean Gini and TB ratio are weighted by sample size. 95 percent confidence intervals based on 600 bootstrap resamples. Total $N = 24,600$.

of social network involvement in job search, derived from nine distinct data sets, ranked by sample size and with a combined N of more than 24,000 unique observations. The estimates are centered around a TBR of 1.07, indicating no consolidation with income overall. Exact results depend on the operationalization of social ties in the different data sets. For example, using social networks has a negative and significant association with income in the Multi-City SUI data—suggesting a potentially interesting case of inverted advantage—but the relationship is positive and significant in the GSS and the Social Capital USA data. Five out of eight estimates are greater than one (positive effect) but only two are statistically significant. Three out of eight estimates are below one (negative effect/inverted advantage) and one is significant. This variation in the estimates partly reflects non-sample error, such as different ways of defining social ties or differences in the sample frames or non-response bias across data sets. But overall, there seems little to no association between income and social ties in job search. Rich people find their jobs via networks at the same (high) rate as everyone else.

Distilling Results: The Inequality–Consolidation Curve

How do these measures and results aggregate to a deeper understanding of inequality and social ties? We pool together all our evidence in a last analysis that distills into a broad inequality–consolidation curve.

Considering multiple measurements of social ties, we have 47 estimates of both inequality in social ties and their consolidation with income, estimated from 15 unique data sources with a combined 142,000 unique (person-wave) observations. Across analyses, we compute the average Gini and average top-bottom ratio, weighted by the sample size of each analysis. First, the average Gini for social ties is 0.50, meaning that inequality in social ties overall is nominally higher than inequality in family income (0.47). Similar to other forms of advantage and opportunity, social ties are distributed very unevenly across U.S. society. Second, the average measure of consolidation between social ties and income is 1.8, meaning that the top 10 percent of income earners have 80 percent more ties than those in the bottom decile of income.

We report the inequality–consolidation curve in Figure 5, which shows the relationship between two features of social ties: their dispersion (inequality) and their consolidation with income. This plot summarizes all the findings in this study by plotting the Gini coefficients on the x axis against the adjusted TBRs on the y axis. Each point in the scatter plot represents a social tie outcome variable (such as network closure or group participation) analyzed with one data source (such as the GSS, all available waves combined).

At the origin (bottom left) of the graph are empirical cases showing both low dispersion and low consolidation—cases where social ties are broadly distributed across the population and show little class gradient. The upward slope indicates that as the dispersion of social ties increases—and inequality in access to social connections grows—the top-bottom ratio rises as well. The more unevenly a given type of social tie is distributed in society, the more it tends to be concentrated among the rich.

For social ties to be seen as a unique and separate axis of social differentiation, the inequality–consolidation curve would need to be relatively flat. Moreover, for social ties to actually reduce or offset inequality, the graph would need to be

