No Kid Is an Island: Intergenerational Mobility and Peer Effects

Preliminary draft, please do not circulate.

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Abstract

This paper investigates the influence of exposure to schoolmates from different family backgrounds on children's intergenerational mobility. Using administrative data on Danish students born between 1980 and 1988, I find that that a one standard deviation increase in average schoolmates' parental earnings results in a 2.89% increase in lifetime earnings for low SES children. Moreover, I find the relation of the effect with parental background to be U-shaped, with children from average parental background being unaffected and those from high-SES families experiencing similiar effects as those from low-SES families. When educational attainment and labor market participation are considered, I find that children exposed to better peers increase their educational achievements and their chances to be employed in high paying occupations and to cover managerial positions. Further, I decompose the portion of the effect due to spillovers in human capital formation from peer effects and parental influences on the labor market. I find that spillovers in human capital formation are offset by increased competition from higher human capital schoolmates, while netowork advantages inherited from former schoolmates explain most of the effect. Overall, these results provide evidence on the joint nature of social mobility: children climb the earnings' ladder with respect of their parents, and in doing so, their peers play a crucial role.

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1 Introduction

Parental income and investments are crucial for children's human capital formation and skills' development (Becker and Tomes, 1979; Cunha and Heckman, 2007; Carneiro et al., 2021). At the same time, as members of neighborhoods and schools, children influence each other through peer effects (Epple and Romano, 2011; Sacerdote, 2011). As a consequence, the connection between exposure to peers and transmission of inequalities across generations might play a crucial role in determining access to opportunities.

This hypothesis is supported by several facts. First, families vaule high-achiving peers when choosing neighborhoods (Eshaghnia et al., 2023) and schools (Abdulkadiroglu et al., 2020) for their kids. Second, heterogeneity in relative social mobility across neighborhoods (Chetty et al., 2014), along with evidence on the beneficial effects of moving a child away from disadvantaged locations (Chetty and Hendren, 2018; Chyn, 2018; Chetty et al., 2016) have established the importance of neighborhoods for access to opportunities[1]. Finally, Chetty et al., 2022, documents a strong association between social connectedness to high-SES individuals and upward economic mobility.

In this paper, I test whether and how exposure to schoolmates from different parental backgrounds affect children lifetime economic outcomes. Intuitively, I account the process of intergenerational transmission of inequalities to be interdependent across households: each child is influenced by her parents, her peers, and potentially peers' parents too. Leveraging on rich administrative data from Denmark, I focus on the transmission of earnings inequality and I investigate whether this exposure effect exists and through which channel (human capital spillovers vs network effects) is at play.

While the hypothesis of *purposive sorting* (Heckman and Landersø, 2022) with parents anticipating peer effects for their offsprings when choosing neighborhoods and schools has been formulated in the literature, different causal mechanisms might define the structure of such influence. For example, a child might be affected by spillovers in human capital formation as a consequence of being schooled with schoolmates from higher earnings families. This might be the case if high-SES children are disproportionately higher-achieving peers or better role models. However, high-SES peers might provide an advantage because of theit (or thier parents') connections resulting in more

[1] see Mogstad and Torsvik, 2021 and Chyn and Katz, 2021 for a review of the literature on *neighborhood effects*.

valuable referrals or employment opportunities on the labor market. Finally, children from different parental backgrounds might be affected differently from each of the channles outlined above.

To address these questions, I use administrative data on the universe of Danish children born between 1980 and 1988. For those cohorts, I document two motivating facts: significant intergenerational persitence in pre-tax earnings and school segregation by parental earnings. Children's *inherit* their parents' earning levels and do so sorrounded by peers experiencing similar family backgrounds. As a consequence, if peer effects are at play, the effect of parental earnings on offsprings' earning potential might be amplified by the exposure to schoolmates who are experiencing a similar parental background.

To identify the causal impact of peers' parental background on access to opportunities, I implement a within-school across-cohorts design (Hoxby, 2000; Black et al., 2013; Carrell et al., 2018; Brenøe and Zölitz, 2020). In doing so, I restrict the comparison among students who attended the same high school in different cohorts. This addresses the primary concern for identification: endogenous sorting into peer groups. The main assumption is that parents do not internalize cohort-specific deviations from the school secular trend in school composition due to lack of coordination in timing of births and relevants costs in manipulating entry into school. To support this assumption, I document that peers' parental earnings residuals, after controlling for school-specific time trends, are uncorrelated with children's parental earnings. A furhter concern revolves around unobserved contextual factors being potentially correlated with school composition and individual outcomes. However, fluctuations in local economic conditions are unlikely to be driving the results, given the robustness of the results to the inclusion of cohort-by-municipality fixed effects. Moreover, I argue that it is unlikely that families have perfect foresight on cohort-specific deviations from secular trends in determinants of school effectiveness (eg.: teacher hiring, infrastructure) before enrollment. This assumption is validated by the estimates not being affected from the inclusion of highly nonlinear school-specific time trend and other school observables (cohort size, gender composition) being uncorrelated with students' parental backgrounds.

To decompose the role of spillovers in human capital from network effects on the labor market, I develop a model encompassing both processes. Resuming to a linear-in-means model as in Manski, 1993 allows me to express the reduced form estimate of the impact of peers' parental background as the sum of four different mechanisms. Initially, Earnings are affected by increases in human capital due to *spillovers while in school*. Upon employment, earnings are influenced by own and peers' human capital levels (*spillovers after school*), by peers' success (*schoolmates' network*) and own parents' and peers' parents' (*schoolmates' parents' network*) influence on the labor market.

To achieve identification of the model, endogenous sorting and simoultaneity issues extensively explored in the literature (Manski, 1993) must be addressed. Accounting for school-specific time trends allows me to deal with endogenous sorting reliying on the same assumption outlined above. However, I am still left with the impossibility to separately identify the impact of a peer's characteristics (parental earnings or human capital) from the impact of the same peer achieving better outcomes (education or earnings), since the former are conducive of the latter. As far as human capital accumulation is concerned, I do not distinguish the two effects[2]. Thus, *spillovers while in school* are estimated as the combined influence on educational achievement due to direct exposure to higher-SES parents and to their children, who achieve higher levels of education themselves.

To separately identify the effect of more successful former schoolmates on the labor market from exposure to their higher human capital, I exploit variation in earnings due to former schoomates' coworkers' wages. Under the assumption that coworkers' wage affect the wage of a given individual[3] and former schoolmates of the same individual only though improvements in the wage of that individual, former schoolmates' coworkers' earnings serve as a valid instrument to identify the effect of changes in peers employment outcomes, conditional on their level of human capital. Exploiting a similar exclusion restriction to identify endogenous peer effects, my approach can interpreted as a partial population experiment Moffitt, 2001. Moreover, relying on peers (coworkers) of peers (former schoomates), I am reliying on the identification introduced by Bramoullé et al. (2009) and De Giorgi et al. (2010).

Finally, to distinguish the impact of parental earnings on human capital from that on earnings due to parental network effects, I exploit variation in parental earnings after children completed education due to parents' coworkers'. I argue that this is the rel-

[2] I am working in this direction exploiting non-overlapping peer groups due to exposure different primary schools for identification.

[3] peer effects on the workplace are extensively documented in the literature, see for example: Mas and Moretti, 2009 and Cornelissen et al., 2017.

evant variation: conditional on two parents having access to the same earnings while their kids were accumulating human capital, I identify the impact of them being linked to coworkers who fare better (or worse) when their kids are on the labor market themselves.

I find that a one percentile increase in schoolmates' parental earnings results in a 0.06 percentiles' increase in earnings between the age of 28 and 32. This accounts for one third of the residual correlation between childrens' and parental earnings. Notably, I find significant heterogeneity of exposure effects, with the effect being 3 times larger than the averge for children of parents from the bottom quartile (low SES) and the top quartile of the earnings' distributions (high SES). The magnitude of these effects is such that increasing the average schoolmates' parental background by one standard deviation (11.35 percentiles) for children from low-SES families, increase their earnings by 3 percentiles, resulting in a 2.9% change in nominal terms.

Subsequently, I document the impact of being exposed to peers from more affluent families on education and labor market outcomes. For low SES children, I document that a one standard deviation increase in average schoolmates' parental earnings increases the probability of obtaining a college degree by 3.1% and the probability of being employed in managerial occupations by 4.9%. For these outcomes, the effect is decreasing in parental background, being close to zero for children from high-SES families.

To guauge the contribution of labor market network in driving the effect, I exploit plant-level employee-employer data to asses wheter the children in the sample joined a plant where a peer (or a peers' parent) was working before. I find that 1 student out of 3 (5) joins a plant where a former scholmate (a former schoolmate's parent) was previously employed. However, when I consider the effect of exposure to schoolmates from higher earnings families on the probability of joining a firm where a schoolmate (or a schoolmates parents) is previously employed, I find a no effect for anyone but children from the top of the parental earnings distribution. When exposed to one standard deviation in average schoolmates' parental earnings increases the probability of joining a plant where a schoolmate (a schoolmate's parent) by 9.2% (11.3%).

