Who Leads? Relative Age Effects on Social Capital*

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Abstract

This paper studies the causal effect of being the oldest within a school cohort on social capital. Using a fuzzy regression discontinuity design and data from Facebook, we find that boys who are older than their classmates make 11% more friends in high school. This social advantage is associated with leadership roles, with relatively older boys 42% more likely to become class president than their relatively younger peers. Men who were relatively older during childhood have larger social networks in adulthood, and disproportionately sort into management and entrepreneurship. Our findings suggest that small age differences in peer composition can have persistent effects on social and economic outcomes.

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There is a growing consensus that social capital — broadly defined as the networks, social skills, and relationships that individuals build (Glaeser, Laibson and Sacerdote, 2002) — is an important determinant of economic and other life outcomes (Sacerdote, 2001; Deming, 2017; Chetty et al., 2022). However, much less is known about how social capital is formed, and why some individuals are better able to build social connections than others. In this paper, we argue that one's age relative to their peers within a school cohort — their relative age — affects social capital accumulation.

To evaluate this mechanism, we analyze individual-level data on 33 million U.S. Facebook users with a fuzzy regression discontinuity design around kindergarten entry cutoff dates. By comparing individuals who are born just before and after the cutoff, we identify the reduced-form effect of being older in a school cohort on social capital.[1]

We find that a student's relative age has a significant impact on their social development during childhood. Boys who are relatively older form 11% more friendships in high school and participate more in sports teams and clubs. In contrast, relatively older girls make the same number of friends as their younger peers. This social advantage among boys is associated with a greater propensity to hold leadership roles. In the cross-section, students in the top ventile of within-school friendships are 15 times more likely to hold leadership positions than those in the bottom ventile. Consistent with a social capital mechanism, we show that relatively older boys are 42% more likely to become class president.[2]

The advantages in social connections and leadership opportunities for boys persist into adulthood and strongly predict career outcomes. Men who were relatively older in school have larger and more connected social networks, and are more likely to to be married. By linking job titles on Facebook to the O*NET occupational database, we further show that relatively older men disproportionately enter socially intensive occupations such as management and entrepreneurship. This result is consistent with a traditional Roy model in which individuals sort into occupations according to comparative advantage. Taken together, our results suggest that small age differences in peer composition during schooling can shape long-term outcomes. While this relative age advantage ultimately stems from a complex bundle of interacting channels, including early test score gains and physical differences, our findings highlight the formation of childhood social capital as an important and persistent mechanism.

[1] As argued in Cascio and Schanzenbach (2016), this reduced-form approach combines three separate effects which are collinear: age at school entry, age-at-outcome, and age relative to peers.

[2] This estimate is nearly four times larger than Dhuey and Lipscomb (2008). A key difference is that we use birthday-level variation in relative age, while that paper quarter of birth variation.

Prior studies have identified causal effects of relative age on a broad range of outcomes. These include test scores and educational attainment (Bedard and Dhuey, 2006; Datar, 2006; McEwan and Shapiro, 2008; Elder and Lubotsky, 2009; Cascio and Schanzenbach, 2016; Solli, 2017; Dhuey et al., 2019); mental health and learning disabilities (Thompson, Barnsley and Dyck, 1999; Elder, 2010; Evans, Morrill and Parente, 2010; Layton et al., 2018; Dee and Sievertsen, 2018); crime and risky behaviors (McAdams, 2016; Depew and Eren, 2016; Cook and Kang, 2016; Landersø, Nielsen and Simonsen, 2017; Peña, 2019; Johansen, 2021); and career outcomes (Black, Devereux and Salvanes, 2011; Fredriksson and Öckert, 2014; Røed Larsen and Solli, 2017; Dustmann, Puhani and Schönberg, 2017).

We contribute to this extensive literature in three ways. First, we use rich administrative data to establish social capital as an important channel through which relative age affects (men's) career outcomes. Much of the prior literature has focused on human capital mechanisms, and the few papers that examine social capital have relied on cross-sectional survey data and find inconsistent results (Fumarco and Baert, 2019; Yamaguchi, Ito and Nakamuro, 2023; van Aalst and van Tubergen, 2021). Our analysis overcomes this data limitation by leveraging longitudinal data from the universe of U.S. Facebook users to construct granular measures of social capital from observed friendship networks. Second, we show that the effects of relative age on social capital persist into adulthood by following a panel of individuals from high school into their mid-thirties. This persistence is notable because it suggests that our results are driven by relative age differences rather than absolute age differences, since the latter diminish as individuals grow older (Black, Devereux and Salvanes, 2011). Third, we demonstrate that relative age shapes career paths more broadly than previously thought. While earlier work has focused on right-tail outcomes like winning a Nobel Prize (Fukunaga, Taguri and Morita, 2013), becoming a business leader (Du, Gao and Levi, 2012) or politician (Muller and Page, 2016; Tukiainen, Takalo and Hulkkonen, 2019; Li and Hu, 2022; Al Yussef, Heyndels and Le Boulaire, 2023), we find that relative age influences career choices for the typical worker.

The social capital mechanism can also help to reconcile a puzzle in the relative age literature. In early grades, relatively older students achieve higher test scores (Bedard and Dhuey, 2006; Elder and Lubotsky, 2009). However, the test score advantage of being older fades out substantially by the end of high school (Hurwitz, Smith and Howell, 2015).[3] This suggests that factors beyond academic achievement are critical

[3] This likely reflects "age-at-test effects" which mechanically fade over time, as the percentage

to understanding why relative age affects later career success. Moreover, while the test score effects of relative age are comparable for boys and girls (Elder and Lubotsky, 2009), the career advantages have been shown to be largest in traditionally male-dominated fields such as business and politics. Consistent with this gender-specific pattern, we find larger relative age effects on social capital among boys than girls, and show that these social advantages for boys persist into adulthood.

Our findings also contribute to the growing economics literature on social capital. Prior studies have shown that social connections influence a range of outcomes including test scores and educational attainment (Sacerdote, 2001; Black, Devereux and Salvanes, 2013; Bifulco, Fletcher and Ross, 2011; Fletcher, Ross and Zhang, 2020), labor market outcomes (Gee, Jones and Burke, 2017; Carrell, Hoekstra and Kuka, 2018; Lleras-Muney et al., 2024) and economic mobility (Chetty et al., 2022). We complement these papers by identifying a key determinant of social network formation, showing the persistence of social skills into adulthood, and highlighting the association between social capital development in childhood and career outcomes.

The remainder of the paper proceeds as follows. Section I describes our data sources. Section II outlines our identification strategy. We then present our main empirical findings in Section III. Finally, Section IV concludes.

I Data

We use data from Facebook, one of the world's largest social media platforms, to measure social capital. Our baseline analysis sample consists of 33 million U.S. Facebook users born between 1983 and 1997.[4] We restrict to these birth cohorts to maximize sample coverage among individuals who joined Facebook during childhood or adolescence, rather than as adults. To be included in our sample, users must have been active on the platform in the 30 days prior to April 21, 2026, and have attended high school in a state with a uniform kindergarten entrance cutoff.[5] We also require users to have at least 100 friends on Facebook to capture individuals who are active on the platform and whose virtual network likely resembles their offline network.

difference in age between the oldest and youngest students shrinks (Black, Devereux and Salvanes, 2011; Cascio and Schanzenbach, 2016).

[4]In the Online Appendix, we replicate our main results in select OECD countries with high-rates of Facebook usage and a consistent kindergarten entry cutoff: (Canada, Italy, Japan, Norway, Sweden and the United Kingdom) for the same birth cohorts.

[5]This excludes individuals who attended high school in CO, MA, NJ, PA, VT or VA. In these states, kindergarten entrance cutoffs can vary by school district.

From the platform, we observe rich individual-level data on friendship networks, parent-child linkages, schools attended, group memberships, event participation, and employment histories. Though friendships on the platform are established virtually, we interpret them as a proxy for real-world connections, consistent with the findings in Jones et al. (2013). Following Chetty et al. (2022), we construct contemporaneous and parental socioeconomic status (SES) ranks using a machine-learning algorithm trained on features such as precise geographic location and cellphone price. Additionally, users self-report demographic data including gender and date of birth. While these fields are self-reported, they appear to be highly accurate. Panel A of Online Appendix Figure A-1 shows that the distribution of birth dates in our data has a 0.91 correlation with that in the Center for Disease Control and Prevention Vital Statistics.[6] The accuracy of the date of birth field may reflect a well-known feature on the platform. Under the default privacy settings, users' friends are notified on their self-reported birthdays.

We complement the Facebook data with five external data sources. First, we use kindergarten entry cutoff dates from Dhuey and Lipscomb (2008). In most U.S. states, children are required to turn five by September 1st to enter kindergarten in a given year, although the exact cutoff date varies across states and over time.[7] We match Facebook users to state- and year-specific kindergarten cutoffs based on their high school state and birth year.[8] Second, we incorporate data on high school characteristics from the National Center for Education Statistics (NCES). Third, we link occupational characteristics from the O*NET database (Version 28.1), which contains detailed information on the skills and tasks for over 800 occupations, classified using Standard Occupational Codes (SOCs). Fourth, we match data on entrepreneurship from Fluegge and Bailey (2024), which identifies entrepreneurs on Facebook based on users' self-reported job titles linked to external data on business ownership. And fifth, we use data on approximately 200,000 U.S. and Canadian scientists from the *American Men and Women of Science* (41st Edition). This rich biographical database contains the birthdate and birthplace of prominent scientists and includes measures of their scientific productivity (e.g., publications and academic awards). Further details on these external datasets are provided in the Data Appendix.

[6] We exclude individuals with a self-reported birthday of January 1 since this is the default date assigned at account creation, and a few specific dates that are over-represented in our data: 2/29 (leap day), 4/1 (April fools day) and 4/20.

[7] We thank Elizabeth Dhuey for providing updated data on state cutoff dates.

