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Rising Inequality and Intergenerational Mobility: The Role of Public Investments in Human Capital

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Abstract

One consequence of the rise in inequality witnessed over the past 40 years is its potentially negative impact on intergenerational mobility if parents at the bottom of the income distribution invest significantly less in their children's human capital. I consider whether public investments in children can potentially offset the inequality of private investments. Specifically, examining changes in public spending in 25 Organization for Economic Co-operation and Development countries over the period 2000–2009, I find that increases in spending on health are most strongly associated with reductions in the importance of family background and declines in inequality in the production of child human capital as measured by the Program for International Student Assessment test scores among 15-year-olds. Public spending on family support, housing, and education are also moderately related. In contrast, increased spending on the elderly is associated with increases in the importance of parental background and inequality of child test scores. These results suggest that public investments in child human capital have the potential to offset the potentially negative impact of increasing income inequality on intergenerational mobility and inequality of the next generation. Further research firmly establishing a causal relationship is needed.

Keywords

inequality; human capital; investments; health; education

1 Introduction

After decades of decline, income inequality began to rise in the mid-1970s, a trend that continues today. The European Commission has recently documented how earnings inequality, as measured by the 90/10 ratio, increased between 1979 and 2000 in 10 of 15 Organization for Economic Co-operation and Development (OECD) countries and fell in only one (European Commission 2010). Policymakers have voiced concern over the growth in income inequality, as there exist strong associations between inequality and diminished growth, higher crime, drug use, and persistent poverty (Wilkinson and Pickett 2009).

More recently, inequality has been linked to low levels of intergenerational mobility. Corak's work (2013) documents a strong cross-sectional correlation in income inequality

and intergenerational mobility across OECD countries, referred to as the 'Great Gatsby Curve'. Corak's work (2013) includes a discussion of why greater inequality might cause a decline in intergenerational mobility. The rationale is rooted in economic models of investment in child human capital developed by Becker and Tomes (1979, 1986) and adapted by Solon (2004). These models predict that as inequality rises, so will the difference in child human capital investments made by parents at the top and bottom of the income distribution. This would, in turn, lead to a decline in intergenerational mobility and an increase in the inequality of human capital (and therefore earnings) of the next generation. But while these models focus largely on private investments made in children, there is scope for public investments as well. Indeed, Corak's work (2013) continues 'the reasons for the difference in the intergenerational elasticities across countries have to do with the different balances struck between the influence of families, the labor market and public policy in determining the life chances of children' (page 85), though he does not go on to examine this empirically.

In this article, I examine the potential role of public policy and specifically, public investments in human capital, in reducing both intergenerational elasticities and inequality of child human capital. The main hypothesis is that in societies in which public investments in child human capital are increasing, the relative importance of private investments in the production of child human capital should decrease and we should see a decline in intergenerational elasticities as well as a decline in inequality of child human capital.

To examine this hypothesis, I use individual-level Program for International Student Assessment (PISA) test score data for 15-year-olds in 25 OECD countries for the years 2000 and 2009 to generate three measures of intergenerational transmission and inequality of human capital. The first measure is defined as the elasticity between parental socioeconomic status (SES) and a 15-year-old child's test scores, calculated over all students in a country in a particular year. The second is the ratio of child test scores of those with parents in the top 25% of the SES distribution to those with parents in the bottom 25% of the SES distribution. The third measure is a measure of the inequality of child human capital and is defined as the distance between those children at the top of the cognitive test score distribution and those at the bottom (the 90:10 ratio) within a country and year.

Based on these three measures, I first document a strong positive correlation between inequality of parental SES, low levels of intergenerational mobility (as reflected in a strong elasticity between parental SES and child test scores), and inequality of child human capital (as reflected by the 90:10 ratio in child test scores). In an effort to control, at least in a crude way, for other confounding factors that might be correlated with both intergenerational elasticities and inequality, I focus on changes in these measures within a country over the past decade, with a country-fixed effect specification. I find that countries that experienced the biggest increases in inequality of parental SES witness the biggest increases in intergenerational elasticities and inequality of child test scores.

I follow this with an exploration of how changes in both inequality and intergenerational elasticities within a country over time might be associated with changes in spending on social programs including education, health, family support, housing, and labor support

programs. In considering which social programs to examine and what associations we might expect to find, I relied heavily on the existing micro evidence on the effectiveness of different public programs in increasing child human capital and improving child well-being more generally as collected in a recent review of the literature (Aizer and Doyle 2013).

I find that increases in spending on health are associated with the greatest reductions in the correlation between parental SES and child test scores and reductions in child test score inequality. Spending on housing, family support, and education (the latter with respect to math scores) is more moderately associated with these outcomes. Not surprisingly, spending on the elderly has the opposite relationship: it is associated with increases in intergenerational correlations and increases in inequality of child human capital. This may reflect the fact that spending on the elderly likely crowds-out spending on the young.

There are two main contributions of this work. First, I provide empirical evidence consistent with the hypothesis that inequality affects intergenerational mobility by changing the distribution of child human capital. To do so, I showed that as parental SES becomes more unequal in a society, so too does the human capital distribution of the next generation. Second, I provide evidence that increased public spending on children has the potential to reduce any negative impact of increasing income inequality on intergenerational mobility and inequality of the next generation. These results, although based on an analysis that includes basic controls for potential confounding, should be viewed as largely suggestive. Future work establishing a causal relationship between public spending on child human capital and improvements in intergenerational mobility and inequality of the next generation is needed.

2 Background

2.1 Human capital production: the roles of private and public investments

A child's human capital is determined by his or her initial endowment, private and public investments in the child, and luck. Parents affect both the initial endowment (through genetic inheritance) and all private investments. Strong intergenerational correlations between parental income and children's human capital observed in micro data provide some evidence that private investments are an important component of child human capital.¹ If there were no public investments and a child's human capital were driven exclusively by private (parental) investments, then inequality of child human capital would rise with inequality of parental income, as the children of parents with more resources would receive greater investments in their human capital, whereas the children of the poor would receive fewer. However, if public investments can substitute for private investments, then as public investments in children increase, the influence of parental SES on child education should diminish, resulting in both an increase in intergenerational mobility and a decrease in educational inequality (see Viaene and Zilcha 2001; Holter 2011 for more theoretical treatment).²

¹This is also consistent with the importance of endowments, which are inherited from parents.

²If public and private investments are complementary, we would not expect a reduction in inequality.

2.2 Empirical work on intergenerational correlations and inequality: evidence from the cross-section

Consistent with the above, there is a strong empirical link between inter-generational mobility and inequality across countries. Previously mentioned work by Corak (2013) documents this, as does other work. For example, in a 2010 report, the OECD presents evidence that intergenerational social mobility is lower in more unequal European societies, based on the 2005 EU-SILC database. In fact, they document a 0.56 correlation between the Gini coefficient (the measure of inequality) and intergenerational wage persistence (as measured by the distance between the wages of men whose fathers have tertiary schooling and men whose fathers have less than secondary schooling).

