Health Endowments, Schooling Allocation in the Family, and Longevity: Evidence from US Twins*

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Abstract

We analyze data from the Minnesota Twin Registry (MTR) and the Socioeconomic Survey of Twins (SST), combined with new mortality data, and contribute to two bodies of literature. First, we demonstrate a beneficial casual effect of education on health and longevity. Literature results on this subject based on natural experiments and twin studies are controversial despite a long history of research. Second, we shed light on how families allocate resources among siblings, another controversial question. We show that if one twin has a poorer health endowment parents will compensate for the difference with more schooling. We argue that we can expect a bias towards detecting a reinforcement case. Despite the bias we still find evidence of compensating behavior. For identification we rely on identical genes in monozygotic twins, gene variation in dizygotic twins, and shared family background in all twins, and control for the key background characteristics of birth weight and disabling injury. We account for measurement error in reported years of schooling.

Key words: health endowments, intrafamily resource allocation, education, health, longevity, twin study

JEL codes: I12, I140, I240, J130, J24

1 Introduction

This paper contributes to understanding two controversial questions that are important for both economic theory and policy: (1) whether education causally affects health and longevity and (2) whether parents compensate or reinforce differences in endowments among their children. As answers to both research questions may differ by country, to inform policy makers in the USA it is particularly useful to provide evidence based on quality US data. Our analysis is based on a major US twins dataset called the Minnesota Twin Registry (MTR), combined with its follow-up conducted by economists, called the Socioeconomic Survey of Twins (SST), and our own recent collection of individual mortality data.

Despite a considerable body of literature, the question regarding the causal relationship between education, health, and longevity is still unresolved. This question is often addressed in the literature by using changes in compulsory schooling laws or birth of twins as natural experiments.[1] Compulsory schooling laws identify the effect only for those students who would otherwise not gain further education. Papers using twin fixed effects usually identify the average effect of a single additional year of schooling.

[1] Examples of other methods include randomized controlled trials, which usually work at low levels of education such as preschool (e.g., Conti et al., 2016), military draft used as instrument for men's education (e.g., Buckles et al., 2013), and methods that explicitly model unobserved heterogeneity (e.g., Hong et al., 2018). See Grossman (2015) and Galama et al. (2018) for recent surveys.

The compulsory schooling instrument for the US is weak and therefore is not useful for reliable estimation of the effect of interest, while results for other countries are mixed (see Galama et al., 2018, for a survey). Twin fixed effect estimates are limited to available twins registries, among which only a small number are large, representative, and old enough to reliably study longevity. Lundborg et al. (2016) use Swedish twins data and find strong effects of education on longevity for both men and women. Madsen et al. (2010) and Behrman et al. (2011) use Danish twins data and find no effects. However, Van Den Berg et al. (2015) use the same data but a different methodology and find an effect on mortality for men but not for women. Behrman et al. (2015) use the Chinese Adult Twins Survey to study effects of education on health and health-related behaviors for a pooled sample of men and women and find a number of effects on important determinants of mortality: improvements in general and mental health and reductions in smoking and the number of chronic diseases.

There are few results based on US twins, and they tend to show little or no effect, a result that contrasts with our own findings. Kohler et al. (2011) estimate twin fixed effects for monozygotic twins using SST data and conclude that there is no effect of education on health. However, the authors use only one outcome, self-reported health, an outcome known to be predictive of mortality but subject to measurement error. Furthermore, the authors perform their estimation only for the subsample of female twins. Using the same SST data and the same methodology, but instead investigating both genders and several health-related outcomes including newly collected mortality data, we complement these results with new estimates.[2] While we confirm the statistically insignificant result reported by Kohler et al. (2011), our estimates for a larger set of health-related outcomes and both genders provide evidence in favor of the effect of education on health-related outcomes.

Amin et al. (2015) also use the MTR data (among other datasets) and the twin fixed effects estimator, but combine the MTR data with another dataset called the Mid-Atlantic Twin Registry (MATR) to increase sample size. We compare their results with ours, which are acquired from the sample of only MTR data. The authors report estimates for the pooled sample of men and women only, and concentrate on three health outcomes: self-reported health, BMI, and overweight. Our results for overweight based on MTR include a strong and statistically significant gender difference in effects, a strong beneficial effect for men, no effect for women, and no statistically significant effect for the pooled sample. Thus, pooling data for overweight-related variables may mask important relationships. Similarly to the authors' estimate, our pooled sample estimate for self-reported health is positive. Amin et al. do not investigate outcomes that capture mortality or specific physical health problems. Arguably, these two outcomes are more objective health measures than self-reported health.