[8] To the extent that users attended schools in multiple states, this will introduce measurement error and attenuate our results.

II Empirical Strategy

We estimate the intent-to-treat (ITT) effect of relative age on social capital using a fuzzy regression discontinuity (RD) design. Our running variable, (assigned) relative age (R_i), is defined as the difference in days between individual i's birthdate and the closest state- and year-specific kindergarten entry cutoff. Formally, for individual i who turned five in year t and attended high school in state s, we define:

$$R_i = \text{Birthdate}_{ist} - \text{Cutoff}_{st}$$

Students with $R_i > 0$, born just after the cutoff, are assigned to be the oldest in their cohort. Those with $R_i < 0$, born just before the cutoff, are assigned to be the youngest. Since some students may delay or accelerate entry, R_i reflects *assigned* rather than realized relative age.[9]

Let $Y_i(1)$ and $Y_i(0)$ denote potential outcomes for individual i if assigned to be relatively old or young, respectively. Our outcomes include measures of social networks (size and composition), participation in groups and clubs, and career choices. Using a standard fuzzy regression discontinuity framework, the ITT effect of being relatively old is given by Equation (1), so long as $E[Y_i(1)|R_i]$ and $E[Y_i(0)|R_i]$ are smooth at $R_i = 0$ (Lee and Lemieux, 2010).

$$\text{ITT}_{RD}(Y) \equiv \lim_{R_i \downarrow 0} E[Y_i(1)|R_i] - \lim_{R_i \uparrow 0} E[Y_i(0)|R_i] \tag{1}$$

We estimate Equation 1 using the following regression model

$$y_i = \alpha_0 + \alpha_1 f(R_i) + \beta_{ITT} D_i + \alpha_2 D_i \cdot f(R_i) + \Pi X_i + \epsilon_i \tag{2}$$

where y_i is the outcome of interest, D_i is an indicator for being relatively old ($R_i > 0$), $f(R_i)$ is a polynomial function of the running variable, and X_i is a vector of covariates. The coefficient β_{ITT} captures the ITT effect of being relatively older.

Our baseline specification uses a linear function of R_i, omits covariates, and applies a uniform kernel with a bandwidth of 15 days on either side of the cutoff.[10] The bandwidth of 15 days reflects the typical variance in gestational length (Jukic et al.,

[9]Deliberately delaying kindergarten entry is a common practice and often referred to as *redshirting*. In our data, children who are intentionally held back will be coded as being relatively young, which attenuates our estimates of the effect of being relatively old.

[10]We also drop observations within one day of the cutoff to reduce ambiguity in relative age assignment. This forms a donut-hole, fuzzy RD design.

2013). Although the running variable is discrete, we follow Kolesár and Rothe (2018) and cluster standard errors at the high-school-state level, rather than by R_i. In the Online Appendix, we verify the robustness of our results to several alternative specifications: (i) including quadratic terms in $f(R_i)$, and (ii) controlling for month-of-birth fixed effects to account for seasonal patterns (Buckles and Hungerman, 2013).

Table 1 assesses the validity of the RD design. Panels A and B show that students on either side of the cutoff have similar demographics[11] and attended comparable high schools. A potential concern is that Facebook usage could vary discontinuously at the cutoff, in which case observed differences might be driven by how individuals use Facebook rather than true differences in their social behavior. However, Panel C shows that there are no meaningful differences in Facebook usage at the cutoff. Furthermore, Panel B of Online Appendix Figure A-1 implements a McCrary Test. While the estimate is statistically significant due to the large sample size, the magnitude of the density difference is economically modest and inconsistent with systematic parental manipulation of precise birth timing around the cutoff.

We do not observe actual kindergarten start dates in the Facebook data.[12] As we cannot observe compliance directly, our primary results are reported as ITT estimates of cutoff assignment. To approximate the local average treatment effect (LATE) for compliers, we rely on Bassok and Reardon (2013), who find that approximately 80% of students born within a month of the cutoff date comply with the assignment rule. We scale our ITT estimates by dividing them by this 0.8 compliance rate, using the delta method to adjust the standard errors. In this context, the compliers are the students who start school on time, becoming the oldest if $R_i > 0$ and the youngest if $R_i < 0$. Since almost all non-compliance takes the form of assigned relatively younger students delaying entry (Bassok and Reardon, 2013), our baseline ITT estimates likely represent a lower bound of the true relative-age effect among compliers.[13]

To make our results easier to interpret, we occasionally express the results as relative risk ratios (RRRs), normalizing β_{ITT} by the control mean at the cutoff.

$$RRR = \frac{\alpha_0 + \beta_{ITT}}{\alpha_0}$$

[11] The one exception in Table 1 is calendar birth cohort. This discontinuity is a mechanical artifact driven by states with January 1 school-entry cutoffs, which naturally place late-December births and early-January births—who are just days apart in age—into different calendar birth years.

[12] While this could be inferred from high school graduation dates coupled with strong assumptions regarding grade progression, this field is poorly reported on the platform.

[13] This is especially true for boys and children in high-income famillies, who are significantly more likely to be held back than girls and children from low-income families.

This allows us to compare effects in percentage terms across outcomes with different base rates. An RRR of 1.1 implies a 10% higher outcome for relatively older students at the cutoff. Standard errors for RRRs are calculated using the delta method.

III Results

We begin by examining how relative age affects the number of high school friends made by boys and girls.[14] Panel A of Figure 1 shows the relationship between relative age and the number of high school friends from the same or adjacent cohorts.[15] Boys who are relatively older make 10.59 (s.e. 0.63) more high school friends than their relatively younger peers, a difference of 11% or 0.11 standard deviations (SD). By contrast, the effect of relative age on friending among girls is approximately zero (0.01 SD). This finding is consistent with prior work showing that boys are more sensitive to environmental and contextual factors (Autor et al., 2016; Bertrand and Pan, 2013). Given these large gender differences, we focus the remainder of our analysis on boys and men, and report results for girls and women in the Online Appendix.

To better understand the determinants of these friendship patterns, we next analyze participation in high school activities. We assign students to sports teams and clubs based on the names of Facebook Groups joined during high school and an algorithm described in the Data Appendix. For example, we infer that a member of the "Palo Alto HS Basketball '18" group played basketball in high school. Online Appendix Figure A-2 shows that relatively older boys are 32–55% more likely to join sports teams (Panel A) and clubs (Panel B). While there are positive participation effects for both boys and girls, the participation effect is especially strong for boys in non-sports clubs like band and choir.

One feature of these non-sports clubs is that they often combine boys and girls, whereas most sports teams are gender-specific. Building on this observation, Panel B of Figure 1 tests for gender homophily by examining friendships separately by the gender of the friend. Strikingly, about 74% of the additional friendships of relatively older boys are with girls. This suggests that same-gender activities like sports teams cannot fully explain why relatively older boys make more friends.[16] On the other

[14] We cannot observe social networks prior to high school because users must be 14 years or older to create a Facebook account.

[15] We include friends in adjacent cohorts to make our results more robust to differential compliance on either side of the kindergarten cutoff date.

[16] However, we cannot rule out that the social returns to excelling in sports are such that relatively older boys are better able to befriend girls.

hand, it is consistent with the increased exposure to mixed-gender clubs like choir, drama and band.

We next consider whether these differences in social connections affect other outcomes in high school. Since prior work has found a positive association between social capital and school leadership (Kuhn and Weinberger, 2005; Black, Grönqvist and Öckert, 2018), we primarily focus on leadership positions. Leadership is measured using membership in Facebook groups related to student government and leadership councils.[17] To ensure we capture only high school leadership positions, this analysis is restricted to Facebook groups joined before the year in which the user turned 18.

Panel A of Figure 2 shows a strong association between the number of high school friendships and the likelihood of holding a leadership position. Students in the top ventile of high school friendships are approximately 15 times more likely to be in leadership groups than those in the bottom ventile. One potential mechanism for this pattern is reverse causality. Under this interpretation, leaders acquire more friends after assuming leadership positions. However, this is unlikely to be the main explanation since most high school friends are made in the first two years of high school, while leadership positions are typically held in the final year.

Turning to relative age, we replicate the finding of Dhuey and Lipscomb (2008) that relatively older boys are more likely to be school leaders. Panel B shows that relatively older boys are 42% (s.e. 23.0%) more likely to hold leadership positions. Our estimate is nearly four times larger than reported in Dhuey and Lipscomb (2008). This difference could be driven by the fact that the prior study only used variation in the quarter of birth, and better reporting of leadership activities on Facebook. Notably, our estimates of relative age affects on student leadership are of the same magnitude as previous estimates of relative age effects on becoming a politician (Muller and Page, 2016). This suggests that childhood advantages in social connections and leadership experience may help explain the well-documented pattern of relatively older boys being more likely to enter politics in adulthood.

As a robustness check, Figure A-3 in the Online Appendix examines the effect of relative age on membership in the National Honor Society (NHS), a prestigious high school organization that recognizes excellence in "scholarship, service leadership and character." We find that relatively older boys are 117% (s.e. 40.2%) more likely to be in the NHS. This elevated likelihood of NHS membership is consistent with the

[17]We identify such groups by matching regular expressions containing 'student council', 'school council', 'student government' and 'student leadership' to Facebook group names.

idea that relatively older boys are more academically and socially successful in high school. Relatively older girls are also more likely to be in the NHS, though the effect is much smaller in magnitude (23%, s.e. 15.0%).

Next, we analyze whether these social advantages for boys persist into adulthood. Testing for persistence matters for two reasons. First, it helps distinguish between relative and absolute age effects which are both captured in the reduced-form effects that we estimate (Black, Devereux and Salvanes, 2011). The absolute age gap between students — at most twelve months — mechanically shrinks in percentage terms as students enter later grades. Therefore, finding persistent relative age effects suggests that what matters is being older than one's peers, not the age at which outcomes are measured.[18] Second, persistent relative age effects on social capital could explain why relatively older individuals are more likely to become politicians and CEOs. This would fill an important gap in the literature: prior work has focused on human capital mechanisms, which largely fade out by the end of high school (Hurwitz, Smith and Howell, 2015), leaving adult outcome differentials mostly unexplained.