The OECD report further argues that education is the key driver in intergenerational correlations in wages. The authors base their argument, in part, on the fact that once he controls a son's educational attainment, a father's educational attainment no longer affects the son's wages, with some exceptions.³ Based on this, the OECD study concludes that 'policies that facilitate access to education of individuals from disadvantaged family background promote intergenerational wage mobility' (ECD 2010, page 18). The education policies they consider include total resources, early education, tracking, vocational education, and teacher salaries. They conclude that total resources for education matter less than specific policies such as tracking, early childcare, and growth in teacher salaries. These conclusions are based on cross-sectional differences across European countries at a single point in time.

In this article, I go beyond the existing work by considering the role of both education policies (total spending, tracking, and the share in private schools) and other social programs in increasing intergenerational mobility and reducing future inequality of human capital. To inform the analysis, I discuss the existing micro evidence on the effectiveness of various public programs in terms of improving child well-being in the next section.

2.3 Micro evidence on the effectiveness of public programs

The argument that public investments in children can reduce intergenerational correlations and inequality in child human capital relies on the notion that public investments will increase the human capital of children at the bottom of the distribution who otherwise would receive fewer private (parental) investments. But what does the evidence suggest regarding the effectiveness of public programs in increasing child human capital? In a review of the literature, Aizer and Doyle (2013) examine the effects of various child welfare interventions. These include foster care policies, family planning policies, income transfer programs, residential mobility interventions, educational interventions, and public health programs. Although the focus of that review chapter was to highlight the role that economic models and econometric techniques play in the evaluation of public programs, there were a number of relevant findings, which I summarize here.

³The exceptions include Ireland, Italy, Luxembourg, Netherlands, Spain, and the UK.

2.3.1 Foster care—Perhaps the most extreme type of public investment is the government's removal of a parent's custody rights when a child is found to be maltreated by the parents. Research that has sought to establish whether removal improves child outcomes have relied on propensity scores (Berger et al. 2009) or instrumental variable (Doyle 2007) techniques to identify the effect of out-of-home placement. In general, the research has found that removal has little positive effect and in some cases a negative effect on child well-being as measured by teen motherhood, juvenile delinquency, and ultimately, adult incarceration, employment, and earnings.

2.3.2 Family planning policies—There is evidence that access to family planning services reduces fertility (Bailey 2012). What is less clear, however, is the causal impact of fertility on child quality. While the theory supports a clear negative relationship between family size and child human capital (Becker and Lewis 1973), the empirical evidence is less consistent. There is clear evidence that lower fertility improves child well-being through a change in the composition of children born (for example Gruber et al. 1999). Less clear is whether reduced fertility improves the living circumstances among those born (for example, Black et al. 2010 and Angrist et al. 2005).

2.3.3 Anti-poverty programs—There is, in general, little evidence that income benefits children (Mayer 1997; Blau 1999). Indeed, in the cross-section, participation in anti-poverty or welfare programs in the USA is associated with worse child outcomes. There is some work showing that once one controls for maternal characteristics (Levine and Zimmerman 2000) or instruments for welfare receipt (Currie and Cole 1993), welfare is no longer negatively associated with well-being. Almond et al. (2011) estimate the impact of the rollout of the food stamp program in the 1960s, which is essentially a means-tested cash transfer, and find that it improves birth outcomes.

There is greater evidence of positive effects of income transfers that operate outside traditional welfare programs. These include the Earned Income Tax Credit (EITC) in the USA and the child tax benefits in Canada. Dahl and Lochner study (2012) the impact of the EITC on child cognitive test scores in the USA. They find that an additional \$1000 in cash from the EITC raised test scores by 2–4% of a standard deviation. Milligan and Stabile (2011) show that the child tax benefit in Canada has substantial benefits in terms of child health, but less so in terms of improvements in child test scores.

2.3.4 Housing and neighborhood effects—There have been a number of studies based on strong identification strategies estimating the impact of housing mobility on child well-being. Those based on natural experiments include studies by Oreopoulos (2003) and Jacob (2004). Oreopoulos studies placement in public housing in Canada and exploits a long wait list and the availability of different types of housing in different neighborhoods when one has finally proceeded to the top of the list. He finds that the type of housing and income of the neighborhood matters very little in terms of future earnings, income, or welfare receipt. Likewise, Jacob's work (2004) exploits the destruction of high-density public housing in Chicago and removal of families to lower density public housing in higher income neighborhoods on child outcomes and likewise finds no effects. Perhaps the best known housing mobility evaluation is the Moving to Opportunity experiment which randomized

participants to one of two treatment groups or a control group. The treatment groups received either a housing voucher to move from public housing to private housing or a voucher to move with a stipulation that they move to a low-poverty neighborhood. The children were followed up 10–15 years after the initial random assignment. The researchers concluded that housing mobility had small effects on traditional measures of child well-being (health, education, and juvenile delinquency), but some larger positive effects on mental health and happiness.

2.3.5 Educational interventions—Public education differs from most other public programs in two main ways: first, it is compulsory in all developed countries until the child reaches a certain age, typically 14–18 years, and second, eligibility is not means-tested. Moreover, depending on the country, there can be considerable heterogeneity in how the schools are administered and funded and the extent to which they rely on different inputs in the production of education.

Evidence regarding the causal impact of school funding on test scores is lacking. Most education researchers agree that more important than the amount of funding is the way the funds are used to purchase the two main inputs in an education production function: class size and teacher quality. There has been a substantial amount of work attempting to evaluate the effectiveness of class-size reductions in increasing test scores. With respect to class size, there is conflicting evidence that smaller class sizes raise test scores. Studies, including works of Rivkin et al. (2005), Angrist and Lavy (1999), and Hoxby (2000), find small or no effects of reducing class size on test scores. Fredriksson et al. (2013) using Swedish data find that reducing class size by seven students among 10–13-year-olds improves cognitive achievement at 16 years of age by 15 of a standard deviation, improves educational attainment by one-third of year, and increases earnings by 4.2% in adulthood.

Teacher quality is more difficult to measure. Using traditional measures of teacher quality (educational attainment, credentialing, and experience) there appears to be no effect of quality on test scores (Hanushek and Rivkin 2004, 2006; Kane et al. 2008). However, as Hanushek's (1992) and Hanushek and Rivkin's (2010) works show, there appears to be a large variation in teacher quality if one simply looks at gains in test scores associated with individual teachers: with some teachers producing test score gains of only half a year of achievement and others producing three times as much. Hanushek (2011) estimates that having a teacher, one standard deviation above the mean in terms of teacher effectiveness would generate marginal gains of nearly half a million dollars in the future earnings of the student. Dobbie and Fryer (2011) present evidence that attending a 'high-quality' charter school has a positive impact on math, and English test scores. However, the particular intervention studied (Promises Academy in the Harlem Children's Zone) includes better teachers, longer school years, tutoring, early enrollment, and wrap-around services, making it difficult to know which of these improvements in quality is responsible for the improved test scores.

Other factors that can influence the production of education include teacher and student incentives and peer effects. The strongest evidence in favor of teacher incentives comes from randomized experiments conducted in developing countries which suggest that teacher

incentives can significantly improve student test scores (Glewwe et al. 2010). One study based on US school children has shown that providing young students with financial incentives has some moderate effects, but only if structured in a way as to reward not test performance, but performance on more 'intermediate' products such as practicing reading (Fryer 2011).