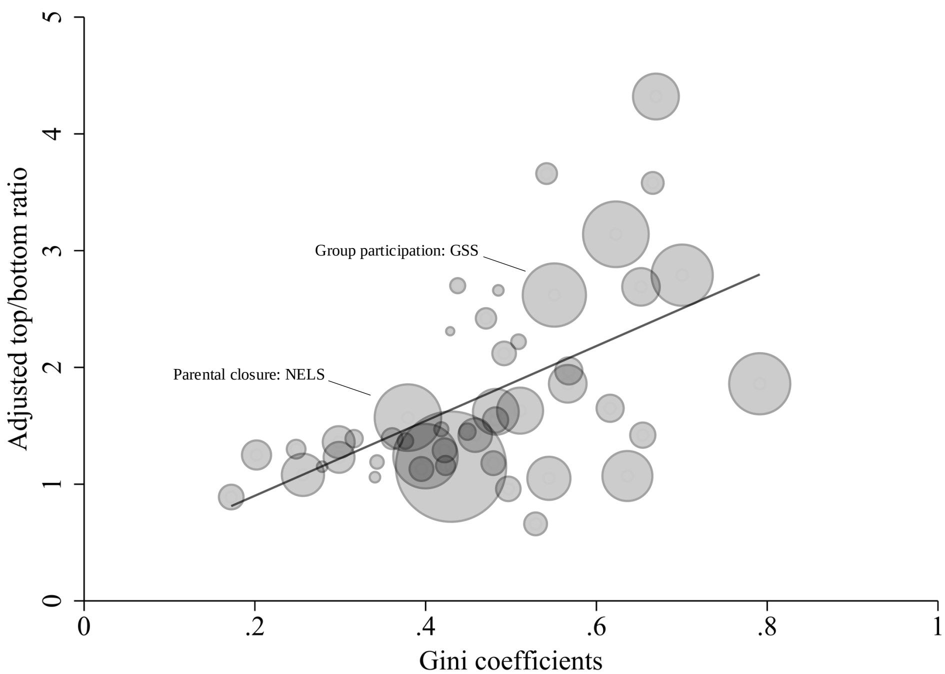

Figure 5: Inequality–consolidation curve. *Note:* This figure presents the adjusted TBR and Gini coefficient of all social tie variables examined in this article, $N = 47$ (underlying $N = 142,305$ person-wave observations). TBRs come from a linear model controlling for age, gender, and race/ethnicity. The sizes of the nodes are proportional to the sample sizes. The average Gini coefficient is 0.50, and the average adjusted TBR 1.8 (both weighted by sample size). The linear slope is 3.2 (se $= 0.73$); TBR $= 0.26 + 3.2*$ Gini.

downward sloping. A negative slope would mean that as dispersion in social ties grows, lower-income earners have more, rather than less, social ties: inverted advantage. In such a downward-sloping curve, an abundance of associational ties helps to compensate for a lack of income, making social conditions more equal across these two resources. However, instances of negative consolidation, where the TBRs are less than one and the poor have more social ties, are very rare. The few occurrences where the TBRs fall below one are primarily associated with social ties in job search, as detailed in Figure 4. The forms of social ties that are most unequal (such as network resources or group affiliations) are also the most class stratified in favor of top incomes. The overall positive slope of inequality–consolidation implies that social ties mostly serve to reinforce economic disparities.

Discussion

Scholars have long reflected on the role of social ties in reinforcing or alleviating inequality in society (DiMaggio and Garip 2011, 2012; Shepherd and Garip 2021). Some authors emphasize that “networks can be used to reduce inequality” (Christakis and Fowler 2009:171). Others caution that network ties may have an unintended “macro-level result of institutionalizing social inequality” (Granovetter 1995:100).

Our contribution lies in rigorously quantifying individual ties across a large and diverse collection of data sets, estimating their dispersion across individuals, and understanding their consolidation with economic resources. Our work compiles large-scale evidence from many high-quality data sources in the United States, resulting in a combined sample of 142,305 person-wave observations across 15 unique data sets. This "big, diverse data" approach offers significant advantages for studying the social world, particularly in a field such as social connectivity, where core concepts are defined and measured in many different ways. By pooling these data sets, we move beyond statistical significance to show robustness across a range of non-sampling errors arising from differences in variable definitions, survey designs, sampling frames, and non-response rates. We use a standardized regression model across all data sets, which helps avoid the pitfalls of p-hacking and overfitting that can occur when model specifications are tailored to individual data sets (Workman et al. 2023; Young and Cumberworth 2025; Young and Holsteen 2017).

Our core findings show that top-income earners consistently have larger, broader, and richer social networks than the poor. High-income earners have 30–40 percent more close friends than low-income earners, a pattern consistent across measures such as name generators and counts of close confidants. Moderate inequality is evident in core networks, with a Gini coefficient of approximately 0.38. Participation in informal groups is more uneven, with a Gini coefficient of 0.57, and increases sharply with income. Top earners are members of twice as many types of groups (e.g., neighborhood associations, sports clubs, and hobby groups) as those in the bottom decile, with disparities particularly pronounced in parent–teacher associations, where top-income parents are four times more likely to participate. Attendance at religious services shows only a weak positive association with income, but more active participation within religious communities (e.g., volunteering) is much higher among high-income earners. In terms of network resources, there is more inequality in friends' income than in own income (Gini of 0.58 vs. 0.47), and the networks of the rich are twice as likely to include individuals with college degrees and prestigious occupations compared to those of low-income earners. These findings highlight larger and better resourced networks as one rises in economic rank. If connections to individuals with higher income, education, and occupational status are beneficial for upward mobility, then social ties function as a force that reinforces existing advantages, limiting their potential to mitigate inequality.

Our pooled analysis of these results reveals what we term the inequality–consolidation curve, which shows a key pattern in our evidence: as inequality in social ties grows, those ties become increasingly concentrated among high income earners. Although there are empirical instances where social ties are distributed more evenly across society, with minimal class-based disparities, these cases remain exceptions rather than the rule. Social ties do not operate simply as an independent resource but frequently interact with economic capital in ways that seem to deepen societal stratification.