When decomposing the average effect[4] of exposing children to schoolmates from

[4] More work is ongoing to estimate this decomposition allowing for heterogeneity of effects based on parental background.

different parental backgrounds, spillovers in human capital formation while in school and network effects from former schoolmates' parents are found to be the main drivers of the mechanism. Namely, spillovers in human capital formation while in school account for 156.1% of the effect. However, this mechanism is then combined with two opposing forces: the higher educational achievemnts of schoolmates decreases earnings (–251.22% of the main effect) while positive network effects due to being in touch with former schoolmates and their parents when navigating the labor market account for 21.95% and 168.29% of the estimated exposure effect, respectively.

This paper complements existing literature on neighborhood effects and intergenerational mobility by proposing and testing a mechanism linking intergenerational mobility and peer effects. The hypothesis of local communities generating persistence of inequalities via local social spillovers finds some of the first formalizations in the work of Durlauf, 1996 and Benabou, 1993[5]. The empirical evidence on the heterogeneity in access to opportunities across geographical areas found in the US in Chetty et al. (2014) and replicated for other countries (e.g.: Deutscher, 2020 for Australia and Güell et al., 2018, Acciari et al., 2022 for Italy) where geographical differences in school quality are less remarkable than in the US, corroborated the hypothesis that there might be important factors other than quality of school and insitutions behind the observed heterogeneity[6]. Finally, Eshaghnia et al. (2023) documents a positive willingness to pay for neighborhoods with access to schools with higher achieving students in Denmark and Heckman and Landersø (2022). In a different context like the US (New York City), Abdulkadiroglu et al. (2020) document that families preferences for schools are not responsive to school effectiveness after controlling for school composition. With respect to this growing strand of literature, the main contribution of this paper is the identification of the causal effect of peer exposure on intergenerational mobility.

A further contribution of this paper is the joint consideration of the effect of peers on human capital and network employment opportunities. In doing so, my paper relates to well explored ideas in the literature of splillovers in the human capital accumulation

[5] Fogli and Guerrieri (2019) and Chyn and Daruich (2023) estimate models characterizing an economy in which local spillovers increase the returns to investment in education for children living in neighborhoods with higher levels of human capital to study the general equilibrium implications of such spillovers for social mobility and evaluate alternative policies such as the MTO program.

[6] Rothstein, 2019, analyzing the correlation between rates of intergenerational mobility and the relation between parental income and children's human capital concludes that one thir in the difference in access to opportunities across neighborhoods cannot be explained by variation in school quality, and suggests it might be explained job networks and local labor markets.

process (pioneered in this context by Benabou, 1993) and the value of social connections as potential referrals-providers on the labor market (an idea first formalized by Montgomery, 1994). When intergenerational mobility is considered, I see the findings of my paper as complementary to those of Dobbin and Zohar, 2023, who, looking at intergenerational mobility in Israel, highlights the role of parental background in granting access to higher paying firms. Moreover, Cattan et al. (2022) find that exposure to highschool classmates whose parents attended elite colleges increases the probability of attending the same institutions in Norway. For a sample of US children, Fruehwirth and Gagete-Miranda (2019) find that parental education of kidergarden schoolamtes increases educational achievements. Overall, these two papers suggest the importance of peers' parents in determining individual educational choices, highlighting the role of exposure to information about elite institutions and spillovers in human capital formation, respectively. Finally, Deutscher (2020) using data from Australia documents a positive peer effect of parental earnings among children born in the same zipcode which are qualitatively consistent with the main results of this paper, althought the focus on larger peer groups like zipcode-cohorts most likely drives the difference in the magnitude of our estimates.

Disentanglement of the role of human capital spillovers from that of network advantages contributes to the discussion on the determinants of inequalities due to participation in different peer groups in two different directions. On one side light is shed on the mechanism trhough which inequalities are replicated by differential exposure to peers, on the other side it is highlighted the necessity to consider schools and labor maket as playing an equally important, but distinguished, role in access to opportunities. This is crucial since the policymaker interested in fostering access to opportunities, should evaluate different set of policies and concerns when considering the role of spillovers in school and on the labor market.

The rest of the paper is organized as follows: section 2 presents descriptive statistics and the institutional framework, section 3 presents the reduced form identification design, section 4 presents the reduced form results, section 5 discusses the semi-structural model, section 6 prensents the estimation results and section 7 discusses the results while 8 concludes.

2 Sample and Institutional Framework

2.1 Sample Selection

Danish administrative registers covering the entire Danish population from 1980 to 2019 are primary data source of this paper. The sample construction relies on linking children to their respective parental backgrounds. To this end, demographic details, including family linkages links, are extracted from the register of households and families (FAIN). Subsequently, each individual is matched with their occupational history, obtained from matched employee-employer data (IDAN and IDAP), as well as their lifetime earnings profile from tax registers (IND). Additionally, information about educational attainment and school attendance is derived from the register of education (UDDA). All the data contained within these registers is collected annually by the central statistical office of Denmark (DST).

The main sample used in this study includes individuals born between 1980 and 1988. The selection of this specific time interval is driven by the availability of information on earnings at the age of 32 for the 1988 cohort, serving as the most recent observation point. I exclude later cohorts due to potential fluctuations in earnings throughout the life cycle which may arise from ongoing educational pursuits during the latter part of the twenties, and could potentially impact the estimation of children's lifetime earnings. Within the designated cohorts of interest, the registers record a total of $791,612$ children. Out of those, $245,052$ who lack parental linkage are excluded. Moreover, children who entrolled in highschool before the age of 14 or after the age of 18 ($50,320$), as well as $45,617$ individuals lacking a school identifier, are dropped from the analysis. Furthermore, $10,033$ children who are not present in the registers upon reaching the age of 30, and 91 cases with missing data on parental earnings, are also excluded. The final sample consists of $440,499$ children. The main characteristics of the sample are summarized in Table 1, while Table 2 reports the main features of the $15,208$ school-cohorts groups across which the children are distributed[7]. The subsequent paragraph provides a detailed description of the key variables employed in the analysis.

[7] $2,313$ schools are included in the sample.

Table 1: Children Summary Statistics

	mean	sd	count
Earnings 28-32, kid	41,211.75	25,645.89	427,831
Father's earnings when kid 0-18	54,796.50	39,654.67	420,586
Mother's earnings when kid 0-18	31,085.52	18,351.42	426,978
Parental avg earnings, kid 0-18	42,626.45	23,931.91	427,831
Rank of earnings 28-32, kid	50.44	28.97	427,831
Rank of avg parental earnings, kid 0-18	50.50	28.87	427,831
Log of earnings 28-32, kid	10.39	1.03	410,687
Log of avg parental earnings, kid 0-18	10.51	0.75	422,794
years of education, kid	13.95	2.41	427,831
years of education, father	12.59	3.36	420,888
years of education, mother	12.44	3.07	427,087
Employed as manager 2008-2016, kid	0.47	0.50	427,831
father among to 10% wages of the plant, (when kid in g 10)	0.28	0.45	270,247
mother among to 10% wages of the plant, (when kid in g 10)	0.15	0.35	285,190

Table 2: School-Cohort Groups Summary Statistics

	mean	sd	count
Cohort	2,001.66	3.13	11,619
School - Cohort size	36.82	85.66	11,619
Avg. parental earnings (USD)	34,836.71	15,869.67	11,619
Avg. parental earnings (percentiles)	39.18	21.70	11,619
Students from $\geq$ 2 mun.	0.68	0.47	11,619
Students from $\geq$ 2 par.	0.67	0.47	11,619

2.2 Variables' Description

Individual Earnings I measure earnings as the sum of employment earnings from the main occupation and self-employment before taxation (*erhvervsindk* in IDAN). I focus on the average earnings between the ages of 28 and 32. By selecting this specific period, I exclude the years when individuals are potentially in education, thereby minimizing potential distortions arising from variations in life-cycle earnings profiles.

Instead of relying on nominal earnings values, I use the percentile ranking of the average earnings measure relative to the distribution of children from the same cohort. By doing so, I abstract from changes in the variance of the income distribution over time, ensuring that the estimates are not influenced by changes in income inequality.

Parental Earnings First, parental earnings are measured as the percentile of the average of earnings over over the first 18 years of life of the kid relative to the distribution of parents of children from the same cohort. This distinguishes the measurement for parental earning from the measure of children earnings in two dimensions. First, parental earnings are measured in the years in which the child is in education. Second, unless otherwise specified, parental earnings are measured for each child as the average of the measure described above among the parents for which data is available.