More recently, researchers have focused on understanding the role of early education. Cunha and Heckman (2007) develop a model that explains why early investments are more productive than later investments in producing human capital. There is growing empirical evidence consistent with this. For example, the Tennessee STAR experiment that randomized kindergarten students to classrooms that varied in terms of class size, teacher, and peer quality showed large short- and long-run gains associated with higher-quality kindergarten classes (Chetty et al. 2011). The Perry Preschool program which randomized families to high-quality preschool has also been shown to have large effects. The Head-Start program, a public preschool program for families below poverty, has been shown to have short-term effects on cognitive achievement (Currie and Thomas 1995, 1999; Garces et al. 2002) that seem to fade by grade 3, but more recently, researchers have found large positive long-term benefits (Ludwig and Miller 2007; Deming 2009.) While there is little evidence that subsidized child outcomes, universal childcare improves child outcomes, this could potentially reflect the fact that effects might be found in some parts of the distribution of children, but not others, as Havnes and Mogstad (2010) have found in their work.⁴

2.3.6 Public health interventions—Children's poor economic circumstances are strongly predictive of worse health, more so as the child ages (Case et al. 2002). Child health is also strongly related to adult health and productivity (Currie 2009). Together, these two facts suggest that improvements in child health among poor families could lower future inequality of earnings. There are two main ways in which public policy can affect child health. The first is through the provision of public health insurance. European countries largely rely on publicly provided health insurance for the majority of the population. In contrast, the USA is one of the only developed countries that relies primarily on private insurance, but provides public insurance to poor families. The evidence regarding the beneficial impact of publicly provided health insurance is strong. Public health insurance expansions have been shown to improve birth outcomes among pregnant women (Currie and Gruber 1996a), improve use of preventive care and reduce child mortality (Currie and Gruber 1996b), increase immunization rates (Joyce and Racine 2005), and reduce avoidable hospitalizations (Aizer 2007).

While the above studies provide strong evidence of the impact of public health insurance expansions on child health outcomes, they do not directly link public health insurance with other measures of human capital such as education attainment or earnings. A second set of studies focusing on direct public health interventions, however, does. These studies include work by Bleakley (2007) who finds that a deworming campaign in the American South resulted in improvements in literacy, educational attainment, and adult income. This is

⁴Havnes and Mogstad (2010) find that universal childcare in Norway has positive effects on children in the lower part of the distribution and are not detected in analyses that focus on estimating the mean effect.

consistent with the work by Miguel and Kremer (2004), showing the positive benefits of a deworming campaign in Kenya in terms of school attendance and long-term adult employment and earnings (Baird et al. 2011).

In sum, evidence based on micro data suggests a positive impact of education (especially geared toward the young), income support, and health interventions on child human capital, with the largest effects for health and no documented effects for housing mobility interventions.

3 Data

The outcomes of interest are not years of schooling or earnings, but rather scores on the PISA reading test among 15-year-olds.⁵ The main reason for using this outcome is data availability: the full distribution of test scores is available for OECD countries for 2000 and 2009, and these data also include information on parental SES. There are PISA test scores for mathematics and science as well. However, the sample sizes for these two tests are half the size of the sample for the reading test. In the analysis that follows, I focus on reading test scores, but also provide results for math and science.

There are advantages and disadvantages of focusing on child test scores. The test scores are comparable across countries owing to the common scale. Moreover, there is evidence that cognitive test scores in late adolescence generally, and PISA test scores specifically, are correlated with better employment outcomes such as lower unemployment and employment in higher status occupations (Lee and Newhouse 2013). Also, test scores do not reflect inequalities in work opportunities, as earnings can. They are also less likely than measures of educational attainment (that is, years of schooling) to reflect individual choices regarding the pursuit of higher education that might be independently motivated, in part, by a family's resources, though test scores do likely reflect some ambition for higher education. A disadvantage of these measures is that they capture human capital at age 15 years and not ultimate human capital attainment. Furthermore, they do not reflect well the noncognitive skills that some interventions (especially early childhood education) have been shown to affect.

I calculate three main outcome measures based on the PISA data. The first is a measure of the importance of parental background in determining child human capital and is the estimated elasticity between an index of parental SES and a child's test scores. I refer to this as the measure of *intergenerational elasticity*. The second measure is related to the first, but more explicitly relates parental background to the inequality in child test scores. It is defined as the ratio of test scores of children whose parents are in the top 25% of the SES distribution and those whose parents are in the bottom 25% of the distribution. I refer to this as a measure of the *inheritance of inequality*. The final measure is a measure of the inequality of child test scores and is defined as the ratio of the test score of the 90th percentile of the test score distribution to the 10th percentile within a country. I refer to this as a measure of the *inequality in child test scores*.

⁵The survey tests literacy in terms of 'general competencies, that is, how well students can apply the knowledge and skills they have learned at school to real life challenges. PISA does not test how well a student has mastered a school's specific curriculum.'

The data on PISA student test scores and parental SES for 2000 and 2009 are linked with data on public spending in different categories from the OECD SOCX and Educational spending databases and available by country and year. Spending is categorized into spending on education, health, housing, family support, labor support, old age, and survivors benefits. The values for spending are the average annual spending over the course of the previous 14 years in the life of a child. The only spending variable that cannot be measured over the previous 14 years is education spending, which is measured only over the previous 3 years because of data limitations.⁶ In the analysis, spending is converted to a percent of GDP. Table 1 lists the countries with consistent data for test scores and spending, the main condition for inclusion in this analysis. Figure 1 shows how social spending has changed over time by country.

The empirical investigation should be characterized as largely descriptive with reasonable attempts to control for important confounding factors. By looking at trends within a country over time (that is, including country- and year-fixed effects), one implicitly controls for anything that might be confounding the relationship between public spending and inequality or intergenerational mobility that is country-specific and fixed over time (for example, fixed attitudes toward inequality and redistribution, or the structure of the labor market). The inclusion of year-fixed effects also controls for global trends in any factors that are common across countries (for example, global recessions or downturns in the economy). In addition to including country- and year-fixed effects, I also control for factors that change over time within a country and might be correlated with spending, as discussed below.

All test score and expenditure measures are presented in Table 1 by country and year.

4 Results

4.1 Measures of intergenerational transmission and inequality: trends and correlations

First, I show how the three measures of intergenerational transmission and inequality vary across countries and over time. The first measure, *intergenerational elasticity*, categorizes to the relationship between the family's SES and a child's score on the reading portion of the PISA test. The measure is obtained by regressing the log of the parent's SES measure on the log of the PISA reading score of the 15-year-old child for each country, including controls for child gender and nativity (irrespective of whether born in the country). In 2000, this measure varied from 0.10 for Finland, the most mobile, to 0.23 for Germany, the least mobile.

The second measure, *intergenerational inequality*, is very much related to the first but explicitly reflects the difference in child test scores between those with parents at the top of the SES distribution and those at the bottom. This measure is obtained by calculating the average test scores of those with parents in the bottom and top 25% of the SES distribution within a country/year and calculating the difference. The difference in 2000 ranged from 49 (Island) to 102 points (Germany), relative to an average test score of 500 points. These

⁶Education spending at the country level is not available before 1998.

correspond to ratios of 1.23 (Germany) and 1.10 (Iceland). The difference is larger than many cross-country differences in average test scores.