[2] One minor difference in methodology is that we control for birthweight and disabling injury, but our results are robust to the omission of these controls.

Our second research question, whether parents of multiple children tend to reinforce or compensate for differences in their children's endowments, is also controversial. This question is an empirical one, as both results are theoretically possible. Some papers show that parents reinforce differences in endowments by investing more in children who have more beneficial endowments (e.g., Aizer and Cunha, 2012; Behrman, 1988; Behrman et al., 1982, 1994; Datar et al., 2010; Frijters et al., 2013; Rosenzweig and Zhang, 2009). Others show that parents compensate for differences by investing more in children with less beneficial endowments (e.g., Black et al., 2010; Del Bono et al., 2012; Halla and Zweimüller, 2014; Pitt et al., 1990). Some other papers find no or little effect (e.g., Abufhele et al., 2017; Almond and Currie, 2011; Royer, 2009). See Almond and Mazumder (2013) for a detailed survey. The most common finding is that parents reinforce endowments. In this paper we argue that we should expect a bias towards detecting reinforcing behavior. Hence, if the true prevailing behavior is compensation it can be misclassified in a statistical analysis as either reinforcement or "no effect." Despite the expected bias toward detecting reinforcement, we find statistically significant evidence of compensating behavior.

The question is, actually, more complex than simply "reinforcement vs. compensation of the endowment," as endowments might differ by type and their effects may vary across different types of family investments. In particular, it is productive to differentiate ability from health and education investments from health investments. In line with this hypothesis, Abufhele et al. (2017) use Chilean data of infants and young children and test whether parents reinforce or compensate for difference in twin endowments related to health and ability with aggregate investments that include maternal time, home environment, and healthy food. The authors detect neither compensation nor reinforcement, but a neutral behavior. In contrast, Yi et al. (2015), who analyse Chinese twins data and use a different methodology and different measures of endowments and investments than Abufhele et al. (2017), find that when a twin receives a health shock between ages 0–3, the other twin receives health investments worth 305 yuan less but education investments worth 182 yuan more at about age 11. This result implies compensation on the health dimension, reinforcement on the education dimension, and net compensation of the health endowment.

In this project we do not have enough data to study the effect of differences in health endowments on differences in health spending, but we can study a more interesting question about effects on differences in education. We view the qualitative answer to the first question as rather obvious. If one sibling is sick and the other is healthy, which one will see the doctor more often? We can expect that the answer to this question for the US should be no different from the answer found by Yi et al. (2015) for China: parents compensate for poor health with more medical treatments. It is less clear which child will receive more education, and we expect that the result may differ by country.

There are major differences between developing countries and the US in terms of pension systems, credit constraints, wealth, culture, and financing of medicine and education. Yi et al. (2015) note that parents in developing countries may have extra motivation to reinforce endowments, as they are much more dependent on their children in retirement. They may invest more in a child who is more likely to bring back high financial returns. In contrast, US parents are less dependent on their children in retirement and might be more inclined to care about equality of child outcomes, which includes ensuring that all of their children avoid adverse outcomes such as being unemployed or having an undesirable job. This paper confirms this intuition and finds that US children with lower health endowments are allocated with more schooling.

As mentioned, we use MTR, SST, and new mortality data merged together. The collection of the MTR data began in 1983 to identify and study twins born in Minnesota. The SST survey followed-up with a sub-sample of the initial MTR participants. We analyze same-sex twin pairs, of which both twins participated in both surveys and both twins provided information about their education levels. Our sample contains 944 twin pairs born between 1936 and 1955. We match the twin respondents from these surveys with information about their mortality gathered from the Social Security Death Master File, the Centers' for Disease Control National Death Index, and contact with surviving relatives.

To estimate the effect of education on longevity, we apply a linear probability model to within-pair differences in order to estimate the extent to which a twin who has had more years of schooling is expected to outlive her twin who has fewer years of schooling. This within-twin-pair approach leverages the common family and genetic background shared by monozygotic twins. We also control for possible confounders in all our models: birth weight and disabling injury. We use the same method to study effects of education on health and health behaviors. To answer the question about compensation vs. reinforcement of health endowments, we adopt the method initially proposed by Behrman et al. (1994) for studying wage earning endowment. For identification we rely on the presence of identical genes in monozygotic (MZ, or "identical") twins, genetic variation in dizygotic (DZ, or "fraternal") twins, and shared family background within all observed twin pairs. To account for measurement error in schooling we use Ashenfelter and Krueger's (1994) method, which takes advantage of twins' reports about their own education and the education of their twin.