School-Cohort I group children by the school (*igninstno* in UDDA) they attended in 10^{th} grade and the year in which they did so.

Education I use information on the highest level of completed education (*hfaudd* in UDDA) to compute years of schooling.

Neighborhood In Denmark, parishes are administrative divisions that are subsets of Danish municipalities. Each individual is geo-located based on the parish of residence in the year they complete 10^{th} grade. I use the term parish and neighborhood interchangeably in the remaninder of the paper.

Occupation I classify occupations by sector of employment (*diskokode* in IDAN). Children are classified accordingly to the last occupation recorded at age 30.

2.3 Institutional Setting: Danish High-Schools

Danish students complete compulsory education by age 16 at grade 9^{th}. After 9^{th} grade, students enroll in high-school. The main choice for education distinguishes high-school which qualify for access to university after graduation and vocational education. An optional 10^{th} grade allows further academic or personal development before enrolling in high-school. Depending on the type of high-school attended (different tracks are available covering alternatively umanities, natural science and social science, or business and socio-economic disciplines, or technological and scientific subjects or vocational training) lenght of the program might range from 2 to 3 years.

Children are allowed to enroll any high-school of their choice, conditional on having successfully completed primary education. Upon enrollment in high school, students are grouped into classes fixed for the whole duration of the progam (2 or 3 year). Students attend the core courses (e.g.: Danish and Mathematics) in those classes, while they form different classes to attend eligile courses (e.g.: French and IT). To abstract from issues arising from endogenous sorting among classes and eligible course, I consider the school-cohort composition to be the relevant peer group.

Figure 1: Sorting across Schools and Neighborhoods

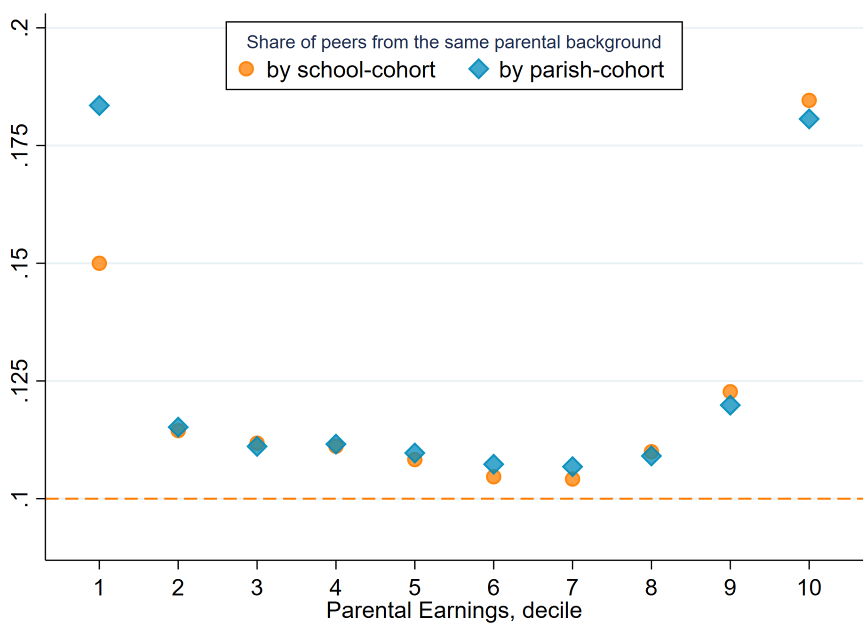


Figure 2: Inheritance of Peers

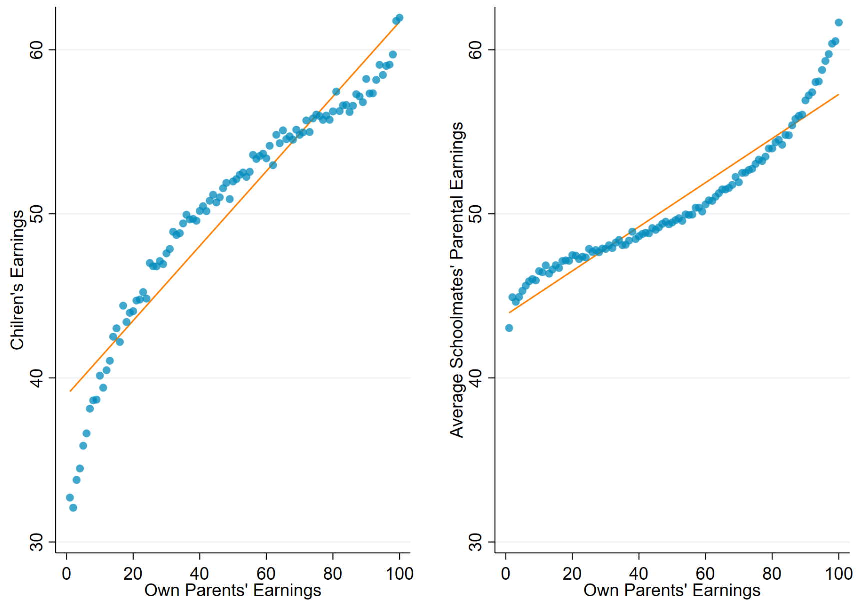


Figure 1 documents the segregation of childre into peer groups based on parental earnings. The graph plots the probability of a peer sharing the same parental background as a kid from each decile of the distribution of parental earnings. If kids were allocated to school-cohorts independently of their family background this probability would be 0.1. The figure can thus be interpreted as evidence of extensive sorting of kids across peers' groups, especially at the top and at the bottom of the distribution. While different mechanism could generate this finding, this evidence is consistent with the notion "purposive sorting" already documented for primary schools in Denmark by Heckman and Landersø (2022) wherein better-endowed parents tend to concentrate in the same schools, leading to a correlation between the income levels of children's parents and the parents of their schoolmates. The same plot depicts the degree of sorting by neighborhood and year of birth, suggesting a similar degree of sorting. This latter comparison is relevant since, in an insitutional context like Denmark where most high-schools have no tuition fees, sorting of households across neighborhoods is expected to play a role in shaping the relation between parental erning levels and school enrollment.

Figure 2 presents observational evidence of the result of this institutional arrangement for inter-generational mobility, suggesting two key mechanisms. First, as appears from panel A, where average earnings for children are plotted by percentile of parental earnings, children from higher-income parents tend to have higher incomes themselves. Second, as appears from panel B, where the average of schoolmates earnings is plotted by decile of parental earnings, children from higher-income parents are also exposed to schoolmates whose parents have higher income levels.

On one hand, this challenges the disentanglement of the effect of parental income from the effect of being exposed to better schoolmates' parents. On the other hand, if exposure to peers outside the family (as schoolmates and schoolmates' parents) matters, this level of segregation would result in children from higher-income families enjoying a double advantage: the first from their own family background and the second from the peers they are potentially exposed to. The identification design presented in the next section will overcome the main source of bias due to endogenous selection of children into peer groups, while the discussion of the results will highlight the interplay between the exposure effect and the reinforcement of intergenerational transmission of income levels due to parents' residential and school sorting.

3 Reduced-form Identification

As highlighted above, children are not randomly allocated to schools. Thus, it is reasonable to expect that: (*i*) households sort in different schools (and neighborhoods) according to their earnings; (*ii*) unobservable characteristics of the children are correlated with parental income. If the two conditions just outlined realize, a naive regression of classmates' parents' earnings on children's outcomes would be biased. Part of the estimated effect would be due to the intragroup correlation of individual unobservable characteristics of the students. In this section, I introduce the identification strategy of this paper: exploiting variations in parental earnings within school and across cohorts results in the identification of the effect of exposure to schoolmates' parents. The identification strategy employed in this study builds on the work of Hoxby (2000) and is subsequently applied in similar contexts such as Black et al. (2013), Carrell et al. (2018), Deutscher (2020), and Brenøe and Zölitz (2020).