The third and final measure reflects the *inequality in child test scores* within a country. It is the ratio of the reading score for the 90th percentile to the 10th percentile: the higher the ratio, the greater the inequality. This measure varies from 1.52 for Finland to 1.78 for Luxembourg and Poland (for 2000).

There appears to be no universal trend in these measures over the period 2000–2009. Figure 2A–C plot these three measures by country for 2000 and 2009. Those countries above the 45-degree line exhibit an increase in the measure, while those below exhibit a decrease. It is clear from these figures that while many countries witnessed increases in these measures of intergenerational elasticity and inequality of parental SES and child human capital over time, just as many witnessed decreases.

However, within countries, these three measures do trend together over time. Countries that witnessed the greatest increase in inequality of parental SES, as measured by the 90:10 ratio of parental SES, also witnessed the greatest increase in the inequality of child test scores, as measured by the 90:10 ratio of child test scores (Figure 3A). It is also true that those countries that witnessed the greatest increase in intergenerational elasticity and intergenerational inequality also witnessed the greatest increase in child test score inequality over the period 2000–2009 (Figure 3B and C).

We next turn to an examination of whether changes in public investments in social programs correlate with trends in intergenerational transmission and inequality of child human capital.

4.2 Are greater public investments associated with declines in either intergenerational transmission or inequality within a country over time?

Over the period from 1985 to 2009, OECD countries generally witnessed an increase in spending on social programs as a percent of GDP (Figure 1). In Table 1, I present the share of GDP devoted to social programs by country. The numbers, presented in the second panel of the table, reflect not spending in 2000 or 2009, but rather the average spending over the life of a child who was 15 years old in 2000 or 2009. Spending on social programs as a share of GDP increased on average from 26.1% of GDP to 27.8% over this period, with the largest increase in spending in health, followed by smaller increases in family and 'other' spending which includes old age, survivors, and disability support (programs geared mainly to the elderly population). Spending on education as a percent of GDP actually fell slightly, on average, over this period.

I explore whether the increase in spending on social programs is related to student test scores in terms of (i) decreasing the importance of parental background in child test scores as measured by intergenerational elasticities or intergenerational inequality; (ii) decreasing test score inequality; or (iii) increasing test scores at any or all points in the distribution of test scores. To do so, I estimate the following:

$$\begin{aligned}
\Delta Y_c = & \beta_1 \text{Ln}(\Delta \text{Health})_c \\
& + \beta_2 \text{Ln}(\Delta \text{Family})_c \\
& + \beta_3 \text{Ln}(\Delta \text{Labor Support})_c \\
& + \beta_4 \text{Ln}(\Delta \text{Housing})_c \\
& + \beta_5 \text{Ln}(\Delta \text{Other Social})_c \\
& + \beta_6 \text{Ln}(\Delta \text{Education})_c \\
& + \beta_7 \Delta \text{SES}_c + \beta_8 \Delta \text{Education Policies}_c \\
& + \beta_9 \text{Ln}(\Delta X)_{c^\varepsilon}
\end{aligned} \tag{2}$$

Where Y_c is defined as the change or difference for each country between 2009 and 2000 in (i) the intergenerational elasticity between parental SES and child test score; (ii) the ratio in test scores of those with high and low parental SES; (iii) child test score inequality (90:10); and (iv) the change in test scores at the bottom 10%, top 10%, and median of the distribution of test scores.

Spending is measured as the log of spending as a percent of GDP. The category 'Other Social' includes old age, disability, and survivors benefits and as such represents spending on the elderly, primarily. Defining spending as the $\ln$ (% of GDP) implicitly controls for any changes in GDP over the past 15 years. I also control for the median SES index of parents in the country as well as the 10th and 90th percentile of the SES index in the country, population size, the share young, and the share elderly, and the two variables that capture differences in education policies that others have found to be related to inequality: the share of students in schools with ability grouping (for example, tracking) and the share in private schools (Pfeffer 2008). Country- and year (2009)-fixed effects are included which essentially transform all variables in the regression into first differences within a country. All regressions are weighted by country population and standard errors and are corrected for within country correlations over time.

The results for reading test scores (Table 2) suggest that of the different types of social spending, spending on health is most strongly associated with reductions in the importance of parental background in determining child test scores as measured by the intergenerational elasticity between parental SES and child test scores (Column 1) and the difference in test scores of children at the top and bottom of the SES distribution, referred to as intergenerational inequality, (Column 2). These coefficient estimates imply strong relationships: an increase in health spending of 1% point is associated with a nearly 70% reduction in intergenerational elasticities, and a 14% reduction in intergenerational inequality, evaluated at the overall mean. Spending on family support also seems to be associated with increases in intergenerational mobility, though the estimates, while statistically significant, are much smaller than the estimates for health. Interestingly, other social spending (spending on the elderly), is associated with an increase in intergenerational elasticity and inequality. This would be expected if spending on the elderly crowds out spending on the young. The lack of an association between education spending and intergenerational mobility may reflect the fact that there is little variation in education spending across countries over this period or the fact that the education spending measure

does not reflect spending when the children were youngest (due to data limitations) where the micro evidence has found the largest effects.

We also examine how spending affects the 90:10 ratio of test scores (Column 3). This measure differs from the previous measure in that it does not necessarily reflect the disparity in test scores of those with relatively rich or poor parents, only the overall variance or inequality in test scores in the population of children. Spending on health, family support, and housing appear to be associated with reductions in the 90:10 ratio, with a much larger coefficient estimate on health spending. Again, other social spending which consists largely of spending on the elderly is associated with increases in the 90:10 ratio. Surprisingly, spending on labor support is also positively related to the 90:10 ratio (though it is uncorrelated with intergenerational elasticity or inequality).

When spending is associated with a decline in the 90:10 ratio, it is usually operating through a greater improvement in scores at the bottom of the distribution (health, family support, and housing) than the upper part of the distribution (Columns 4–6). In contrast, when spending is associated with an increase in the 90:10 ratio (as it is for other spending and, to a lesser extent, labor support), it is operating through a greater reduction in test scores at the bottom of the distribution relative to the top of the distribution.

I repeat the above for math and science test scores (Table 3) for which the patterns differ from reading. In particular, with respect to math test scores, education spending appears to be associated with reductions in intergenerational elasticities and inequality (Table 3, Columns 1–2) that are as large as the reductions associated with health spending. For the science test scores (Table 3, Columns 4–6), the estimates are similar to those found for reading test scores, though slightly smaller and less precise, perhaps due to the reduced sample of science test takers.

Overall, the findings suggest that spending on the elderly is associated with both increases in the importance of parental background in determining child test scores and increases in inequality of child test scores. In contrast, spending on health is associated with particularly large improvements in intergenerational mobility and reductions in inequality of human capital of the next generation. Spending on family support and housing is also positively associated with improvements in intergenerational mobility and reductions in inequality, though less so. If one considers math test scores, education spending is also associated with improvements in intergenerational mobility and reductions in inequality. This may imply that the production functions for reading and math test scores differ significantly, with math responding to interventions geared specifically to acquiring math skills and reading scores responding more to interventions geared at general improvements in underlying human capital.