Figure 3 shows how relative age shapes social networks in adulthood. Panel A shows that relatively older males make an additional 1.77 friends per year between the ages of 21 and 30, compared to their relatively younger peers. Combined with the gaps in network size documented in high school, this accumulates to a substantial difference in social capital in adulthood. Panel B shows that relatively older men have 21 (s.e. 5.3) more friends (3.5% or 0.04 SD), as measured in their mid-thirties. Panel C considers the size of the second-degree network, which captures the number of friends-of-friends. We find that relatively older men have 7,880 (s.e. 2555.6) more friends-of-friends, a 2.9% increase compared to their relatively younger peers.

However, network size is a crude proxy for social capital because it fails to capture how one's friends are connected to each other, or the structure of their social network. To the extent that a person's friends are also friends with each other, they are less likely to provide access to new information or opportunities (Granovetter, 1973). On the other hand, the presence mutual friends can strengthen existing ties and help reinforce social norms (Jackson, 2020). We therefore examine a commonly used measure of network structure: the support ratio, which captures the share of a person's friends with whom they have at least one mutual friend. Panel D of Figure 3 shows that relatively older men have more interconnected networks, with a support

[18] In contrast, most of the literature looking at relative age effects on test scores attributes gaps to differences in absolute age at the time of testing (Cascio and Schanzenbach, 2016).

ratio that is 0.02 SD higher than their relatively younger peers. This suggests that the social networks of relatively older men are more cohesive, which may help them maintain stronger social ties and better access support from their friends.

We have shown that the social advantages of relatively older boys persist into adulthood. To begin to understand the mechanisms through which relative age affects social capital accumulation, we next examine differences in friendship formation. Friendships on Facebook are reciprocal. However, in each pair, one user initiates a friendship request and the other responds (accept or reject). There are two possible channels through which relatively older students could make more friends, holding constant the friendship acceptance rate: they could either send more friend requests or receive more friend requests from others. The former would be consistent with a story in which relatively older men are more proactive in forming friendships. On the other hand, receiving more friend requests could suggest they are seen as more valuable friends. We find more support for the latter hypothesis. Panel E of Figure 3 shows that relatively older students have initiated a smaller fraction of their friendships, though the effect is modest in magnitude (0.3 percentage points).

Lastly, Panel F examines how relative age shapes marriage rates, an important social institution which often associated with greater economic stability and a reduction in loneliness. We find that relatively older men are 1.5 percentage points more likely to be married, a 4.2% increase relative to their younger peers. This result is consistent with our earlier finding that 74% of the additional friendships formed by relatively older boys are with girls, since the vast majority of marriages are between men and women. This suggests that the cross-gender social skills and networks that develop during adolescence translate into advantages in the marriage market. And to the extent that marriage itself generates further social and economic returns, this channel may amplify the long-run consequences of relative age.

We next examine whether these persistent differences in social capital affect labor market outcomes. Under a traditional Roy model of occupational choice, individuals sort into occupations based on their comparative advantage. If relatively older men develop stronger social skills early in life, we should expect them to choose careers where the return to these skills is greatest. To test this hypothesis, we analyze users' self-reported job titles on Facebook. About 30% of users report their job title on Facebook (e.g., Teacher).[19] After cleaning these job titles by removing special

[19]Pancel C of Table 1 shows that there is no difference in occupation reporting rates for relatively older vs. younger men.

characters and standardizing common phrases, we use fuzzy string matching to link them to Standardized Occupation Codes (SOCs) from the Bureau of Labor Statistics. The SOC system provides a detailed, hierarchical classification of occupations, from broad categories like "Management" to specific positions like "Elementary School Teacher." Panel A of Figure A-4 in the Online Appendix shows that the distribution of jobs reported by US Facebook users closely matches the overall U.S. labor market, suggesting that our sample is representative of the broader workforce.

Panel A of Figure 4 visualizes how relative age affects occupational choice across ten of the most common 2-digit occupation codes.[20] For each occupation, the figure plots the relative risk ratio (RRR) of being in that occupation for relatively older men compared to their relatively younger peers. An RRR above 1 indicates that relatively older men are more likely to work in that occupation, while an RRR below 1 indicates they are less likely. We find that relatively older men are 5–10% more likely to work in management, engineering and business roles, and 5–10% less likely to work in production and the arts. These findings are consistent with the idea that relatively older men are drawn to occupations that require strong social skills.

To analyze these occupational sorting patterns systematically, we turn to the the O*NET database (Version 28.1), which provides detailed measures of the skills required and tasks performed in different occupations. Following Deming (2017), we quantify skill demands across three broad dimensions: social skills, cognitive ability, and task content.[21] Social skills capture the degreee of team-based work, and the ability to coordinate and communicate with others. Cognitive ability reflects the demand for non-routine analytical skills, such as problem-solving and critical thinking. Task content measures the extent of routine manual or cognitive work, such as assembly line work or data entry.

Consistent with our hypothesis, Panel B of Figure 4 shows that relatively older men disproportionately sort into occupations that require strong social skills. In particular, relatively older men choose occupations that require 0.04 SD (s.e. 0.01) more social skills and 0.05 SD (s.e. 0.01) more non-routine analytical skills. On the other hand, there is no significant association between relative age and the nature of task content across occupations. Together, these findings suggest that the social advantages conferred by relative age in childhood have lasting consequences for career trajectories, drawing men toward more socially-intensive roles. Notably, these

[20]We focus on the 2-digit level of the SOC classification to ensure sufficient sample sizes within each occupation, while still capturing meaningful differences in job types.

[21]Please refer to the Data Appendix for a detailed definition of each skill sub-index.

effects are not confined to the right-tail of the earnings distribution. This is important because studies focusing exclusively on CEOs and politicians may significantly understate the aggregate labor market consequences of relative age effects. If even modest shifts in occupational sorting toward more socially-demanding roles translate into earnings gains, as shown in Panel B of Figure A-4 in the Online Appendix, the cumulative economic impact of relative age differences could be substantial.

Finally, we explore relative age effects on two notable occupations using external data; entrepreneurs and academic scientists.[22] These occupations are of particular interest because of the large externalities they generate for the broader economy through job creation and scientific discovery. Panel C of Figure 4 shows that relatively older men are nearly 10% more likely to become entrepreneurs, consistent with prior research documenting that leadership ability and strong social skills are defining traits of successful entrepreneurs (Kerr, Kerr and Xu, 2018). By contrast, Panel D indicates that relatively older individuals are 14.4% (s.e. 7.07) less likely to become prominent scientists.[23] This negative result is difficult to reconcile with the traditional human capital view of relative age effects. If tests scores and cognitive ability were the predominant channel, we would expect relatively older individuals to be overrepresented in science, not underrepresented. Instead, these findings again point toward a persistent social capital mechanism, in which childhood advantages in social capital steer men toward careers where the returns to social skils are larger, and away from more solitary pursuits like scientific research.[24]

IV Discussion and Conclusion

We have shown that being among the oldest in a school cohort has lasting effects on social capital formation and labor market outcomes. In high school, relatively older boys make more friends—particularly with girls—and are more likely to become class president. These social advantages persist. In adulthood, relatively older men build

[22]Data on entrepreneurship comes from Fluegge and Bailey (2024), which identifies firm founders by linking their Facebook Business Page to third-party data on U.S. establishments using name, location, and publicly available contact information. Data on academic scientists comes from the *American Men and Women of Science*, a comprehensive directory of leading U.S. and Canadian scientists. Refer to the Data Appendix for more details.

[23]While the AMWS directory provides raw counts of scientists rather than individual probabilities, we know that the underlying population of births is approximately continuous across the kindergarten cutoffs. Therefore, the observed percentage drop in total scientist counts equivalently represents a drop in the individual likelihood of becoming a prominent scientist.

[24]While scientific collaboration is common, academia rewards individual contributions more than other professions like entrepreneurship, where relationship-building is central to success.

larger and more connected networks, and are more likely to be married. These persistent differences in social skills are also reflected in career choices, with relatively older men disproportionately sorting into management and business roles that demand strong social skills. These results suggest that small age differences within school cohorts can have lasting effects on economic outcomes through the mechanism of social capital formation.

To assess the external validity of our results, we test whether these findings replicate in six OECD countries with high-rates of Facebook usage and a uniform kindergarten entry cutoff: Canada, Finland, Japan, Norway, Sweden and the United Kingdom. Figure A-5 in the Online Appendix shows that relative age effects on social capital replicate across all six countries, with relatively older men having 3–5% larger social networks in each. This consistency is important for two reasons. First, it underscores that what matters is being older than one's peers, not the exact age when school starts. Kindergarten begins at age 5 in Canada and the United Kingdom, age 6 in Japan and Norway, and age 7 in Finland and Sweden (Bedard and Dhuey, 2006). And second, it suggests that relative age effects on social capital are a universal feature of childhood social development for boys, which may help explain the well-documented over-representation of relatively older individuals in politics and leadership roles across countries.

From a policy perspective, our findings are particularly relevant for determining rules around school entry. In the U.S., some parents deliberately delay their child's school entry, a practice known as "redshirting", to ensure their child will be among the oldest in class. Prior research has shown that this practice is highly unequal, with white and high-income families substantially more likely to redshirt their (male) children (Bassok and Reardon, 2013). Our results suggest that this practice may widen inequality, through its persistent effects on social capital and career outcomes.

Given these equity concerns, some policymakers have proposed reforming school entry rules. One prominent suggestion is to delay kindergarten entry for all boys by one year (Reeves, 2022). However, such a policy is unlikely to eliminate the relative age advantage, as students would still vary in age within their new cohorts.[25] More promising approaches might focus directly on helping younger students build social connections, through encouraging participation in extracurricular activities and leadership opportunities.