I estimate the following model:

$$Y_i = \beta_0 + \beta_1 X_i + \beta_2 \bar{X}_{-i} + \gamma_{s(i)} + \tau_{s(i)} c(i) + \gamma_{c(i)\times m(i)} + \varepsilon_i \tag{1}$$

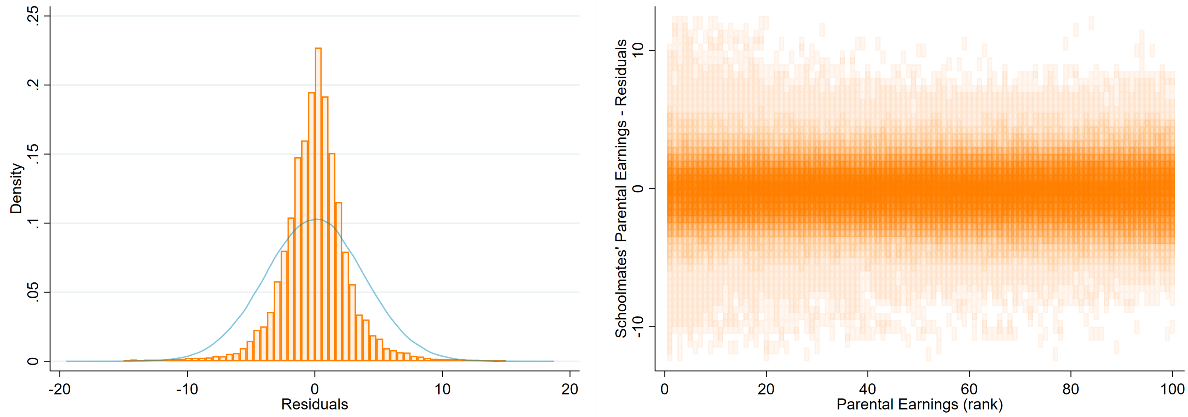
Y_i and X_i represent earnings (in percentiles) for each child i and her parents, respectively[8]; $\bar{X}_{-i}$ is the leave-one-out mean of parental earnings (in percentiles) across the schoolmates' of i, where I consider as schoolmates those children enrolled in the same school in the same cohort, excluding i. Moreover, $c(i)$, $s(i)$ and $m(i)$ denote the cohort, the school and the municipality[9] of individual i, respectively. Hence, $\gamma_{s(i)}$,$\tau_{s(i)}c(i)$ and $\gamma_{c(i)\times m(i)}$ are sets of school-fixed effects, school time trends and and cohort-by-municipality fixed effects, respectively.

Taken together, $\gamma_{s(i)}$ and $\tau_{s(i)}c(i)$ control for school-specific time trends. The main rationale for including a school-specific time trend is to avoid bias in the estimation of β_2 due to endogenous selection of children into schools resulting in correlation between schoolmates' parents and children's unobservable characteristics. The estimation of the model in equation 1 relies on within-school comparisons and exploits only cohort specific deviation from school specific secular trends in school composition. The main identifying assumption is that deviations from school-specific time trends in average parental earnings do not induce contemporaneous changes in the composition of student cohorts. Two mechanisms underlay the credibility of this assumption: parents are unable to perfectly anticipate the exact timing of birth of potential classmates and it is costly for families to adjust the timing of entry of children into school.

To support the validity of the idenfitfying assumption, Figure 3 presents some features of the leave-one-out mean of parental earnings across the schoolmates' of each individual ($\bar{X}_{-i}$), measured as the deviation from school-specific time trends. Panel A of Figure 3 compares the distribution of the residuals (orange bars) to a normal distribution (blue line). Panel B Figure 3 plots the bivariate distribution of the residual (vertical axis) and the parental earnings (horizontal axis) for each child in the sample. The distribution of the residual is centered at zero, symmetric, and independent of parental earnings. It is not the case that a higher realizations of the residuals are associated with higher parental earnings: I interpret this as evidence against the possibility of parents strategically reacting to deviation from the school time trends in cohort composition.

[8] Earnings are measured at the age 28 – 32 for children and between age 0 and 18 of theis child for parents.

[9] As measured at the time of enrollment.



(a) Panel A

(b) Panel B

Figure 3: Residual of Schoolmates' Parental Earnings.

Additionally, Table Table 3 presents a comparison of the standard deviation of $\bar{X}_{-i}$ before and after accounting for school-specific time trends, documenting that approximately one-third of the variation in average earnings of classmates' parental earnings cannot be predicted by this approach: this is the variation exploited for identification. Finally, since a crucial assumption is that linear time trends are a good approximation for parental expectations of school quality, robustness checks will test different specifications of school-specific time trends, including non-linear time trends (up to the third order) and moving averages, computed for each cohort taking the average the two adjacent cohorts before and after.

Table 3: Residual Variation in Schoolmates' Parental Earnings

	mean	sd	count
Schoolmates' Parental Earnings	50.64	11.35	424,154
Schoolmates' Parental Earnings - residual (linear trend)	-0.00	3.86	424,154
Schoolmates' Parental Earnings - residual (nonlinear trend, 2nd order)	0.00	3.86	424,154
Schoolmates' Parental Earnings - residual (linear trend, 3rd order)	-0.00	3.86	424,154
Schoolmates' Parental Earnings - residual (moving avg.)	0.00	3.63	418,581

A further potential concern is that deviations from school-specific time trends in parental earnings may be correlated over time with other environmental factors, such as fluctuations in local economic conditions at the time of graduation or in school quality. The inclusion of cohort-by-municipality fixed effects $\gamma_{c(i)\times m(i)}$ in the main specification ensures that the results are not driven by unobservable factors varying over time at the municipal level where the student lives at the time of enrollment. This control prevents the estimates from being confounded by local economic conditions at the time of graduation and high school drop-out rates.

However, potential correlation between deviations from school-specific time trends and, unobservable, time-varying characteristics of the school is not ruled out. While it is unlikely that a temporary deviation from the average composition of parents in a school immediately affects the quality of the school, it is possible if parents were directly involved in school activities. In such cases, exposure effects estimated in equation 1 would capture the combined effect of being exposed to better schoolmates' parents per se and their implicit impact on school quality. However, given the age of the students and the type of education considered, direct inteventions from parents on factors determining school quality will be assumed to be second order.

4 Results

The coefficients obtained by estimating eq. (1) via OLS are reported in Table 4.

Table 4

	(1)	(2)	(3)	(4)	(5)	(6)
Rank of avg parental earnings, kid 0-18	0.205***	0.186***	0.181***	0.181***	0.181***	0.181***
	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
Schoolmates' Parental Earnings		0.203***	0.090***	0.061***	0.061***	0.061***
		(0.017)	(0.017)	(0.013)	(0.013)	(0.013)
Observations	419688	416212	416189	416189	416189	416189
Cohort × Mun. FE						
School FE	No	No	Yes	Yes	Yes	Yes
School t trend (1st order)	No	No	No	Yes	Yes	Yes
School t trend (2nd order)	No	No	No	No	Yes	Yes
School t trend (3rd order)	No	No	No	No	No	Yes
School Moving Avg						
R^2	0.12	0.12	0.14	0.15	0.15	0.15

Cohort, municipality, gender, childrens' and parents' yr birth FEs are included.

SEs in parentheses are clustered at the school-cohort level.

* p<0.10, ** p<0.05, *** p<0.01

Column (1) includes as a regressor the parental earnings of each individual and controls for cohort-by-municipality fixed effects. The estimated coefficient suggests that an increase in parental earnings from the 25^{th} to the 75^{th} percentile is associated with an increase of 10.85 percentiles in their children's earnings. Considenring that the average kid from parents at the 25^{th} percentile ranks at the 46^{th} percentile by the age of 28-32, this is equivalent to increasing her earnings by 13.5% from $40,000\$$ to $45,400\$$[10].

Column (2) includes in the regression the leave-one-out average parental earnings among the schoolmates. Column (3) replicates the same regression including school fixed-effects and columns (4) to (6) include school-scpecific time trends, with each column allowing for higher order non-linearities. Finally, column (7) replaces school-specific time trends with a less parametric measure of the variation in average school quality over time: the moving average of parental earnings. Such moving average is computed for each cohort taking the average parental earnings from the two adjacent cohorts before and after. Note that the reduction in sample size is due to the fact that this variable is by construction missing for the first and the last two cohorts.

The coefficient estimated on schoolmates' parental earnings in column (2) indicates a positive and significant relationship between classmates' parental earnings and children's own earnings. However, when school fixed effects are included in the regression in column (3), that estimate decreases substantially. The significant drop in the coefficient is consistent with the hypothesis that the correlation between children's earnings and the earnings of their classmates' parents is driven, at least partially, by endogenous selection. In interpret it as evidence of the initial positive relationship observed in column (2) being influenced by factors related to the sorting of children across schools based on parental income or other unobserved characteristics.

A smaller, but still relevant, decrease in the size of the coefficient is registered comparing estimates in column (3) with those in column (4), suggesting that variation across cohorts within the same school in school quality was determining part of the effect detected by simple within-school comparison in column (3). However, comparing the coefficient on schoolmates' parental earnings in column (4) with the coefficients in columns (5)-(6), where non-linear higher-order specifications of the time trends are

[10]In compliance with DST regulations, the earning levels reported are not the actual percentiles. The amount reported as earnings for perentile c is the average earnings among all the individuals between percentile c and $c-1$, rounded to the closest hundreds.

implemented, we find that the estimates are not significantly different: the inclusion of higher order approximations of the time trends does not have a substantial impact on the estimated coefficient. I interpret this as suggestive evidence that the linear time trends capture the essential variation in the relationship between exposure to schoolmates' parents and children's earnings outcomes. For this reason, in the rest of the paper non-linear time trends will be excluded from the reported results.