The finding that health spending exhibits the strongest association with intergenerational mobility and inequality warrants further investigation. In particular, unlike some of the other spending measures (education, family support), which are specifically geared toward children, the measure of health spending captures spending on the entire population, not just spending on children. Furthermore, it does not necessarily reflect changes in child health. In

the next section, I explore (i) how changes in spending on health over time relate to the quantity of inputs into the production of child health as well as child health and (ii) whether and how changes in inputs/child health are related to changes in reading test scores.

4.3 Health spending, health inputs and child health

4.3.1 Relationship between health spending and child health inputs/child health

I begin with the question of whether and to what extent changes in health spending at the level of the country correspond to changes in child health inputs and health. The OECD measures of child health inputs that I use are the number of pediatricians per 1000 and the share of physicians who are pediatricians. A third measure of health inputs, though not exclusive to children, is the number of hospital beds per 1000. The OECD measure of child health used is infant deaths per 1000 live births. While the OECD currently collects additional measures of child health, most have not been collected for long enough or consistently enough to be included in this analysis.⁷ I argue that infant deaths, while not perfect, are a reasonable measure of child health for two reasons. First, infant mortality rates are highly correlated with other measures of population health, more generally, such as the disability-adjusted life expectancy (Reidpath and Allotey 2003). Second, the leading cause of infant mortality is low birth weight, which has, in turn, been linked to important long-term outcomes such as height (a marker of child nutrition and health), intelligence quotient, and educational attainment (Black et al. 2007).⁸

As with the measures of health spending, I calculate 15-year averages over the period 1985–2000 and 1994–2009 for the three measures of health inputs. This is done because we are ultimately interested in how spending over the course of the child's life affects cognitive achievement as measured by the score on the PISA test which is administered to 15-year-olds in 2000 and 2009. For the three measures of health inputs, the first two increase over this period by 10%, but the number of hospital beds declines nearly 20%, coincident with a nearly universal reduction in the average length of hospital stay over this period and a shift toward outpatient care.

Estimates of the extent to which changes in spending on health correspond to changes in child health inputs and health are presented in Table 4. I regress each of the above three measures of child health inputs (pediatricians per 1000, share of physicians who are pediatricians, and hospital beds per 1000) and infant deaths per 1000 live births on measures of spending on health and education as well as all controls previously included in Tables 2 and 3.

The results show that an increase in health spending is associated with an increase in health inputs geared toward children. A standard deviation increase in health spending leads to a doubling of the number of pediatricians per 1000 evaluated at the mean, while an increase in education spending has a small negative relationship with the number of pediatricians (Table

⁷Another potential measure of child health that has been collected for many years is the immunization rate for diphtheria, pertussis, and tetanus, as well as measles. However, the rates are very high even at the beginning of the period (over 90%), so that there is little scope for improvement over time.

⁸One can reasonably assume that a reduction in the infant mortality rate is likely correlated with a reduction in the rate of low birth weight.

4, Column 1). To explore whether the estimated effect on pediatricians reflects an increase across the board in the number of physicians or whether pediatricians are disproportionately affected by changes in public health spending, I present the estimates with respect to health spending and the share of physicians who are pediatricians in Column 2 of Table 4. I find that over this period, increases in health spending did disproportionately affect spending on child health as measured by the share of physicians who are pediatricians: an increase in health spending of 1% of GDP leads to a 42 % increase in the share of physicians who are pediatricians over this period. Our third measure of health inputs is the number of hospital beds per 1000 in the country, which, because it is not child-specific, differs significantly from the previous two measures of inputs. While an increase in spending is associated with an increase in the number of hospital beds, the estimate is very imprecise.

Next, I present results for the infant health measure. These estimates are imprecise, but display a generally positive relationship between health spending and child health: as spending increases, infant mortality declines (Table 4, Column 4). The lack of precisions is not entirely surprising given the rarity of infant deaths. Future work should attempt to estimate this relationship with richer measures of child health than infant mortality.

Overall, the evidence shows that increases in health spending correspond to an increase in health inputs geared toward children, but the evidence with respect to improvements in health is less clear, though suggestive of a positive relationship.

4.3.2 Relationship between child health inputs/child health and reading test scores—

Next, I explore the extent to which increases in child health inputs or improvements in child health are associated with reduced inequality of child human capital as measured by reading test scores. For the former, I estimate the extent to which increases in pediatricians and hospital beds correspond to reductions in intergenerational elasticities, intergenerational inequality, and inequality of child human capital, as well as improvements in test scores throughout the distribution. To do so, I regress the usual outcomes (intergenerational elasticity, intergenerational inequality, test score inequality, and test scores at the 10%, 90%, and median) on the above measures of health inputs as well as spending on education and the controls included in Tables 2 and 3.

I find that increases in the number of physicians per 1000 during the first 15 years of a child's life is very positively related to reductions in the intergenerational correlations in human capital and inequality in test scores (Table 5, top panel, Column 1). For example, a one-standard deviation increase in pediatricians per 1000 is associated with a 61% decline in intergenerational elasticities and a 21% decline in intergenerational inequality, evaluated at the mean. When looking at associations across the distribution of test scores, the estimates are not precise but generally show that increases in the number of pediatricians are associated with reductions in child test score inequality, with greater improvements at the bottom of the distribution and small reductions at the top. Increases in the number of hospital beds are also associated with reductions in intergenerational correlations and inequality (Table 5, second panel). A standard deviation increase in the number of hospital beds is associated with reductions in intergenerational correlations of 12% and inequality of 5% evaluated at their respective means.

Next, I look at the relationship between improvements in infant mortality and reading test scores (Table 5, third panel). Reductions in infant deaths are associated with reductions in intergenerational transmission and inequality (significant at the 10% level) as well as declines in test score inequality, though the associations are moderate in size. A standard deviation decline in infant deaths is associated with a 6–10%-decline in intergenerational elasticity or inequality.

5 Conclusion

Policymakers and academics have become increasingly alarmed by the rise in inequality witnessed in developed countries over the past 40 years. Of particular concern are its implications for intergenerational mobility. If rising income inequality results in reduced private investments in child human capital among parents with the fewest resources relative to those with the greatest resources, the result will be a reduction in upward mobility and an increase in the inequality of human capital of the next generation.

However, it is possible for public investments to offset the impact of rising inequality on the human capital of the next generation. In this article, I examined the potential for public spending to offset the unequal distribution of private resources among parents to equalize child human capital. To do so, I used the PISA test score data for 15-year-olds in 25 OECD countries in 2000 and 2009 merged with spending on social programs (health, education, family support, housing assistance, labor support, and spending on the elderly). I find that increases in spending on the elderly are strongly associated with increases in the importance of family background in producing child human capital and increases in inequality of child human capital. In contrast, spending on health is most strongly associated with reductions in the relationship between parental resources and child test scores and reductions in the inequality of child test scores. Spending on housing and family support are more moderately associated with such improvement. This is particularly true for reading test scores. For math test scores, spending on education is also strongly related to improvements in intergenerational mobility and reductions in inequality of human capital.