[25]There may be other reasons to delay school entry for boys, such as developmental readiness, even if this would not close the gap in social capital between the oldest and youngest boys in a class.

Several important questions remain for future research. How do relative age effects vary with student demographics or school characteristics? Does the social capital mechanism help explain why relative age has been associated with improved health and well-being? And how do the social advantages of being relatively older interact with early differences in cognitive and academic development that have been shown in prior work? Answers to these questions may help design better policies to support relatively younger students in the classroom and beyond.

Data Appendix

Facebook Data

Sample Construction

Our analysis sample consists of U.S. Facebook users who have been active on the platform in the last 30 days prior to April 21, 2026. We restrict to users born between 1983 and 1997, who attended high school in a state with a uniform kindergarten entrance cutoff. We also exclude users born on the following dates to avoid measurement error in the running variable arising from misreporting: 1/1, 2/29, 4/1 and 4/20. The final sample consists of 33 million users, which corresponds to a coverage rate of more than 50% of the true population.

Variable Definitions

High School: We follow the methodology in Chetty et al. (2022) to identify the high school that each user attended based on self-reports and graph-based imputation.
High School Friends: The number of friends on Facebook who attended the same high school in the same or adjacent cohorts.
High School Clubs: A binary variable indicating whether the user is a member of a Facebook group related to a specific type of high school club. These groups are identified by matching regular expressions containing 'club', 'team', 'squad', 'society', 'group' and 'association'. We exclude groups containing 'alumni' or 'graduates' in the name, and restrict to groups with fewer than 50 members. Club types include sports teams (basketball, football and soccer), band, choir and drama. We further require users to have joined these groups prior to age 18.
High School Leadership: A binary variable indicating whether the user is a member of a Facebook group related to high school leadership. These groups are identified by matching regular expressions containing 'student council', 'school council', 'student government' or 'student leadership'. We further require users to have joined these groups prior to age 18.
Occupation: We clean self-reported job titles before fuzzy string matching them to over 800 Standardized Occupation Codes (SOCs). Cleaning involves removing special characters, translating (if necessary), converting to lowercase, and removing common stop words. We fuzzy match these cleaned job titles to the Alternate Titles listed in the O*NET (Version 28.1) database using the *token sort ratio* algorithm from the fuzzywuzzy package in Python. We drop matches with a score below 75 and retain the highest scoring match for each self-reported job title.

School Entry Cutoff Dates

For the United States, data on the timing of school entry by state from 1940 onward was generously provided by the authors of Dhuey and Lipscomb (2008). We match users to a state based on the state in which they attended high school. We exclude states with non-uniform cutoff dates (i.e., where thekindergarten entrance date varies by school district) and years with missing data.

For the other OECD countries we analyze, we use the cutoff dates from Bedard and Dhuey (2006): January 1 for Canada, Finland, Norway and Sweden, April 1 for Japan, and September 1 for the United Kingdom.

High School Characteristics

Data on high schools and their characteristics are publicly available from the National Center for Education Statistics (NCES), the primary federal entity for collecting data from U.S. high schools. We obtain measures of the total number of students in grades 9 through 12, the percent of students eligible for free or reduced lunch (in public schools), and racial shares (Black, White, Asian, Hispanic and Native American) from the 2017-18 Common Core of Data and Private School Universe Survey.

Occupation Characteristics

We use the O*NET database (Version 28.1) to characterize the skills and tasks required in different occupations. Using this data, we replicate the ten indices used in Deming (2017), standardized with a mean of 0 and a standard deviation of 1.

- Social Skills: Measures a person's ability to understand others' reactions, coordinate with others, persuade, and negotiate.
- Interact: Captures how well an individual can explain information to others, communicate within and outside their organization, and build relationships.
- Coordinate: Assesses the ability to organize and direct the activities of a team or group to accomplish tasks.
- Reasoning: Measures the ability to comprehend written material and apply logical thinking to solve problems.
- Number Facility: Assesses a person's proficiency in basic arithmetic operations like adding, subtracting, multiplying, or dividing.
- Information Use: Evaluates how well an individual gathers, processes, and analyzes information to solve problems.
- Non-routine Analytical: Captures the capability to solve complex problems that require creative or analytical thinking.
- Service: Measures the tendency to care for others and seek ways to help people.
- Routine: Assesses the degree to which a job involves repetitive tasks and the level of automation.
- Req. Social Interaction: Captures how often a job requires face-to-face or other forms of communication with others.

External Occupation Data

Entrepreneurship

Data on entrepreneurship comes from Fluegge and Bailey (2024). Entrepreneurs are identified in the Facebook data through a matching process that links users' self-reported job titles and employers on their Facebook profiles to business pages. Specifically, users who list a Facebook page as their employer and include terms like "founder," "owner," or "CEO" in their job titles are identified as potential firm owners. To validate these inferences, candidate business pages are linked to third-party data on U.S. establishments using name, location, and publicly available contact information. This method successfully identifies about 695,000 firm founders.

American Men and Women of Science (AMWS)

The American Men and Women of Science (41st edition) profiles the careers of over 200,000 U.S. and Canadian-based scientists. Entries are limited to those who have made significant contributions in their field. For each individual, the AMWS provides information on their field of study, institutional affiliations, professional accomplishments and demographics (place and date of birth). We restrict the sample to scientists who are born in the United States in 1940 onward because we do not have information on the cutoff dates for school entry in earlier years. The final sample consists of 27,000 scientists across various fields.

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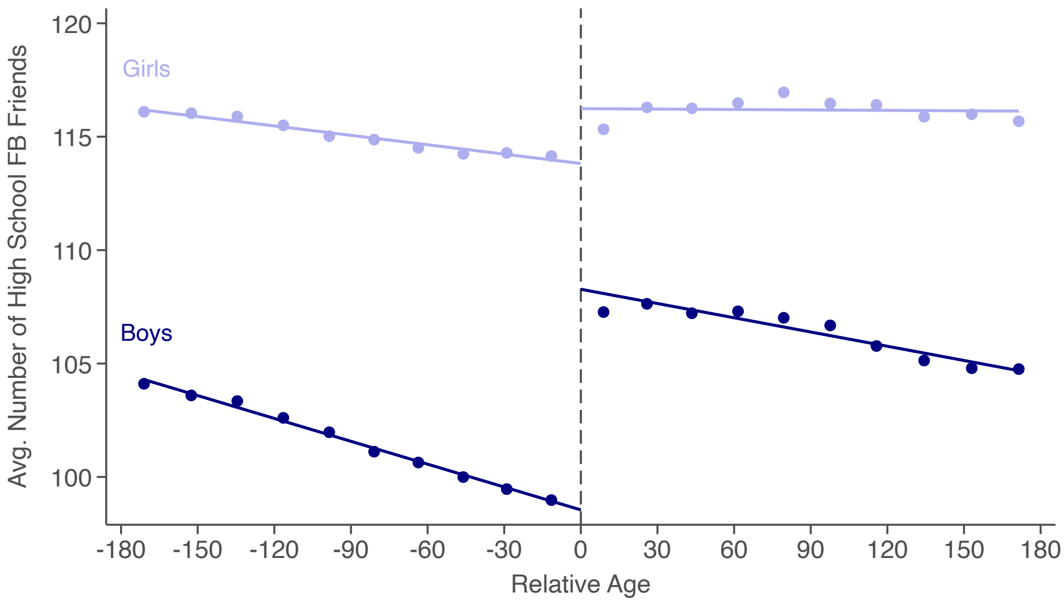
TABLE 1: SUMMARY STATISTICS

Variable	Sample: All	Males	Females	RD Estimates: Control Mean	ITT
	(1)	(2)	(3)	(4)	(5)
A. Demographics					
Birth Cohort	1990.372	1990.444	1990.310	1990.558	-0.826
	(4.183)	(4.161)	(4.201)		(0.131)
Parent Income Percentile	54.723	53.596	55.706	54.402	-0.118
	(26.902)	(27.254)	(26.552)		(0.096)
B. High School Characteristics					
Fraction Free/Reduced Lunch	0.488	0.486	0.489	0.491	0.001
	(0.244)	(0.243)	(0.245)		(0.002)
Fraction Students White	0.528	0.533	0.525	0.528	-0.001
	(0.318)	(0.318)	(0.319)		(0.004)
C. Platform Usage					
Days Active in Last 28 Quintile	3.000	2.917	3.070	3.011	0.001
	(1.414)	(1.434)	(1.393)		(0.006)
Relationship Status Listed	0.831	0.826	0.836	0.830	0.004
	(0.375)	(0.379)	(0.370)		(0.002)
Current City Listed	0.831	0.841	0.823	0.833	0.001
	(0.375)	(0.366)	(0.382)		(0.001)
Hometown Listed	0.811	0.818	0.805	0.810	0.003
	(0.391)	(0.386)	(0.396)		(0.001)
Occupation Listed	0.335	0.319	0.348	0.333	0.002
	(0.472)	(0.466)	(0.476)		(0.002)
Sum of Fields Listed	2.809	2.804	2.813	2.807	0.010
	(1.001)	(0.994)	(1.006)		(0.005)
D. McCrary Density Test					
Density				0.288	-0.017
					(0.001)
Observations	33.174 M	15.230 M	17.944 M		