The coefficient of interest is significantly different from zero and its magnitude is stable across the board, with a drop from .1 to .06 when school time trends are included as opposed to simple school fixed effects. In light of the considerations above, my preferred specification is that of column (4). In this specification, the coefficient of interest is positive and statistically different from zero at 99% confidence level. A natural benchmark to interpret the magnitude of this coefficient is to compare it with the correlation in earnings between children and their own parents: exposing children to higher earnings classmates' parents has an effect as large as $\sim$ 33% of the correlation in earnings between parents and children.

A second perspective to appreciate the economic magnitude of the coefficient is from the perspective of the child of the household at the 25^{th} percentile of the earnings distribution. This child earns on average $\sim 38,900\$USD/yr$ by the age of 28-32. If exposed to an increase of one standard deviation increase[11] in schoolmates' parental hes earnings would increase to $\sim 39,400USD/yr$[12]. Assuming the earnings at age $28-32$ as a proxy for lifetime earnings, this implies a 1.25% increase in lifetime earnings.

[11] 11.35 percentiles.

[12] In compliance with DST regulations, the earning levels reported are not the actual percentiles. The amount reported as earnings for perentile c is the average earnings among all the individuals between percentile c and $c-1$, rounded to the closest hundreds.

4.1 Heterogeneity of the effect across Socioeconomic Status

Figure 4: Exposure Effect by SES

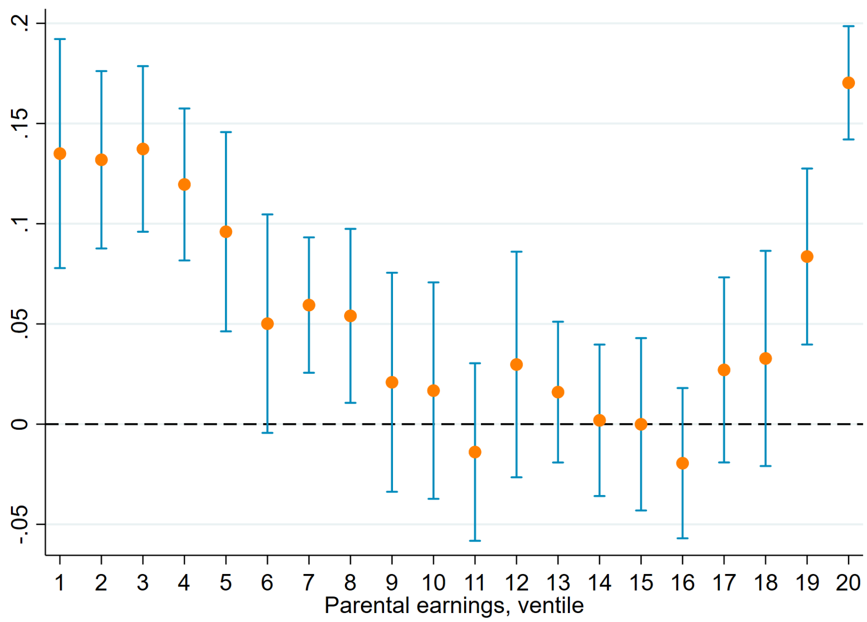


Figure 4 depicts the heterogeneity of the exposure effect parental background. The graph reports the point estimate and the 95% confidence intervals of the marginal effect of exposure to schoolmates' parental earnings implied by including in the model from eq. 1 a full interaction between the schoolmates' parental earnings and a set of dummies for each ventile of the distribution of own-parental earnings. The table with the full results is reported in the Appendix. The graph shows a decrease in the size of the effect with respect the parental background: children from higher-earning families are less affected than those from low-level earnings, with the coefficient being above .1 for the first quaritle, and gradually decreasing towards zero, increasing again when considering children from the top of the distribution of parental earnings.

It is suggestive to compare this finding with the degree of segregation highlighted by Figure 1. Those tracts of the population which are more segregated (the two extrema of the distribution) are more affected by exposure effects. Moreover, this degree of heterogeneity might be interesting per se if one considers that welfare policies are usually targeted at families at the bottom of the earnings distribution. To appreciate the economic magnitude of the effect, consider a child whose parents rank at the bottom quartile of the earnings distribution. The model predicts that this child earns on average $\sim 38,000 USD/yr$[13] by the age of 28-32. If exposed to a 20 percentiles increase in schoolmates' parental earnings her earnings would increase to $\sim 39,100 USD/yr$. Assuming the earnings at age 30 – 32 as a proxy for lifetime earnings, this implies a 2.9% increase in lifetime earnings.

4.2 Exposure Effect on lifetime outcomes: education and occupation

In this section I present evidence on the effect of long-term economic outcomes other than income. In particular I will focus on educational attainment, characteristics of the firm and occupation of main employment at the age of 30. For each outcome of interest I re-estimate the model substituing the dependent variable with the relevant variable. For ease of comparability estimates are reported in the graph as semi-elasticities[14] and the independent variable (schoolmates' parents average earnings) has been rescaled by its standard deviation. As a consequence, the parameters are interpretable as the percentual change on the variable of interest due to an increase in one standard deviation in peers' quality. In the Appendix I present the result of the same regressions in levels. Moreover the regression model includes a full set of interactions between schoolmates' parents earnings and a set of dummies for each decile of the distribution of parental earnings. Thus allowing for the identification of heteronegeous effects along the the distribution of students' family backgrounds. Before turning to the results in Figure 5, table Table 5 presents an overview of the variables considered.

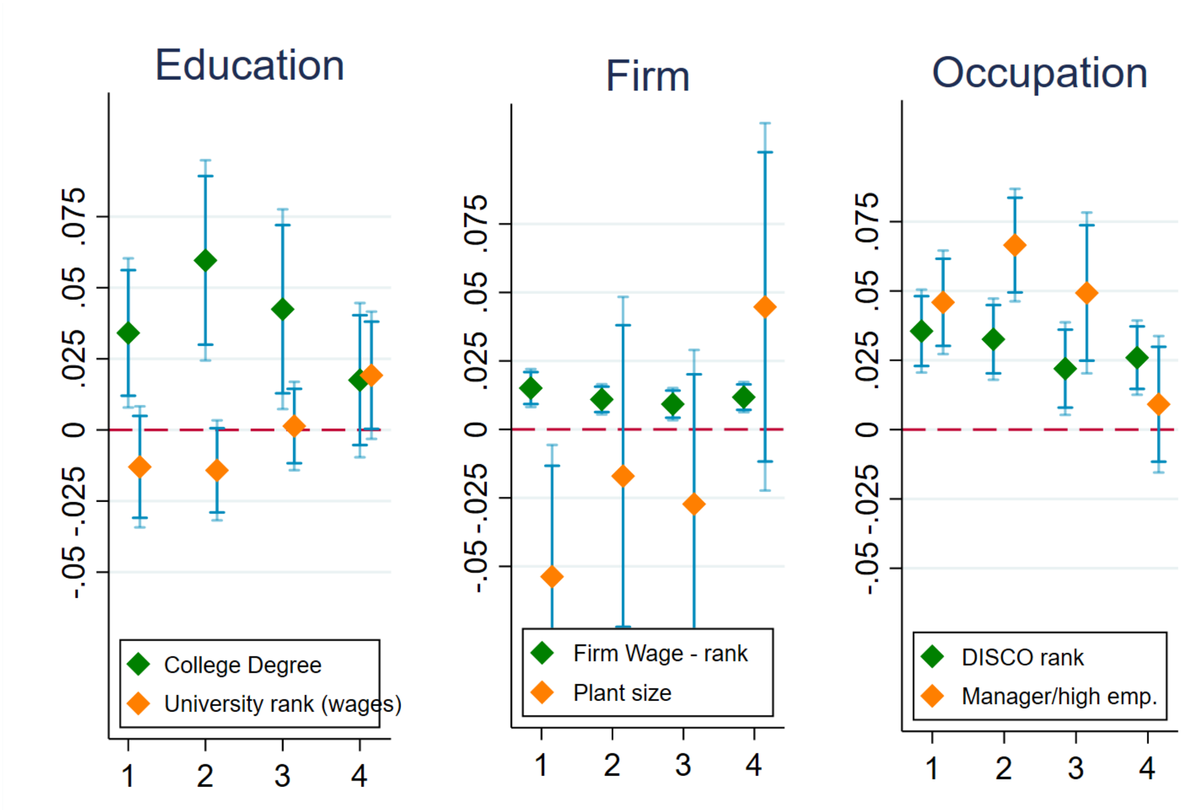
Table 5

	mean	sd	count
University Degree	0.41	0.49	427,831
Universirt rank	52.47	26.54	154,587
Plant size	473.84	1,224.13	318,891
Plant FE	66.73	20.71	360,946
Mangerial Occupation	0.49	0.50	427,831
Occupation Rank	53.61	28.47	313,291

[13]The earning levels reported are not the actual percentiles. In compliance with DST regulations data on percentiles are confidential. The number I report in the text is the average earnings among all the individuals at a given percentile, rounded to the closest hundreds.