Upon further inspection of the results for health spending, a clear pattern emerges between the quantity of health services for children (as measured by the number of pediatricians) in a country and test scores. As health services for children increase, test scores of all children rise, but more so for those at the bottom of the test score distribution, resulting in a decline in both inequality of test scores and the importance of parental background in determining test scores. The results suggest that public investments in child human capital, and particularly health, have the potential to offset the negative impact of the rising income inequality on the mobility of the next generation, whereas spending on the elderly may have the opposite effect, most likely due to crowding out of spending on children. These findings, based on trends over time within a country, while an improvement over examination-based cross-sectional relationships, are only suggestive. Further work establishing a causal relationship between public spending, intergenerational mobility, and inequality of child human capital is needed.

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Figure 1.
Social Spending as % GDP over time.

Figure 2.

(A) Intergenerational elasticity, 2009 and 2000. (B) Intergenerational inequality, 2009 and 2000. (C) PISA test score 90:10, 2009 and 2000.

Figure 3.

(A) Change in inequality in parental Socio-Economic Index (SEI) and change in inequality in child test scores, 2000–2009. (B) Change in child test score inequality and change in intergenerational elasticity, 2000–2009. (C) Change in inheritance of inequality and change in intergenerational elasticity, 2000–2009.

Average reading scores and social spending, 2000 and 2009

PISA reading scores for 15-year-olds														
	2000						2009							
	Elasticity	Inequality difference	Inequality ratio	50%	90:10	90%	10%	Elasticity	Inequality difference	Inequality ratio	50%	90:10	90%	10%
AUS	0.18	83	1.17	534	1.70	657	386	0.18	76	1.16	515	1.69	634	375
AUT	0.21	72	1.15	505	1.66	615	369	0.20	94	1.22	478	1.76	598	341
BEL	0.22	99	1.21	530	1.74	636	365	0.23	110	1.24	519	1.70	630	371
CAN	0.15	68	1.14	528	1.62	645	398	0.14	53	1.11	515	1.62	629	389
CHE	0.19	91	1.20	502	1.70	619	364	0.16	59	1.13	499	1.63	608	374
DEU	0.23	102	1.23	505	1.75	627	358	0.21	85	1.18	504	1.68	614	366
DNK	0.17	75	1.16	504	1.65	616	372	0.16	78	1.17	485	1.62	591	366
ESP	0.15	63	1.13	501	1.57	596	379	0.15	71	1.16	493	1.63	594	365
FIN	0.10	51	1.10	554	1.52	655	431	0.12	48	1.09	536	1.54	640	414
FRA	0.17	81	1.17	509	1.63	617	379	0.20	95	1.21	506	1.76	624	355
GBR	0.20	94	1.19	528	1.67	651	390	0.20	79	1.17	495	1.67	614	369
GRC	0.14	70	1.16	478	1.74	594	341	0.17	83	1.19	491	1.65	603	365
HUN	0.22	87	1.20	485	1.65	597	362	0.23	91	1.20	504	1.60	610	381
IRL	0.16	75	1.15	532	1.59	645	406	0.19	80	1.18	507	1.63	612	375
ISL	0.11	49	1.10	514	1.62	619	383	0.12	53	1.11	507	1.66	617	372
ITA	0.16	69	1.15	494	1.63	603	369	0.16	76	1.17	498	1.65	605	366
LUX	0.20	100	1.25	450	1.78	563	316	0.26	113	1.27	485	1.79	602	337
NLD	0.17	74	1.15	552	1.55	649	420	0.17	69	1.14	520	1.56	627	401
NOR	0.19	70	1.15	514	1.74	634	364	0.18	65	1.14	506	1.62	620	382
NZL	0.18	79	1.16	536	1.72	657	382	0.23	83	1.17	532	1.68	648	385
POL	0.20	82	1.19	474	1.78	593	334	0.16	75	1.16	509	1.58	618	391
PRT	0.22	94	1.22	484	1.71	596	348	0.19	81	1.18	493	1.60	598	373
SWE	0.16	70	1.14	523	1.61	629	391	0.19	80	1.17	503	1.68	621	370
USA	0.19	89	1.19	500	1.76	629	358	0.19	82	1.18	500	1.67	622	371
Average, unweighted	0.18	78	1.17	508	1.67	621	372	0.18	78	1.17	503	1.65	614	372
Average, weighted	0.19	85	1.18	504	1.71	624	366	1.12	81	1.18	501	1.67	617	370

	Social spending as % GDP													
	2000							2009						
	Total	Education	Health	Labor	Housing	Family	Other	Total	Education	Health	Labor	Housing	Family	Other
AUS	17.74	3.03	4.66	0.40	0.22	1.95	7.48	18.29	1.04	5.39	0.39	0.21	2.74	8.51
AUT	26.25	6.58	5.70	0.36	0.07	2.07	11.47	33.47	5.54	6.59	0.57	0.10	2.80	17.86
BEL	30.26	4.34	6.44	1.16	0.00	2.39	15.93	32.50	6.29	6.91	1.15	0.05	2.58	15.52
CAN	24.46	6.28	6.41	0.52	0.61	0.71	9.93	23.07	5.84	6.56	0.38	0.51	0.95	8.82
CHE	23.49	2.43	4.44	0.39	0.11	1.16	14.96	27.89	1.94	5.40	0.65	0.14	1.39	18.37
DEU	31.80	5.64	7.41	1.06	0.24	1.94	15.51	32.80	4.89	8.10	1.08	0.42	2.07	16.25
DNK	34.03	7.58	4.85	1.17	0.66	3.33	16.44	34.59	7.35	5.55	1.69	0.70	3.45	15.85
ESP	25.44	5.39	5.07	0.58	0.13	0.39	13.88	25.95	4.95	5.56	0.66	0.19	0.93	13.65
FRA	33.50	6.39	6.76	0.95	0.82	2.69	15.89	34.88	5.99	7.44	1.07	0.85	2.99	16.54
GBR	24.51	5.15	5.22	0.51	1.45	2.23	9.94	25.98	5.54	6.06	0.34	1.50	2.84	9.70
GRC	21.15	4.43	4.11	0.24	0.40	0.70	11.29	24.02	4.27	5.17	0.22	0.55	1.06	12.75
HUN	15.58	6.52	6.11	0.43	0.06	0.32	2.14	18.32	2.26	5.56	0.37	0.41	2.33	7.39
IRL	22.30	5.51	4.88	1.13	0.59	1.62	8.57	20.23	5.20	5.25	0.87	0.36	2.16	6.39
ISL	24.09	8.00	5.95	0.06	0.06	2.39	7.64	25.03	7.94	6.08	0.08	0.20	2.68	8.06
ITA	28.60	5.06	5.62	0.22	0.01	0.78	16.91	30.28	4.80	6.11	0.53	0.01	1.18	17.65
NDL	30.27	5.64	5.48	1.38	0.37	1.57	15.83	27.32	5.64	5.61	1.38	0.38	1.60	12.72
NOR	27.25	6.88	3.88	0.82	0.15	2.71	12.80	29.23	5.63	5.43	0.75	0.17	3.12	14.14
NZL	19.69	0.00	5.41	0.77	0.44	2.47	10.60	25.22	6.52	6.25	0.47	0.76	2.71	8.51
POL	25.33	3.40	4.21	0.37	0.10	1.44	15.80	27.15	5.70	4.23	0.40	0.14	1.10	15.59
PRT	20.15	5.85	4.08	0.41	0.00	0.72	9.09	26.01	5.48	6.15	0.58	0.00	1.05	12.76
SWE	38.11	6.67	6.90	2.17	0.83	4.02	17.52	36.20	6.32	6.51	1.64	0.66	3.29	17.77
USA	21.81	7.07	5.49	0.21	0.00	0.56	8.48	22.87	7.02	6.70	0.14	0.00	0.67	8.32
Average, unweighted	25.72	5.36	5.41	0.70	0.33	1.73	12.19	27.33	5.28	6.03	0.70	0.38	2.08	12.87
Average, weighted	26.10	5.91	5.67	0.51	0.28	1.27	11.78	27.76	5.79	6.48	0.51	0.31	1.50	11.95
Change 2009–2000	1.66	−0.12	0.81	0.00	0.03	0.23	0.16							