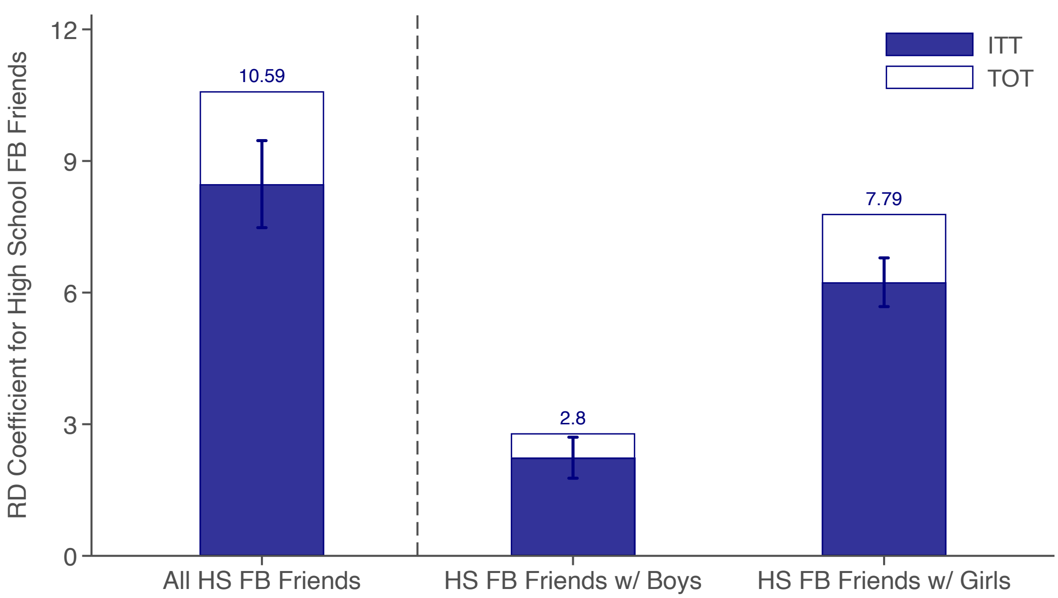
Notes: This table shows summary statistics and balance tests for the analysis sample. To be included, users must be born between 1983 and 1997, be active on the platform in 30 days prior to April 21, 2026, and have attended high school in a state with a uniform kindergarten entrance cutoff. Columns 1-3 report means and standard deviations (in parentheses) for three groups: all users, male users and female users. Columns 4-5 report estimates from the fuzzy regression discontinuity specification in Equation 1 using the full sample. Column 4 reports the control mean for users just below the cutoff, while Column 5 reports the ITT coefficient and standard error (in parentheses). The running variable is relative age, measured in days relative to the kindergarten entry cutoff date. Standard errors are clustered by the state of the high school.

FIGURE 1: HIGH SCHOOL SOCIAL CAPITAL

A. High School Friends



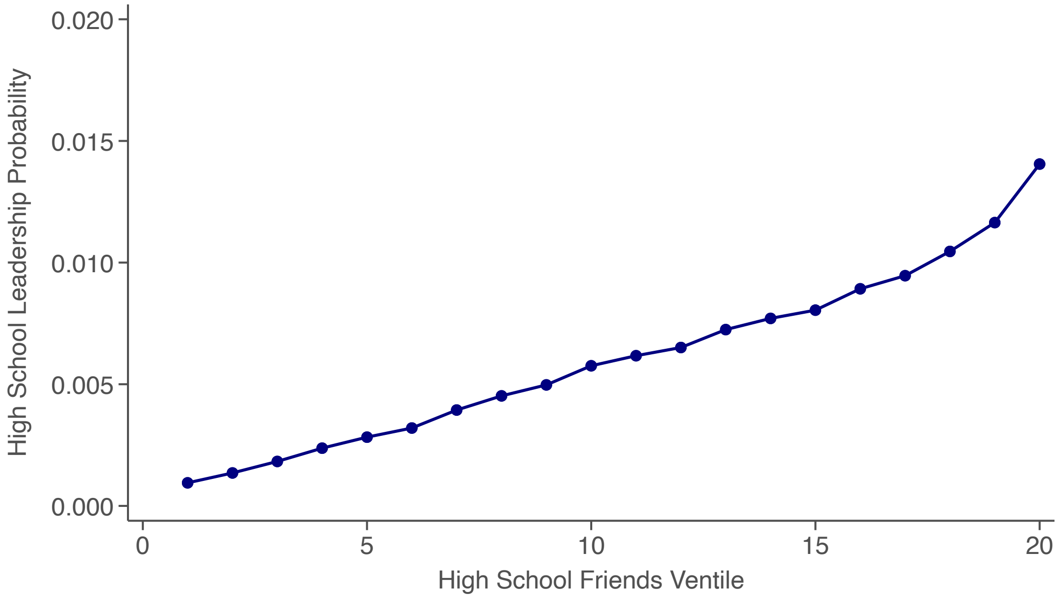
B. Among Boys



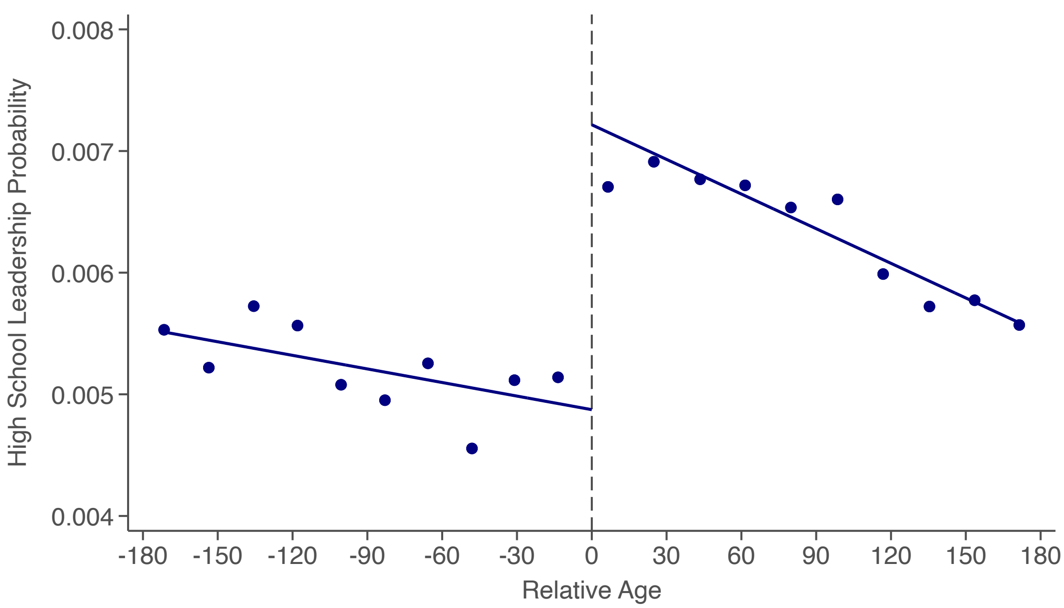
Notes: This figure documents high school friendship patterns by relative age and gender. In Panel A, the x-axis represents relative age (R_i), measured in days relative to the school entry cutoff date ($R_i = 0$). The y-axis shows the average number of friends on Facebook who attended the same high school in the same or adjacent cohorts. Panel B shows the RD coefficients from the specification in Equation 2 estimated on boys only for three different sets of friends: (1) all, (2) boys and (3) girls. 95% confidence intervals are shown in the intervals, and the rescaled treatment on the treated estimate (TOT) is shown in the white bars.