[14]I.e.: the marginal effect of the variable of interes on the outcome, scaled by the predicted outcome.

Figure 5



The left panel of Figure 5 illustrates percentage changes in in the probability of obtaining a University degree due to a one standard deviation increase in schoolmates' parental background. The effect is positve and significant for the whole sample, execpt for students from the top quartile of the parental earnings' distribution.

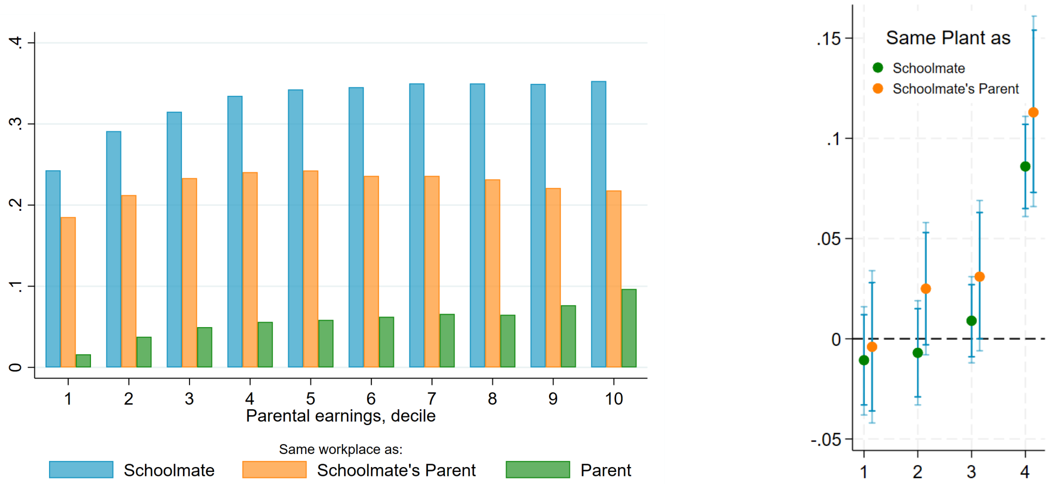
The middle panel of Figure 5 plots the effect of improved peers' quality on two characteristics of the workplace where the kid is employed by the age of 30: a plant-speficic fixed effect from an AKM regression including the whole population of workers in Denmark from 2008 to 2019 (green markers) and the number of employees employed at the plant where the kid is employed by the age of 30 (organge markers). The AKM regression includes fixed effects for the worker, the year and the plant, thus the plant fixed effects used as dependent variable in this exercise represent a measure of the plant component of the variation in earnings. While a positively significant effect of exposure on firm productivity is measured for all children in the sample, only children from the top of the parental earings' distribution are dispropotionately employed in larger plants when exposed to higher parental background schoolmates.

The right panel Figure 5 focuses on characteristics of the occupation of the kid at the age of 30 years old. The coefficients plotted measure the effect on the occupation status (green), as measured by the ranking of occupations according by their average earnings in Denmark in 2019, and on the probability of beig employed as a manager or a high profile employee (orange). While all children in the sample experience an increase in occupational rankigof the order of 3%, the effect on the probability of being employed in managerial positions is even larger (between 4% and 6%) for children from the first, the second and the third quartile. However, it is not distinuishable from zero for children from the top quartile.

Taking stocks, being exposed to schoolmates from higher earnings households increases educational achievement and boosts the probability of being employed in managerial occupations for all children but those from the most afflent familes.

4.3 Exposure Effect and Workplace Inheritance

Before turning to a decomposition of the effect of increase in education levels from the role played by network effects in the nex section, I will present here suggestive evidence on the fact that peer exposure in school affects employment trajectories via network effects. In fact, having classmates from higher-income parents might benefit children once they enter the labor market via referrals or network effects in general. Leveraging on the universe of employer-employee relations observed in the Danish administrative data I collect the employment histories for the children in the sample between the age of 20 and 30 years. For this period, I document 3 main facts. First, 7% of the kids are employed at least once at the same plant where one of their parent worked while they were in high-school. Second, 32% joined a plant were a schoolmate was previously employed. Third, 22% joined a plant were one of the schoolmates' parents was employed while they were in school. Note that the choice of time periods with respect to the age the kid guarantees that the employment relation of the parent (or the schoolmate's parent) pre-exists the one the kid. Figure 6a plots the probability of joining a parent, a schoolmate or a schoolmate parent at their workplace, respectively.



(a) Panel A

(b) Panel B

The probability of inheriting a workplace from a parent is increasing in parental earnings, growing from .04 for children from the first quartile to .1 for children from the highest quartile. This observation is consistent with higher paying occupation-workplaces being more likely to be transmitted along dynasties, for example because of their increased attractiveness to children. Conversely, both the probability or joining the plant of a schoolmate and a schoolmate parent increase with respect to parental background only for children from low SES and reaches a plateau around the fourth decile of the parental earnings distribution.

This is coupled with the fact that, when esposed to higher SES peers, children from the bottom of the earnings' distribution do not increase their chances to join their peers' plants, as children from higher SES families do. This is documented in figure Figure 6b, where the percentage increase in the probability of joining schoolmate (green) or a schoolmate parent (orange) at their workplace due to a one standard deviation increase in schoolmates' parental earnings is plotted separately by quartile of parental earnings. Children from the most affluent families are the the most affected ones, with a one standard deviation increase in the quality of thier peers increasing by around 10% their chances of sharing the workplace with a schoolmate and of inheriting it from a schoolmate's parent.

Considered togheter, the evidence presented in this section is suggestive of a potential channel through which peer effects at the high school level might generate the effect observed in the main results of this paper. If one in six students finds employment at a plant where a schoolmate's parent was previously employed, being exposed to schoolmates whose parents are employed at higher paying firms might improve the advantage experienced by the child when entering the job market.

However, as opposed to spillovers in education achievement that affected children from the middle and low SES, only high SES children appear to increase their chances of joining their peers' network when exposed to higher SES peers. This is compatible with two different processes taking place at the same time. Assuming some degree of substitability between parental investments and peer exposure e diminishing marginal returns in the technology of human capital formation, exposure to higher SES schoolmates generates spillovers in the classroom that increase low SES children investments in education (substituting lack of parental investments), while leaves unaffected high SES children (due to already high levels of parental investments). At the same time, exposure to better peers generates opportunities to leverage schoolmates' network on the labor market: after school, individuals decide whether to give referrals for their schoolmates (or their children schoolmates'). The private nature of the referral decision results in children from high-SES families to be the preferred object of such referrals due to homophily or higher investments in human capital from their families. Separating the role of human capital spillovers from network effects is the contribution of the next section.

5 Accounting for Human Capital and Network Effects: a Semi-structural Model

In what follows, I formalize a model to disentangle the role played by spillovers increasing levels of human capital (H_i) and labor market network effects in determining the relation between exposure to peers' parental background while in school ($\bar{X}_i$) and earnings between the age of 28 and 32 (Y_i). The key challenge in doing so is that exposure to schoolmates from more affluent families may result both in increased levels of human capital and improved network position. I assume human capital to be influenced from parental earnings (X_i), peers' parental earnings $\bar{X}_i$ and peers' human capital attainment ($\bar{H}_i$) according to equation (2).

$$H_i = \alpha + \delta X_i + \gamma \bar{X}_i + \beta \bar{H}_i + \varepsilon_i. \tag{2}$$

I assume earnings to be determined by own and peers' human capital levels (H_i and $\bar{H}_i$, respectively), former schoolmates' earnings ($\bar{Y}_i$), parental earnings after school is completed (X_i') and former schoolmates' parental earnings after school is completed ($\bar{X}_i'$) as described by equation (3). Notably, I also allow individual earnings to be affected from coworkers' earnings (Z_i).

$$Y_i = \alpha' + \pi H_i + \sigma \bar{H}_i + \beta' \bar{Y}_i + \lambda X_i' + \phi \bar{X}_i' + \rho Z_i + e_i. \tag{3}$$

Finally, equation (4) describes the relation between parental earnings while in school X_i with those after school completion X_i'. Also, parental earnings are allowed to be influenced from coworkers' earnings (W_i).