One core question that follows from this study is: why do the rich have more social ties? What underlying mechanisms produce this pattern? Many theorists have suggested that social ties emerge from purposive action and deliberate investments in personal relationships (Burt 1992; Coleman 1990; Lin 2001). From this perspective, one explanation for our findings is that wealthier individuals dedicate more time, energy, and effort to building and maintaining valuable social connections, suggesting that the rich are both more sociable and more strategic in optimizing their network connections. If this view is correct, social tie disparities could potentially be mitigated by encouraging low-income earners to engage in more proactive social outreach and relationship building. Alternatively, the disparity could stem from class bias in how "alters"—one's potential friends or group members—approach social relationships. People may be more inclined to form friendships with high-income individuals and include them in their groups while avoiding similar connections with lower-income individuals (Chetty et al. 2022b). In this view, abundant social ties among the rich results not from their own actions but from external class-based preferences that favor them. Both these perspectives highlight the role of intentional actions in creating a class gradient in social ties, though they differ in terms of what individuals with few social connections can do to address it.

A third, and contrasting, perspective shifts away from purposive action and suggests that social tie inequality mostly arises as a structural by-product of everyday life. New people entering a social environment often find it is already highly structured and stratified by class. Often, individuals are not forming social ties one at a time, but rather joining pre-existing networks that are already structured on class-based foundations. People entering a social space tend to interact with those most local to their social position (Blau 1977). As long as social spaces are segregated by income (Park 2021), the resulting social ties—and the resources flowing through them—will tend to reflect and reinforce pre-existing class differences. In this view, the main reason why rich students tend to have rich friends is because they attend schools with other rich students, are born into families that live in neighborhoods where other rich families live, and attend events or participate in groups that invite other rich people. As long as the focal points of interaction—schools, neighborhoods, workplaces, and recreational spaces—are segregated by income, so will networks be segregated, leading to the consolidation of income with social ties (Feld 1981). This model still implies intentional action at some point in the system but highlights how social tie inequalities can be sustained over time even without conscious efforts. Our overall finding of strong consolidation of income and social ties leaves a number of engaging theoretical questions, calling for more fine-tuned studies that test these mechanisms. Deeper understanding of how social ties disproportionately accumulate at the top is, in our view, a central question for sociology.

A second core question that emerges from this study is: are the resource flows stemming from network connections a force for good in society? Although social ties can offer many benefits for community well-being and social cohesion (Chetty et al. 2022a; Christakis and Fowler 2009; Putnam 2000), many individuals lack access to community resources and do not share in their benefits (Bendeck and Hastings 2023; Smith 2005). Those who are already advantaged tend to reap the greatest rewards when access to resources depends on social ties. In our view, scholars have not fully appreciated the stark inequality in the distribution of ties and their consolidation with economic advantage. If social ties and network connectivity amplify disparities, we need to consider alternative structures and practices that might serve to disentangle economic outcomes from social ties. For example, consider blind auditions, where a candidate's identity and social connections are concealed from decision makers, leaving only the technical merits of their performance to be evaluated (Goldin and Rouse 2000). Under blinded conditions, well-connected candidates cannot rely on social endorsements to compensate for weak performance, while less-connected candidates are not penalized for their lack of insider connections. Blinded economies are becoming increasingly feasible in the online world of work: platforms such as Upwork, Fiverr, and Etsy provide open employment models, allowing anyone to work or offer services on the platform without needing network connections, outside referral, or even to be "hired" by an employer (Vallas and Schor 2020). These are economic spheres where "who you know" is not relevant to a transaction. Given that social ties are strongly skewed toward those with economic advantage, more socially anonymous market structures may offer underappreciated meritocratic and egalitarian benefits.[7]

Finally, we also identify an important counterpoint in the activation of social ties within the labor market. Unlike other domains, the use of social networks for job search does not exhibit a class gradient. Approximately half of the U.S. workforce credits their networks with helping them secure their current job, and this reliance remains remarkably consistent across income levels—poor, middle class, and wealthy alike. This is surprising given our earlier findings that top earners tend to possess larger networks and stronger connections to high-status individuals, which are generally considered advantageous in job searches (Granovetter 1995; Lin 2001). The robust observation that top earners are no more likely to mobilize their social contacts for employment than lower-income earners challenges prevailing theories about the role of social ties in hiring and highlights the need for revised theoretical frameworks to account for this unexpected pattern (Castilla 2005; Granovetter 1995; Lin 2001; Mouw 2003).