FIGURE 2: HIGH SCHOOL LEADERSHIP

A. Probability of Leadership by Friends Ventile

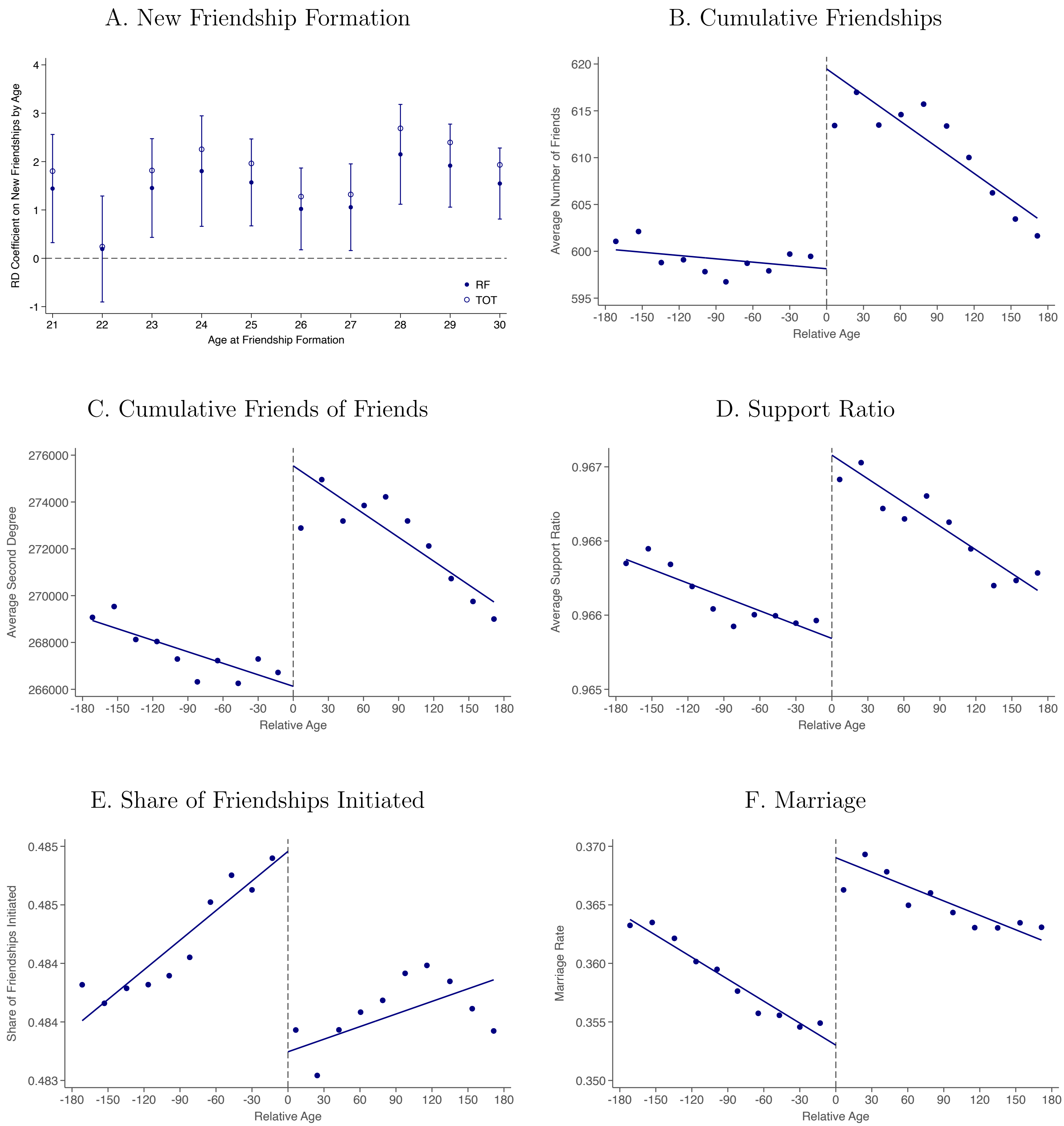


B. Leadership by Relative Age



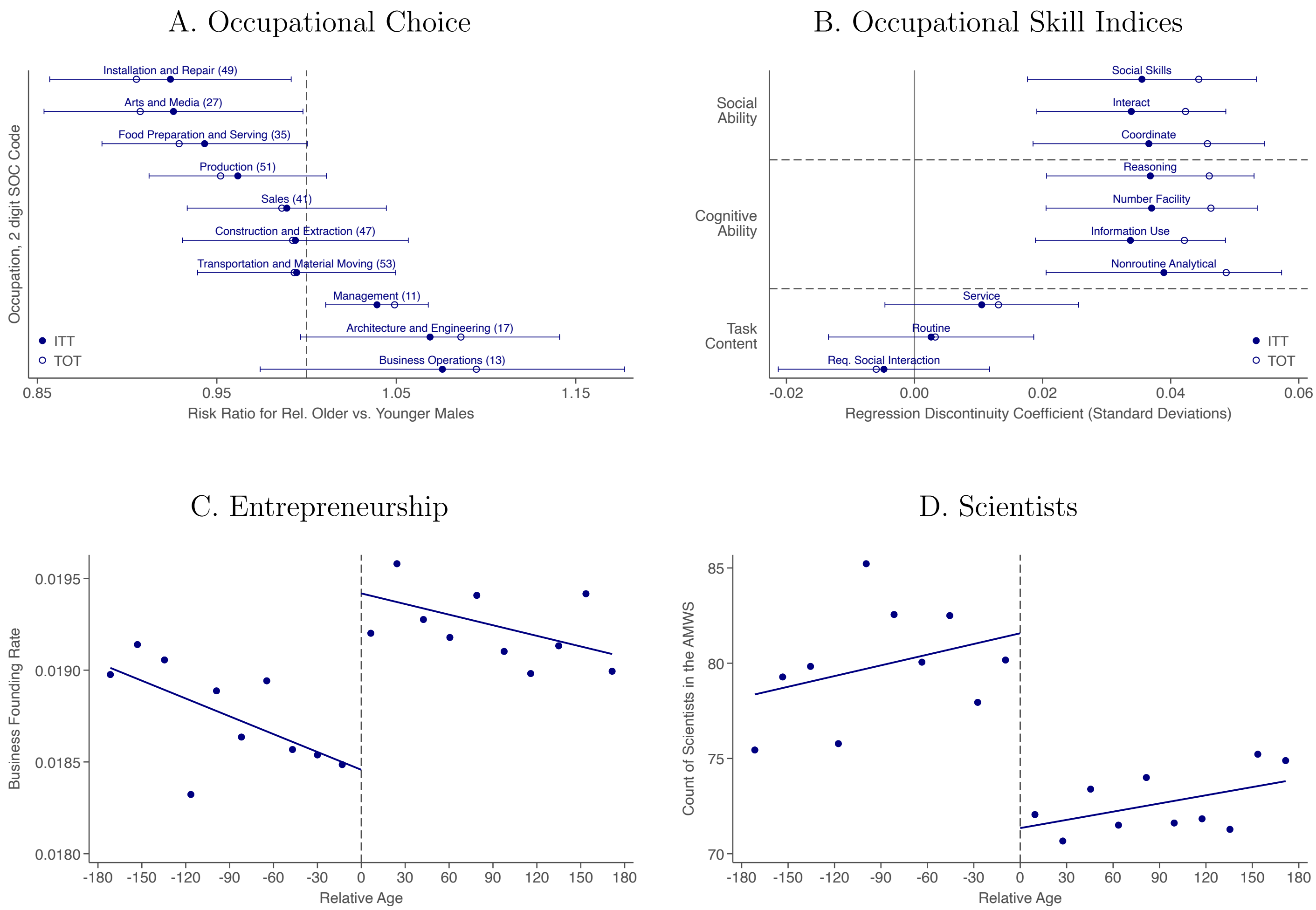
Notes: This figure examines the likelihood of holding a leadership position in high school among boys. In both panels, leadership is proxied by membership of Facebook groups related to leadership (those containing one of the following leadership-related keywords in the group name: 'student council', 'school council', 'student government' or 'student leadership'), and the sample is restricted to groups joined by users prior to age 18. Panel A plots the probability of being in a leadership group against ventiles of the number of high school friends within the same or adjacent cohorts. Panel B shows the average probability of being in a leadership group by relative age.

FIGURE 3: ADULT SOCIAL CAPITAL



Notes: This figure shows six measures of social capital among men by relative age. Panel A shows RD coefficients for the average number of new friendships formed by age. Panel B shows the cumulative number of friends as of April 21, 2026. Panel C shows the cumulative number of friends of friends. Panel D shows the support ratio, or the fraction of a user's friends with whom they share at least one mutual connection. Panel E shows the share of total friendships initiated by the user. Panel F shows the marriage rate, as defined by the user's self-reported marital status on the platform.

FIGURE 4: OCCUPATIONAL SORTING



Notes: This figure analyzes the relationship between relative age and occupational choice among men. Panel A shows RD coefficients for various occupations, classified by 2 digit SOC codes. To aid interpretation, the coefficients are scaled as risk ratios by normalizing each coefficient by the intercept. Panel B shows RD coefficients for ten occupational indices derived from O*NET (Version 28.1) data following Deming (2017), and which are defined in the Data Appendix. Panel C shows the shows rate of entrepreneurship by relative age, drawing on data from Fluegge and Bailey (2024). Panel D shows counts of prominent scientists from the *American Men and Women of Science* (41st edition), who were born in the US from 1940 onward.

Online Appendix

Who Leads? Relative Age Effects on Social Capital

Matthew Jacob and Mike Bailey

APPENDIX TABLE A-1: HIGH SCHOOL SOCIAL CAPITAL

	Boys			Girls		
	Control Mean	ITT (1)	ITT (2)	Control Mean	ITT (3)	ITT (4)
A. HS Friends in Adj. Cohorts						
Num. HS Friends	98.958	8.472	9.722	114.045	0.402	0.488
		(0.505)	(0.784)		(0.580)	(0.743)
Num. Male HS Friends	47.666	2.236	2.642	47.134	-1.396	-1.304
		(0.238)	(0.378)		(0.261)	(0.336)
Num. Female HS Friends	51.293	6.236	7.079	66.911	1.798	1.792
		(0.283)	(0.436)		(0.330)	(0.433)
B. All HS Friends						
Num. HS Friends	151.799	6.620	8.365	168.196	1.042	1.605
		(0.700)	(1.116)		(0.823)	(1.074)
Num. Male HS Friends	70.811	2.027	2.636	70.838	-0.503	-0.235
		(0.319)	(0.526)		(0.376)	(0.491)
Num. Female HS Friends	80.988	4.593	5.728	97.358	1.545	1.840
		(0.405)	(0.642)		(0.463)	(0.622)
Observations in Bandwidth		1.260 M	1.260 M		1.467 M	1.467 M
Controls		No	Yes		No	Yes
Quadratic Running Variable		No	Yes		No	Yes

Notes: This table shows the RD estimates (ITT) of the effect of relative age on the number of high school friends. Panel A reports estimates for friends made in the same or adjacent cohorts, while Panel B includes all friends. For each outcome, columns (1) and (2) show results for boys, while columns (3) and (4) show results for girls. The baseline specification is shown in columns (1) and (3). Columns (2) and (4) add fixed effects for high school state, birth cohort, birth month, and FB usage quintiles, as well as a quadratic polynomial in the running variable. Standard errors clustered by state x birth cohort are shown in parentheses below the coefficients, and the unconditional mean for relatively young individuals is reported in the Control Mean column.

APPENDIX TABLE A-2: HIGH SCHOOL LEADERSHIP

	Boys			Girls		
	Control Mean	ITT (1)	ITT (2)	Control Mean	ITT (3)	ITT (4)
Leadership	0.488	0.166	0.212	0.836	0.235	-.0495
		(0.076)	(0.149)		(0.0941)	(0.165)
Natl. Honor Society	0.609	0.572	0.755	1.44	0.27	0.832
		(0.151)	(0.249)		(0.157)	(0.3)
Observations in Bandwidth		0.197 M	0.197 M		0.246 M	0.246 M
Controls		No	Yes		No	Yes
Quadratic Running Variable		No	Yes		No	Yes

Notes: This table shows the RD estimates (ITT) of the effect of relative age on holding a leadership position in high school. *Leadership* is an indicator variable for membership of a student leadership group on Facebook. *Natl. Honor Society* is an indicator variable for membership of a National Honor Society chapter on Facebook. For each outcome, columns (1) and (2) show results for boys, while columns (3) and (4) show results for girls. The baseline specification is shown in columns (1) and (3). Columns (2) and (4) add fixed effects for high school state, birth cohort, birth month, and FB usage quintiles, as well as a quadratic polynomial in the running variable. Standard errors clustered by state x birth cohort are shown in parentheses below the coefficients, and the unconditional mean for relatively young individuals is reported in the Control Mean column. Control means and ITT estimates are reported in percentage points to aid readability for these low-incidence outcomes.