$$X_i' = \mu_0 + \mu_1 X_i + \mu W_i + \xi_i \tag{4}$$

Writing closed form equations for the recursive functions (2) and (3), one is left with the reduced form relation:

$$Y_i = \psi_0 + \psi_1 X_i + \psi_2 \bar{X}_i + \psi_3 W_i + \psi_4 \bar{W}_i' + \rho Z_i + \frac{\beta'}{1-\beta'}\rho \bar{Z}_i + \tilde{e}_i \tag{5}$$

with :

$$\psi_1 = \pi\delta + \lambda\mu_1$$
$$\psi_3 = \lambda\omega$$
$$\psi_4 = \frac{\beta'\lambda + \phi}{1-\beta'}\omega$$

The advantage of this setup is that it allows for the reduced form effect of exposure to schoolmates ψ_2 to be decomposed in four different additive components as in equation (6).

$$\psi_2 = \underbrace{\frac{\beta\delta+\gamma}{1-\beta}\pi}_{\text{Spillovers in } H \text{ at School}} + \underbrace{\frac{\sigma}{1-\beta'}\frac{\delta+\gamma}{1-\beta}}_{\text{Spillovers in } H \text{ after School}} + \underbrace{\frac{\delta+\gamma}{1-\beta}\pi\frac{\beta'}{1-\beta'}}_{\text{Network Effects}} + \underbrace{\mu_1\left(\frac{\beta'}{1-\beta'}\lambda + \frac{\phi}{1-\beta'}\right)}_{\text{Parental Network Effects}} \tag{6}$$

First, educational achievement is affected by peers' parental background via peer effects (*spillovers while in school*). Second, earning are influenced by both own and fprmer schoolmates' human capital (*spillovers after school*). Third, earnings are also subject to peer effects (*schoolmates' network*) and affected by the labor market position of parents and peers' parents (*schoolmates' parents' network*). A graphical representation of the four different channels is offered in Figure 7.

We expect *spillovers in school* if the process of human capital formation exhibits peer effects. More specifically, this will be the case either if students decision to invest in education is influenced by exposure to their peers parents or by exposure to their schoolmates endogenous effort. Following the established definition of the literature (Manski, 1993), the former is to be interpreted as a direct or exogenous effect, while the latter as an indirect or endogenous effect. I compute *spillovers in school* as the joint combination of the two.

Spillovers in human capital after school might emerge if, upon finishing school and after having completed their education H_i, children were to be affected by peers' hu-

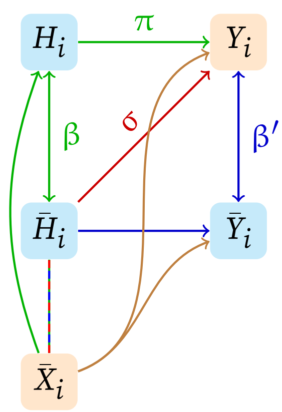


Figure 7: Peer Effects

man capital independently of former schoolmates' earnings $\bar{Y}_i$. The direction of this effect is to be empirically determined: higher educated former schoolmates might for example redirect individuals to more productive activities, thus increasing their earnings, or might in fact represent increased competition, thus reducing individual earnings.

Finally, network effects would capture how much each child benefits from peers employment success. Intuitively, if schoolmates (schoolmates parents) were to provide refererалls dispropotionately to schoolmates (childrens' schoolmates), we would capture a direct relation between variation in earnings among peers (peers and parents of peers).

5.1 Identification

To estimate the decomposition in equation (6), three main identification issues must be faced: endogenous sorting, simoultaneity of human capital and peers' earnings and correlation between parental earnings while in school and afterwards.

First, as in the reduced form case above, endogenous sorting into peer groups might bias the results. To address this concern, I estimate the whole model replacing actual variables with residuals from a set of school-specific time trends. Under the same assumption exploited in Section 3 (agents are unable to anticipate cohort-specific deviation from school trends), this results in considering variation in peers characteristics to be considered as good as random.

Second, peers human capital in equation (5) might affect individual earnings directly or via increases in peers' human capital. To separately identify the effect of more successful former schoolmates on the labor market from exposure to their higher human capital, I exploit variation in earnings due to former schoomates' coworkers' wages.Under the assumption that coworkers' wage affect the wage of a given individual[15] and former schoolmates of the same individual only though improvements in the wage of that individual, former schoolmates' coworkers' earnings serve as a valid instrument to identify the effect of changes in peers employment outcomes, conditional on their level of human capital. Exploiting a similar exclusion restriction to identify endogenous peer effects, my approach can interpreted as a partial population experiment Moffitt, 2001. Moreover, relying on peers (coworkers) of peers (former schoomates) I am exploiting the intuition developed by Bramoullé et al. (2009) and De Giorgi et al. (2010).

Third, parental earnings while the kid is on the labor market are a function of parental earnings while the kid was accumulating human capital in school, thus generating potential collinearity between X_i and X_i'. To distinguish the impact of parental earnings on human capital from that on earnings due to parental network effects, I control for parental earnings when children are in school (up to age 25) and use the variation of parental earnings due to parents' coworkers' when children are on the labor market (age 28-32) to infer parental network effects. I argue that this is the relevant variation: conditional on two parents having access to the same earnings while their kids were accumulating human capital, I identify the impact of them being linked to coworkers who fared better (or worse) when their kids are on the labor market themselves.

In what follows, I measure parental earnings while in school and children's earnings as in the reduced form analysis. I measure human capital as the number of years spent in education by age 25. I measure parental earnings after human capital completion as parental earnings between age 28 and 32. I measure coworkers' earnings as the leave one out average of the wages of workers employed at the same plant.

Finally, I show in the appendix that the paramters composing (5) are identified upon estimation of the following system of equations.

[15] peer effects on the workplace are extensively documented in the literature, see for example: Mas and Moretti, 2009 and Cornelissen et al., 2017.

$$
\begin{aligned}
Y_i &= \psi_0 + \psi_1 X_i + \psi_2 \bar{X}_i + \rho Z_i + \psi_3 W_i + \psi_4 \bar{W}_i' + \frac{\beta'}{1-\beta'}\rho \bar{Z}_i + \tilde{e}_i \\
\bar{H}_i &= \frac{\alpha}{1-\beta} + \frac{\delta+\gamma}{1-\beta}\bar{X}_i \\
H_i &= \frac{\alpha}{1-\beta} + \delta X_i + \frac{\beta\delta+\gamma}{1-\beta}\bar{X}_i + \tilde{\varepsilon}_i \\
X_i' &= \mu_0 + \mu_1 X_i + \omega W_i + \xi_i
\end{aligned}
$$

And noticing $\psi_1 = \pi\delta + \lambda\mu_1$; $\psi_3 = \lambda\omega$; $\psi_4 = \frac{\beta'\lambda+\phi}{1-\beta'}\omega$.

I estimate the parameters both as non-linear combinations of OLS estimators from estimating each equation separately and via simoultaneous GMM estimation. No qualitative difference is detected across the two methods. I present GMM estimates and leave OLS estimator to the Appendix.

6 Semistructural Results

Table 6

δ	0.011	(0.000)
$\frac{\beta\delta+\gamma}{1-\beta}$	0.021	(0.000)
$\frac{\delta+\gamma}{1-\beta}$	0.006	(0.000)
π	9.645	(0.498)
σ	-4.560	(0.1.943)
β'	0.043	(0.030)
ρ	0.539	(0.008)
λ	-0.017	(0.010)
ϕ	0.147	(0.079)
μ_1	0.456	(0.004)
ω	0.249	(0.027)

Table 7

Spillovers in school	$\frac{\beta\delta+\gamma}{1-\beta}\pi$	0.064	(.)
Spillovers after school	$\frac{\sigma}{1-\beta'}\frac{\delta+\gamma}{1-\beta}$	-0.103	(.)
Network	$\frac{\delta+\gamma}{1-\beta}\pi\frac{\beta'}{1-\beta'}$	0.009	(.)
Parental Network	$\mu_1\left(\frac{\beta'}{1-\beta'}\lambda+\frac{\phi}{1-\beta'}\right)$	0.069	(.)
Total	ψ_2	0.041	(.)