Notes: Elasticity refers to intergenerational elasticity or transmission and is the coefficient on Infparental SES0 in a county*year specific regression in which ln(child test score) is regressed on ln(parental SES).

Inequality (difference) refers to the linear difference in child test scores between those with parents in the top 25% of the SES distribution and those with parents in the bottom 25% of SES. Inequality (ratio) refers to the ratio of child test scores for children with parents in the top 25% of the SES distribution to those with parents in the bottom 25% of SES.

50% is the median child test score in the country.

90:10 refers to the ratio of the 90th percentile of child test scores to the 10th percentile.

90% is the 90th percentile of child test scores.

10% is the 10th percentile of child test scores.

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Table 2

Categories of spending (as % GDP) and reading score gains

	(1) Elasticity	(2) Inequality	(3) 90:10	(4) 10%	(5) 90%	(6) 50%
Ln(health spending as % GDP)	-0.197 [0.0284]	-0.162 [0.107]	-1.007 [0.133]	263.0 [15.76]	69.00 [74.42]	153.0 [48.75]
Ln(family support spending as % GDP)	-0.0552 [0.0127]	-0.106 [0.0476]	-0.225 [0.0595]	76.86 [7.031]	49.30 [33.20]	65.75 [21.75]
Ln(housing as % GDP)	-0.0109 [0.0170]	-0.0757 [0.0638]	-0.197 [0.0797]	62.57 [9.420]	33.05 [44.47]	53.71 [29.14]
Ln(education spending as % GDP)	0.00217 [0.0122]	-0.0483 [0.0459]	0.00337 [0.0574]	-23.97 [6.776]	-36.14 [31.99]	-36.18 [20.96]
Ln(labor support spending as % GDP)	0.0431 [0.0128]	0.0345 [0.0482]	0.470 [0.0603]	-143.6 [7.124]	-69.98 [33.63]	-100.8 [22.03]
Ln(other spending as % GDP)	0.104 [0.0318]	0.244 [0.120]	0.775 [0.150]	-271.5 [17.68]	-176.6 [83.49]	-236.9 [54.69]
SES index—top 10%	0.00500 [0.00417]	0.0320 [0.0157]	0.0360 [0.0196]	-8.857 [2.315]	-1.788 [10.93]	-6.230 [7.159]
SES index—bottom 10%	0.00790 [0.00422]	0.00627 [0.0159]	-0.0271 [0.0198]	10.44 [2.343]	7.912 [11.06]	8.883 [7.248]
SES index—median	0.00183 [0.00572]	-0.0188 [0.0215]	0.0247 [0.0269]	-8.121 [3.176]	-4.310 [15.00]	-5.607 [9.825]
Share of population > 65	-1.176 [0.843]	0.473 [3.171]	-21.63 [3.964]	7.879 [468.3]	5.349 [2.211]	6.654 [1.448]
Share of population <15	2.127 [0.409]	4.376 [1.538]	12.83 [1.923]	-4.177 [227.1]	-2.343 [1.072]	-3.288 [702.5]
Country population	0.00466 [0.00136]	0.00567 [0.00513]	0.0475 [0.00642]	-16.91 [0.758]	-11.02 [3.578]	-13.68 [2.344]
Education tracking	-0.0579 [0.0445]	0.147 [0.167]	0.175 [0.209]	-117.2 [24.70]	-138.8 [116.6]	-144.1 [76.40]
Share in private school	0.0713 [0.0533]	-0.111 [0.201]	0.312 [0.251]	-137.0 [29.62]	-109.1 [139.8]	-125.5 [91.61]
Year = 2009	0.0553 [0.00883]	0.0366 [0.0332]	0.306 [0.0415]	-97.36 [4.902]	-50.68 [23.15]	-75.40 [15.16]
Observations	36	36	36	36	36	36
R-squared	0.999	0.992	0.997	0.999	0.989	0.992
Mean of dependent variable	0.181	1.18	1.17	366	624	500

Notes: Standard errors in brackets. All standard errors adjusted for clustering within Country.

Elasticity refers to intergenerational elasticity and is the coefficient in a country*year specific regression in which ln(health test scores) is regressed on ln(health test scores) and controls for gender and nativity.

Inequality refers to the ratio of test scores for those with parents in the top 25% of the SES distribution to the test scores for those whose parents are in the bottom 25% of the SES distribution.

90:10 refers to the ratio of test scores in the 90th percentile to the 10th percentile.

10% refers to the test score of the bottom 10% of the distribution, 90% refers to the test scores of the top 10% of the test score distribution, and 50% refers to the median.