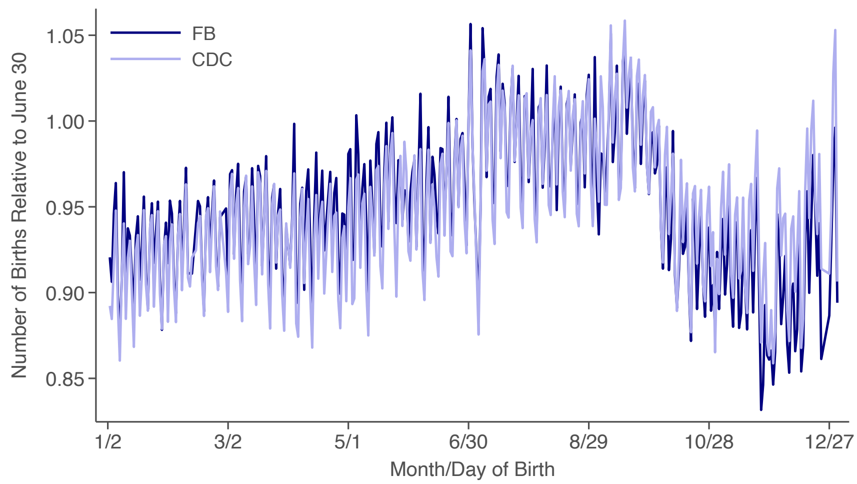
APPENDIX TABLE A-3: ADULT SOCIAL CAPITAL

	Men			Women		
	Control Mean	ITT (1)	ITT (2)	Control Mean	ITT (3)	ITT (4)
Frac. Friendships Init.	0.485	-0.003	-0.004	0.480	-0.001	0.000
		(0.001)	(0.001)		(0.000)	(0.001)
Married	0.357	0.012	0.000	0.414	0.012	-0.001
		(0.004)	(0.004)		(0.003)	(0.004)
Num. Friends	600.996	17.131	6.458	654.227	6.173	7.881
		(4.257)	(5.192)		(3.536)	(4.249)
Num. Friends of Friends	2.68e+05	6303.902	1103.063	2.90e+05	3627.784	2699.904
		(2044.531)	(2461.245)		(1702.367)	(2075.223)
Support Ratio	0.966	0.001	0.000	0.965	0.001	0.001
		(0.000)	(0.000)		(0.000)	(0.000)
Observations in Bandwidth		1.150 M	1.150 M		1.365 M	1.365 M
Controls		No	Yes		No	Yes
Quadratic Running Variable		No	Yes		No	Yes

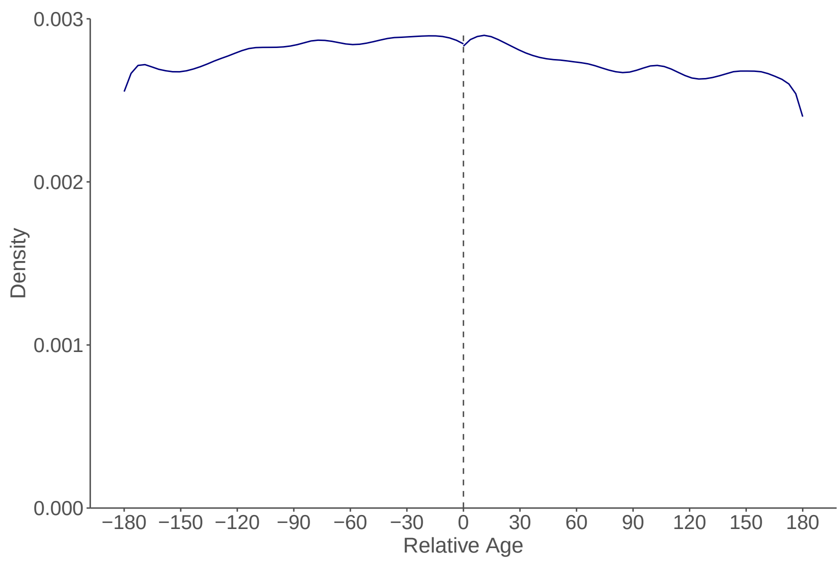
Notes: This table shows the RD estimates (ITT) of the effect of relative age on adult social capital. *Frac. Friendships Init.* is the fraction of a user's total friendships that they initiated. *Married* is an indicator for being married, based on self-reported marital status. *Num. Friends* is the total number of Facebook friends as of April 21, 2026. *Num. Friends of Friends* is the total number of second-degree connections. *Support Ratio* is the fraction of a user's friends with whom they share at least one mutual connection. For each outcome, columns (1) and (2) show results for men, while columns (3) and (4) show results for women. The baseline specification is shown in columns (1) and (3). Columns (2) and (4) add fixed effects for high school state, birth cohort, birth month, and FB usage quintiles, as well as a quadratic polynomial in the running variable. Standard errors clustered by state x birth cohort are shown in parentheses below the coefficients, and the unconditional mean for relatively young individuals is reported in the Control Mean column.

APPENDIX FIGURE A-1: RUNNING VARIABLE VALIDATION

A. Validation of Running Variable



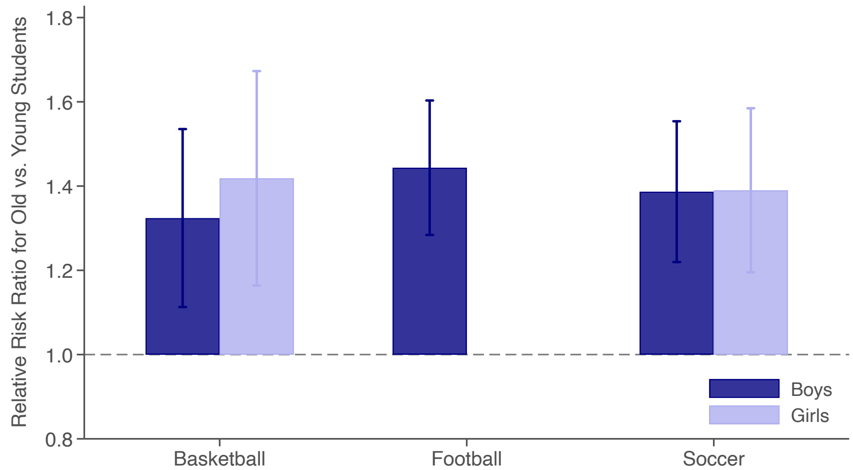
B. Density of Running Variable



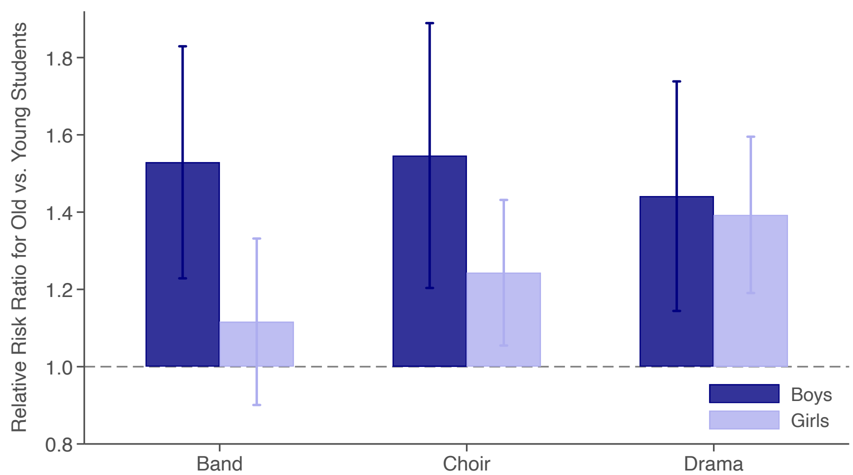
Notes: Panel A compares birth counts by day of the year from Facebook and the CDC Vital Statistics for individuals born between 1994 and 1998. The x-axis represents the day of the year, and the y-axis shows the number of births normalized to the value on June 30. Panel B shows the density of the running variable, relative age, around the cutoff, calculated using the *rddensity* package in R.