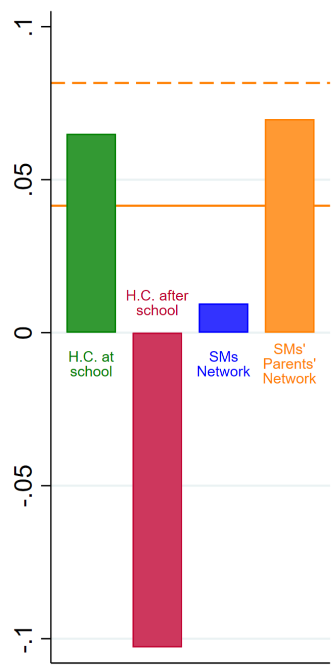


Figure 8

Table 6 reports the parameters identified estimating the system of equations from the last section via GMM where every variable is included as the residual after a set of school specific time trends. The first parameter $\frac{\beta\delta+\gamma}{1-\beta}$ identifies the effect of increasing by one percentile the average schoolmate parental background on the years of education attained. The second captures the same effect on the average years of education of the peer group. As discussed above, those two parameters do not disentangle the role played by direct effects (γ) from that played by endogenous interactions (β). Turning to the wage determination equation, π measures the private returns from one extra year of education while σ captures the direct effect of peers human capital con earnings not mediated by own human capital and peers' earnings. Further, the estimates reveal a negligible endogenous effect: β' is positive but close to zero and estimated with a large standard error. Turning to the effect of parental network, the effect of own parental connections is not distinguishable from zero, while the impact of peers' parental network is positive. Finally, coworkers are found to influence their peers' earnings, with the impact being as large as 0.53 for childrens' coworkers and 0.24 for parents' coworkers.

Table 7 reports the estimates for the contribution of each of the four mechanisms and the overall exsposure effect as specified in equation (5). Figure 8 plots the same decomposition graphically. The results suggest the existence of substantial spillovers in human capital while at school. However, such beneficial effects are more than offset by the negative spillovers from peers' human capital on the labor market. I argue that this last effect might be due to increased competition faced on the labor market because of enhanced peers' supply of human capital. When including in the anylsis the network effect from own and peers' parents, however, the advantage of being exposed to higher SES peers in highscool is unambigous. Individuals in the sample experienced exposure effects in highschool both because of the endogenous relation of earnings profile among former schoolmates and, even more substantially because of the advantages offered by schoolmates parents on the labor market.

7 Discussion

The overall picture drawn in this paper views access to opportunities for children as a joint process, taking place both within and among families who experience some degree of interaction (e.g.: sending their kids to the same school). Specifically, upon joining the same high-school, I document children adult earnigs to be affected by thier peers' employment outcomes. I find that being exposed to a set of schoolmates' parents whose average earnings are one standard deviation higher results in a 1.25% increase in lifetime earnings for the average student. Moreover, this effect is U-shaped with respect to parental background, with low SES children experiencing the same effect to be as large as 2.7%. With this regard, I find low SES children to increase thier educational achievement when exposed to better peers while high SES children experence in the probability of joining a peer's workplace. Finally, upon decomposing the drivers of the estimated effect, I find that on average human capital spillovers while in school (which explain 156% of the effect) are offset by increased competition, while network effects from peers and peers parents account for 21% and 167% of the effect, respectively.

While the within-school across cohorts identification strategy illustrated above is designed to deal with endogenous selection and correlated effects, the results should be interpreted keeping in mind two main caveats. First, the effect of direct interactions with schoolmates' parents is not separately identifiable from the effect of schoolmates' parents mediated from their own kids being peers of each other (i.e.: schoolmates). In other words, since parents invest in their kids' human capital, the estimates presented are both compatible with children having an advantage by being the schoolmates of higher earnings families because of the improved interactions with their schoolmates or because of direct interactions with those adults. Second, combining leave-one-out averages and group fixed effects might result in downward biased estimates. As pointed out by Caeyers and Fafchamps (2020) a mechanical result of including both group-level fixed effects and leave-one-out averages as done in the main specification of this paper results in a mechanical negative correlation between the individual outcomes and the group average since by construction the best member of a group has worse peers than the others. However, the implication of this for the results presented is that, if anything, they are underestimating the true parameters of interest.

Guiding the discussion of the results that follows, two main mechanisms could be envisioned behind the effect of exposure to higher income schoolmates' parent on children future outcomes. The first involves an increase in children's human capital due to interactions either within the school or directly with schoolmates' parents. This would happen if being schooled with a child from an higher-earning family results in having a better schoolmate who potentially improves the process of learning (affecting the classroom environment or through peer effects in general[16]) or in obtaining exposure to different adult role models, who could facilitate the kid to navigate higher education tracks by providing guidance or information. This would be in line with the mechanism of Benabou (1993), where a system of neighborhoods is characterized by the fact that the share of high-educated individuals in each location decreases the cost of achieving higher education for everyone else living in the same location. The second potential mechanism implies an improvement in the position of the child in the social network of the local labor market: children who are schooled with higher

[16] see Sacerdote (2011) for an overview.

earnings schoolmates' parents gain a valuable link which they can leverage on when entering the labor market through the referrals that link might provide to potential employers. This would be consistent with the models of network-based job referrals first introduced by Montgomery (1994) and applied to a neighborhood setting by Bayer et al. (2008).

The increase in the probability of obtaining a degree documented in Figure 5 is consistent with the hypothesis of children accumulating more human capital thanks to exposure to better peers. In particoular, I document that low SES kids increase their chances of getting a University degree by 3.1% when exposed to a one-standard-deviation increase in schoolmates' parental background. On the contrary, no such effect is found for high-SES children. It is worth noting here however, that a slight increase in the university ranking conditional on graduation is measured for high-SES kids. This results is consistent with Cattan et al., 2022 who find that in Norway being in class with children of parents graduated at elites institutions boosts the probability of attending the same institution.

However, the net null result on education coupled with a strong exposure effects when eanings are considered motivates the investigation on the network advantage experienced by high SES children. I document that 1 kid out of 5 joins the plant of a schoolmate parent at least once in the early stage of their career. I couple this with evidence of exposure to schoolmate from more affluent families increasing the probability of actually exploiting network advantages by joining a connected plant for high SES kids but not for low SES (figure Figure 6b).

Finally I devolop a decomposition of the main effect of exposure to higer SES schoolmates on adult earnings accounting for both human capital spillovers and network effects. Overall[17], I find that evidence of substantial spillovers in human capital accumulation within the school that are off-set by increased competition on the labor market due to peers' increased human capital.

I interpret this evidence as suggestive of spillovers in human capital driving the effects for low SES-children and netowork effects for high-SES children. School-level spillovers in human capital are public goods in nature, thus affecting every member of the group. However, assuming parental investments to be substitues of peer esposure in the human capital formation technology, the returns to such spillovers might

[17] More work is ongoing to estimate this decomposition separately by parental background.

be higher for low-SES kids because of lower level of parental investments, while leaves unaffected high SES children (due to already high levels of parental investments). Conversely, the network (and the use individuals make of it) of acquaintances on the labor market is the result of endogenous private decisions. The private nature of the referral decision results in children from high-SES families to be the object of such referrals due to homophily or higher investments in human capital from their families. Separating the role of human capital spillovers from network effects is the contribution of the next section.

The results presented improve our understanding of the close relation between intergenerational mobility and neighborhood effects highlighted in the literature (Chetty et al., 2014) by identifying one channel by which sorting across neighborhoods and schools affect patterns of mobility: children who are exposed to better peers (which might be identified as one of the amenities of better neighborhoods) experience an increase in their human capital and, most likely according to the evidence presented, in preferential access to high-paying occupations.

The evidence collected on the main mechanisms driving those results and the preminent role of network effects circumstantiate the reasons behind the peer effects measured on earnings. In doing so, I document the relevance of network effects as one of the main driver of the exposure effect. In doing so, I present empirical evidence supporting an hypothesis already formulated in the literature (Rothstein, 2019, Heckman and Landersø, 2022) engaged with the identification of the determinants of geographic heterogeneity in access to opportunities.

Moreover, the heterogeneity in the exoposure effect by parental background motivates a further interest in potential reallocation policies (such as school desegregation) to retrieve the socially optimal allocation of peers. In fact, if the estimates here presented were to be confirmed, the large share of population (children from middle income families) who is virtually unaffected by school composition, could be identified as potential reciever of some of the children from low SES families. However, further research is due in this direction to develop a prediction on such a policy. The role of families, and the degree of complementarity between their direct investment and that coming from peer exposure should be taken into account.

8 Conclusion

This paper has shown that exposure to schoolmates from different parental backgrounds affects children's opportunities for economic mobility. When comparing children who attended the same school in different cohorts, those whose schoolmates' had higher average earnings experienced higher earnings themselves when adults. The size of the effect implies that increasing the average earnings for the schoolmates' parents by one standard deviation determines an increase of 1.25% in lifetime earnings, with this effect being 2.89% for children from low socio-economic backgrounds. Moreover, the result highlight the importance of improved access to high-paying occupations due to network effects as a potential mechanism, with one student out of 5 being employed at the same plant where one of his schoolmates' parents was previously employed and exposure to schoolmates from higher earnings familes resulting in increased occupational status. Consistently with this fact, upon decomposing the mechanisms driving the exposure effect, I find that positive spillovers in human capital formation are offset by increased competition, but access to better jobs because of improved connections makes the effect positive. The evidence presented highlights the importance of considering the process of social mobility driven both by parental investments within the family and peer effects emergins from interactions among peers from different families, as members of schools and labor market networks.

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