Table 3

Categories of spending (as % GDP) and gains in math and science scores

	(1) Math test scores		(3)	(4) Science test scores		(6)	(7) Averaged test score		(9)
	Elasticity	Inequality	90:10	Elasticity	Inequality	90:10	Elasticity	Inequality	90:10
Ln(health spending as % GDP)	−0.0771 [0.0317]	−0.0606 [0.0204]	−0.687 [0.259]	−0.182 [0.0264]	−0.131 [0.0994]	−0.695 [0.0879]	−0.171 [0.00147]	−0.132 [0.0679]	−0.858 [0.00427]
Ln(family support spending as % GDP)	−0.0359 [0.0141]	−0.0724 [0.00910]	−0.0874 [0.116]	−0.0894 [0.0118]	−0.131 [0.0443]	−0.334 [0.0392]	−0.0524 [0.000654]	−0.0929 [0.0303]	−0.178 [0.00190]
Ln(housing as % GDP)	0.0106 [0.0190]	−0.0500 [0.0122]	−0.177 [0.155]	0.0176 [0.0158]	−0.0392 [0.0594]	−0.131 [0.0525]	0.00241 [0.000876]	−0.0592 [0.0406]	−0.172 [0.00255]
Ln(education spending as % GDP)	−0.0223 [0.0136]	−0.0683 [0.00877]	−0.0465 [0.111]	0.0916 [0.0114]	0.0660 [0.0427]	0.0860 [0.0378]	0.0205 [0.000630]	−0.0253 [0.0292]	0.0132 [0.00183]
Ln(labor support spending as % GDP)	0.0655 [0.0143]	0.0558 [0.00922]	0.496 [0.117]	0.0881 [0.0119]	0.0835 [0.0449]	0.398 [0.0397]	0.0623 [0.000663]	0.0481 [0.0307]	0.445 [0.00193]
Ln(other spending as % GDP)	0.00989 [0.0356]	0.121 [0.0229]	0.435 [0.291]	0.155 [0.0297]	0.288 [0.112]	0.834 [0.0986]	0.0880 [0.00164]	0.207 [0.0762]	0.635 [0.00479]
SES index—top 10%	−0.00248 [0.00466]	0.0219 [0.00299]	0.00274 [0.0381]	0.000599 [0.00388]	0.0259 [0.0146]	0.0313 [0.0129]	0.000634 [0.000215]	0.0262 [0.000997]	0.0252 [0.000627]
SES index—bottom 10%	0.00358 [0.00471]	0.00118 [0.00303]	−0.0333 [0.0386]	0.00903 [0.00393]	0.00802 [0.0148]	−0.0388 [0.0131]	0.00732 [0.000218]	0.00572 [0.0101]	−0.0232 [0.000634]
SES index—median	0.00758 [0.00639]	−0.00886 [0.00411]	0.0365 [0.0523]	0.0102 [0.00533]	−0.0111 [0.0200]	0.0348 [0.0177]	0.00670 [0.000295]	−0.0128 [0.0137]	0.0268 [0.000860]
Share of population > 65	−2.608 [0.942]	−0.957 [0.606]	−26.13 [7.705]	−4.401 [0.785]	−2.875 [2.954]	−24.93 [2.610]	−2.600 [0.0436]	−0.752 [2.017]	−22.16 [0.127]
Share of population < 15	0.724 [0.457]	2.503 [0.294]	5.055 [3.737]	2.644 [0.381]	4.739 [1.432]	12.84 [1.266]	1.784 [0.0211]	3.697 [0.978]	9.670 [0.0615]
Country population	0.00308 [0.00152]	0.00220 [0.000980]	0.0333 [0.0125]	0.00986 [0.00127]	0.0104 [0.00478]	0.0521 [0.00422]	0.00553 [7.05e−05]	0.00557 [0.00326]	0.0405 [0.000205]
Education tracking	−0.113 [0.0497]	0.0348 [0.0320]	0.0195 [0.406]	−0.109 [0.0414]	0.104 [0.156]	0.332 [0.138]	−0.0955 1.12	0.0888 [0.106]	0.105 [0.00669]
Share in private school	0.0193 [0.0596]	−0.126 [0.0383]	0.211 [0.487]	0.367 [0.0497]	0.227 [0.187]	0.603 [0.165]	[0.00275]	−0.0330 [0.128]	0.347 [0.00802]
Year = 2009	0.0597 [0.00986]	0.0468 [0.00634]	0.301 [0.0807]	0.0951 [0.00822]	0.0696 [0.0309]	0.267 [0.0273]	0.0680 [0.000456]	0.0487 [0.0211]	0.284 [0.00133]
Observations	36	36	36	36	36	36	36	36	36
R-squared	0.999	1.000	0.990	0.999	0.994	0.999	1.000	0.997	1.000

Notes: Standard errors in brackets. All standard errors adjusted for clustering within Country.

Elasticity refers to intergenerational elasticity and is the coefficient in a country*year specific regression in which ln(child test scores) is regressed on ln(parental SEI) and controls for gender and nativity.

Inequality refers to the ratio of test scores for those with parents in the top 25% of the SEI distribution to the test scores for those whose parents are in the bottom 25% of the SEI distribution.

90:10 refers to the ratio of test scores in the 90th percentile to the 10th percentile.

Table 4

Changes in health spending and health inputs over time

	(1) Pediatrician/1000	(2) % Pediatricians	(3) Hospital beds/1000	(4) Infant deaths/1000
Ln(health spending as % GDP)	0.0772 [0.00978]	1.647 [0.631]	5.388 [4.281]	-7.589 [6.613]
Ln(education spending as % GDP)	-0.0123 [0.00671]	-0.532 [0.644]	-0.706 [0.992]	1.354 [2.674]
SES index—top 10%	0.000875 [0.00355]	0.133 [0.234]	0.0748 [0.262]	-0.214 [0.381]
SES index—bottom 10%	-0.000943 [0.00157]	-0.158 [0.170]	0.0557 [0.216]	0.241 [0.510]
SES index—median	0.00201 [0.00119]	0.0535 [0.142]	-0.164 [0.311]	0.478 [0.535]
Share of population > 65	-0.257 [0.227]	-40.67 [42.19]	16.75 [54.65]	-81.67 [83.18]
Share of population <15	0.167 [0.125]	-4.686 [15.90]	22.62 [26.13]	6.531 [56.85]
Country population	0.000283 [0.000117]	0.00735 [0.0146]	0.0116 [0.0324]	0.0887 [0.0784]
Year = 2009	0.00708 [0.00581]	0.191 [0.370]	-1.828 [1.201]	-2.243 [1.240]
Observations	36	35	39	40
R-squared	0.999	0.998	0.966	0.951
Mean of dependent variable	0.11	3.8	5.97	8.7

Notes: Standard errors in brackets. All standard errors adjusted for clustering within Country. All controls included in Table 2 also included.

Table 5

Changes in health inputs and changes in reading test scores

	(1) Elasticity	(2) Inequality	(3) 90:10	(4) 10%	(5) 90%	(6) 50%
Pediatricians per 1000, average over past 15 years	-1.979 [0.465]	-1.883 [0.766]	-5.065 [3.004]	901.1 [756.0]	-374.6 [391.9]	116.3 [427.4]
Observations	38	38	38	38	38	38
R-squared	0.981	0.970	0.881	0.912	0.976	0.974
Total hospital beds per 1000, average over past 15 years	-0.0100 [0.00271]	-0.0118 [0.00714]	-0.0364 [0.0102]	6.986 [2.645]	-1.928 [3.522]	2.125 [3.372]
Observations	39	39	39	39	39	39
R-squared	0.979	0.918	0.891	0.879	0.933	0.904
Infant deaths per 1000 live births	0.00501 [0.00301]	0.00646 [0.00350]	0.0294 [0.0112]	-7.960 [1.842]	-2.516 [2.139]	-4.579 [1.630]
Observations	42	42	42	42	42	42
R-squared	0.931	0.911	0.817	0.861	0.936	0.923
Mean of dependent variable	0.181	1.18	1.17	366	624	500

Notes: Standard errors in brackets. All standard errors adjusted for clustering within Country.

Elasticity refers to intergenerational elasticity and is the coefficient in a country*year specific regression in which lnfrchld test scores is regressed on lnfrparental SEI and controls for gender and nativity.

Inequality refers to the ratio of test scores for those with parents in the top 25% of the SEI distribution to the test scores for those whose parents are in the bottom 25% of the SEI distribution.

90:10 refers to the ratio of test scores in the 90th percentile to the 10th percentile.

All controls included in Table 2 also included.