APPENDIX FIGURE A-2: HIGH SCHOOL SPORTS AND CLUBS

A. Sports



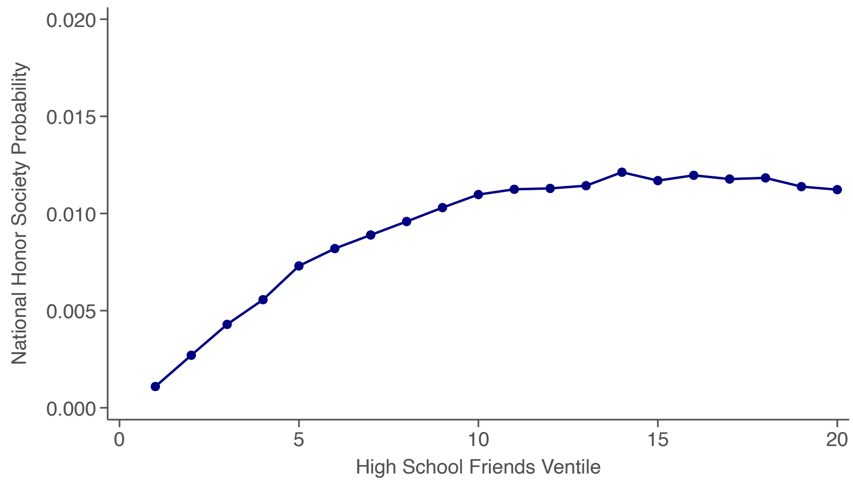
B. Clubs



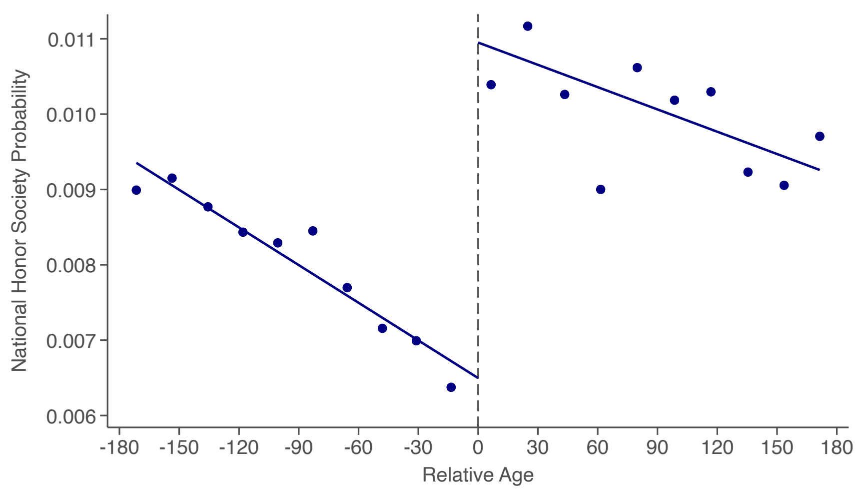
Notes: This figure shows the average participation rate in sports teams and clubs by relative age. Boys are shown in dark blue and girls are shown in light blue. Participation is proxied by membership of Facebook groups, as outlined in the Online Appendix. Panel A looks at participation in sports while Panel B looks at extracurricular groups. To aid interpretation, the RD coefficients are scaled as relative risk ratios by normalizing each coefficient by the intercept. 95% confidence intervals are shown in the intervals.

APPENDIX FIGURE A-3: NATIONAL HONOR SOCIETY

A. Probability of National Honor Society by Friends Ventile



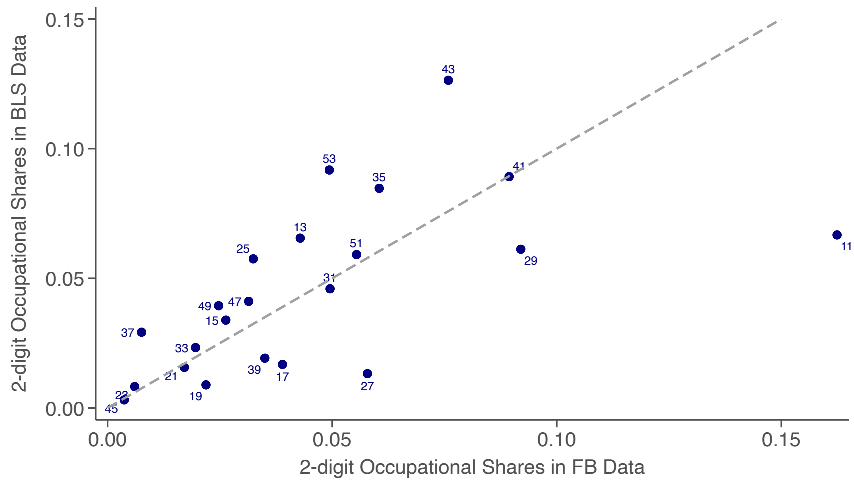
B. National Honor Society Membership by Relative Age



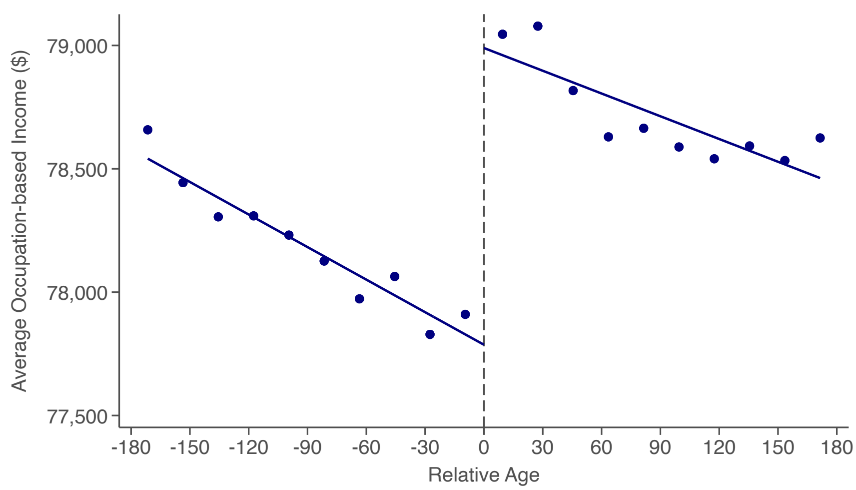
Notes: This figure replicates Figure 2, using membership of the *National Honor Society* (NHS) to proxy for high school leadership. Participation in the NHS is inferred from membership in Facebook groups joined prior to age 18 and which contain the phrase 'National Honor Society' in the group name. Panel A plots the probability of being in the NHS group against ventiles of the number of high school friends within the same or adjacent cohorts. Panel B shows the average probability of being in the NHS by relative age.

APPENDIX FIGURE A-4: FACEBOOK OCCUPATION DATA

A. Occupation Validation

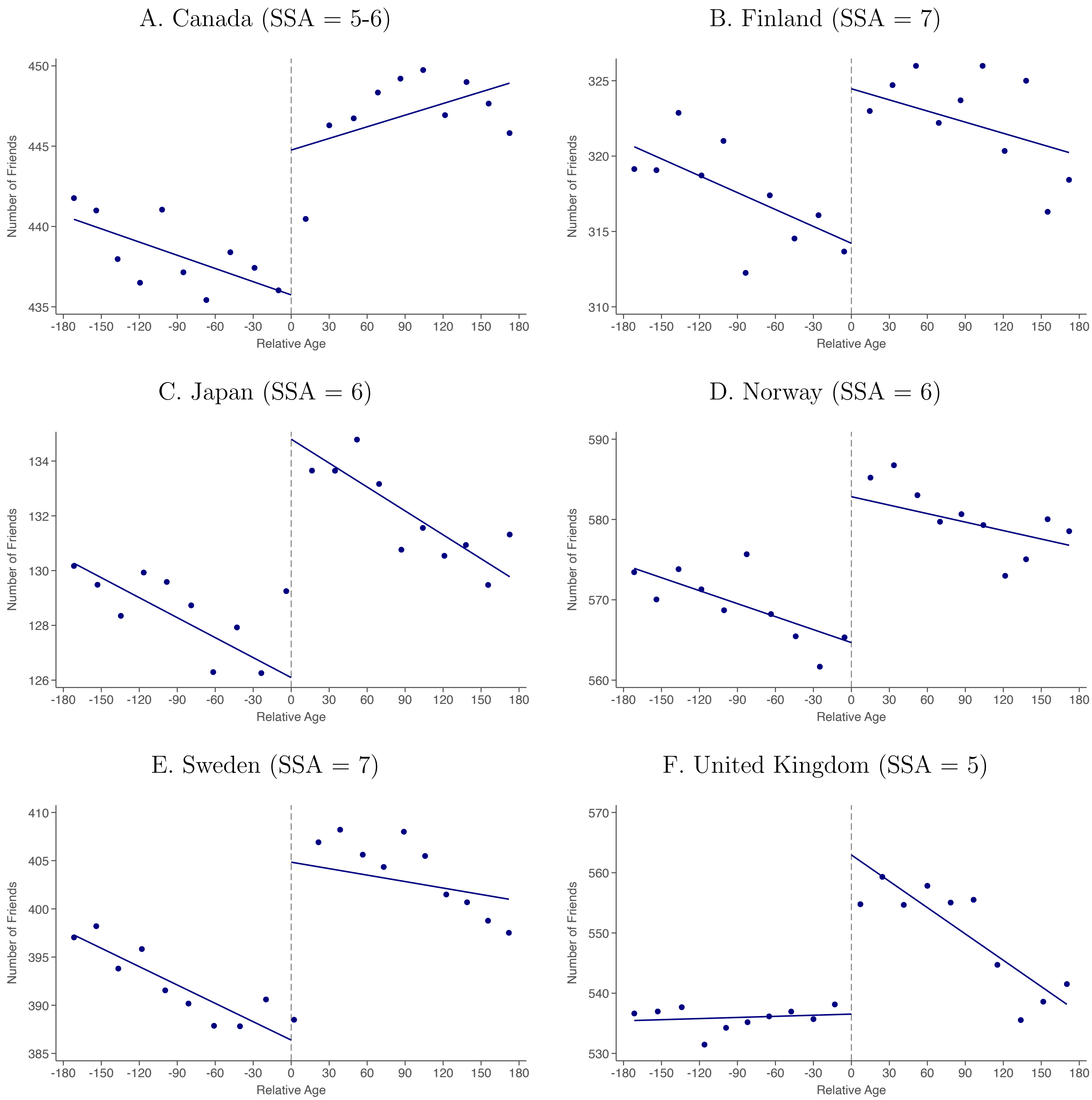


B. Occupational Income RD



Notes: Panel A shows the distribution of 2-digit SOC Major Groups on Facebook vs. the Bureau of Labor Statistics Occupational Employment and Wage Statistics (May, 2022). Each self-reported occupation on Facebook is matched to a SOC Major Group using a fuzzy matching algorithm as described in the Online Appendix. The dashed grey line represents the 45-degree line. Panel B shows the relationship between relative age and occupational-income. This income measure is calculated by merging average incomes by occupation from the Bureau of Labor Statistics to self-reported occupations on the platform.

APPENDIX FIGURE A-5: RELATIVE AGE EFFECTS ACROSS COUNTRIES



Notes: This figure shows the relative age effect on adult social capital across six OECD countries with different school starting ages (SSAs). In each panel, the country name and SSA are shown in the title. The series are restricted to male users born between 1983 and 1997 who have a predicted home-location in each listed country. The x-axis represents relative age, measured in days relative to the country-specific school entry cutoff date. The y-axis shows the average number of friends (within-country) on Facebook, measured as of April 21, 2026.