At the same time, this finding does not necessarily imply complete network equality in the job market: even if social ties are activated equally across the income spectrum, the benefits it yields can differ significantly. Network assistance in securing a high-income job is more valuable than help in accessing a low-income job. Thus, while high- and low-income workers may rely on network support at similar rates, the rewards for the former may be much greater. Still, this does not help explain why high-income earners are not more likely (rather than equally likely) to use their networks resources for job attainment. At minimum, this robust, stylized fact needs to be incorporated into standard models of social ties in the labor market.

This finding suggests that the conversion of social ties into social capital is very imperfect. Some aspects of what is commonly termed "social capital" might be better understood as social *consumption*. Although social capital emphasizes the instrumental value of relationships—such as leveraging a network to secure employment or access exclusive knowledge—social consumption refers to social interactions as an intrinsic component of a fulfilling life, driven by personal enjoyment, emotional connection, and overall well-being. This distinction shifts the focus from economic utility to subjective well-being while still underscoring significant inequalities in access to social opportunities. Limited social ties may signal low levels of well-being, even when those ties are not directly linked to economic advantages. Research has shown that social time with friends and family is a key determinant of daily subjective well-being (Young and Lim 2014). In these cases, inequality in social ties remains a key aspect of social stratification but is unlikely to compound inequality—similar to how buying an expensive car or a vacation home (economic consumption) reflects economic disparity without necessarily reinforcing it further.

Directions for Future Research

We have attempted to provide a concise and through account of social ties, their distribution, and their consolidation with economic well-being. Inevitably, there are important limitations that should be priorities for future work. First, while this study has focused on relationships between income and social ties, the framework easily extends to other key factors related to inequality, such as sex, race, and ethnicity, which have so far only been included as control variables. Ultimately, we aspire to calculate consolidation within a multidimensional space that encompasses many socio-economic distinctions (Zhao and Garip 2021), revealing more about how social ties interact with various unique aspects of inequality.

Second, we advocate research that broadens the scope of economic resources to include wealth. Although income and wealth are closely related, they are far from perfectly correlated, and wealth disparities tend to be significantly larger than income disparities (Berman, Ben-Jacob, and Shapira 2016). Currently, there are few data sets that measure both social ties and wealth, but as scholars pursue a deeper understanding of wealth inequality and as more data on wealth becomes available, research in this area will become increasingly valuable (Pfeffer and Waitkus 2021). Social ties may well be more closely consolidated with wealth than income, particularly through their joint intergenerational transfer within families over time.

Finally, this study is limited to the United States, but international comparisons are a natural extension. How much do these results reflect a distinctively American society? For example, does European capitalism offer different dynamics of opportunity and advancement through social networks? European countries generally have lower income inequality and have experienced less growth in inequality over time (Blanchet, Chancel, and Gethin 2022). Do they also have less social tie inequality and lower consolidation with class? In more egalitarian societies, do social ties play a greater role in alleviating poverty and supporting opportunity than they do in the United States? Exploring these differences could provide deeper insights into the underlying mechanisms at work.

Each of these scope conditions points to directions for future research and underscores the importance of continuing to build "big, diverse data" resources—broadening the scope of inquiry and deepening the evidentiary base.

Notes

1 For datasets in which more than five alters are enumerated, we top code the network size at five to make the network sizes comparable across data sets and to previous studies.

2 This measure extends the commonly used 90-10 ratio (which compares top- and bottom-decile values of a single variable) to assess how one variable (social ties) is distributed across the deciles of another variable (income).

3 Age is measured as a continuous variable, gender is measured as a binary variable, and race is measured as a simple categorical variable with four groups: (1) white, non-Hispanic, (2) black, (3) Hispanic, non-black, and (4) other. For datasets that do not have the ethnicity variable—for example, GSS prior to 2000—the race variable has three groups: (1) white, (2) black, and (3) other.

4 The Lorenz curve for income is drawn based on 2019 CPS-ASEC family income data. The sample size is 92,006. We dropped respondents who are younger than 15 years old, and those who have missing or negative values in family income. We use this estimate as a point of reference in all our Lorenz curve graphs.

5 One could also calculate this as the average rather than the total income of friends, and the TBR remains roughly 2.

6 In addition, if finding a job through informal search or employee referral leads to higher retention and job duration (Castilla 2005; Fernandez et al. 2000; Marsden and Gorman 2001), then jobs found via networks will be a larger share of all jobs at any one time.

7 Similarly, we question whether referral-based hiring practices in business—where companies incentivize employees to recommend potential hires—are beneficial enough to justify their potential downsides. Although these practices may provide administrative convenience, they can also contribute to social closure around employment opportunities, reinforcing existing inequalities and limiting access for those outside established networks (Smith 2005).

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