2 Data

We use multiple data sets, gathered between 1983 and 2017, which longitudinally describe the lives of a set of twin pairs who were born in Minnesota. Each pair in the sample was raised together.

2.1 Minnesota Twin Registry

Collected by researchers at the University of Minnesota, the Minnesota Twin Registry (MTR) represents a major twin study conducted in the US. As described in Krueger and Johnson (2002), the MTR was initiated in 1983 and includes data on twins born in Minnesota between 1936 and 1955. The MTR staff identified the twins retrospectively from their birth records and contacted twins to ask for their participation in surveys in person, by mail, and over the phone. The MTR staff located about 80% of the identified twins. Among those who were located, about 80% agreed to participate. There were 4307 twin pairs in which both twins participated. MTR participants answered survey questions about an array of topics, including their education and health backgrounds, and researchers gathered participants' birth weight data directly from their birth certificates.

2.2 Socioeconomic Survey of Twins

In 1994, MTR respondents from same-sex twin pairs were re-surveyed in the Socioeconomic Survey of Twins (SST), which gathered further information from each twin regarding labor market participation, wages, health, and education.[3] The SST has been used in a number of influential publications in economics (e.g., Antonovics and Town, 2004; Behrman and Rosenzweig, 2002, 2004; Behrman et al., 1994). SST respondents were also asked to provide information about

[3] See Behrman and Rosenzweig (1999) for a more thorough description of the SST.

their parents, siblings, spouses, and children. Importantly for our analysis, the SST asked each twin to report education for both herself and the other twin, meaning that we have two separate observations on years of schooling for each twin who is part of a participating SST pair. 1325 intact twin pairs returned valid SST questionnaires (Behrman and Rosenzweig, 2002).

2.3 Mortality Data

To construct mortality data for these twins, we gathered data from both the Social Security Death Master File and the Centers for Disease Control's National Death Index. Research on the reliability of these databases in identifying deaths found that over 90% of deaths are correctly identified by each database (Hauser and Ho, 2001; Wentworth and Rasmussen, 1983). We further improve precision by comparing data from alternative sources, as well as contacting next-of-kin in some cases.

The available mortality data up to year 2014 provides us with a 20 year risk period window between the initial date when living twins participated in the SST and the date when the mortality status of respondents was last observed.

2.4 Characteristics of the Twin Sample

The MTR sample is almost entirely white, which is consistent with the historical demographics of Minnesota. We exclude from the estimation sample two twin pairs with at least one non-white parent, since the data are insufficient for a reliable study of the minority population.[4] Our twin sample thus consists of twin pairs who are white and the same sex, and in which both twins provided education information and also participated in both the initial MTR and the follow-up SST surveys. This gives us a sample of 674 male and 1214 female twins, whose characteristics are described in Table 1. Although twins are generally similar to one another, they do differ in education level by over one year on average. Twins have lower birth weight on average than singletons, but the MTR twins in our sample are otherwise reasonably representative of their Minnesota birth cohort (Krueger and Johnson, 2002).

In the initial surveys conducted in the mid 1980s, respondents indicated whether they had experienced any disabling injury. From the 1994 SST survey, we also obtained respondents' self-rated overall health on a five-point scale (1 being bad and 5 being excellent), as well as dummy variables for a report of any "family, job, or health problems due to alcohol use" and for any report of specific physical health problems from a list.[5]

[4] In 1960, non-whites represented 1.2% of Minnesota's total population (US Census Bureau, 1960). Conditional on all other criteria for inclusion of twin pairs to the estimation sample, there are only two pairs of twins with non-white parents.

[5] Respondents were asked about a list of physical health problems which included migraine headaches; hay fever; frequently occurring skin rash; hearing impairment; high blood pressure; heart condition; and loss of function in the neck, back, arms, or legs.

Table 1: Summary Statistics

Variable	Year of observation	Males		Females	
		Mean	Standard Deviation	Mean	Standard Deviation
(A) Individual Twins					
Year of birth	1936-1955	1947.7	5.4	1947.9	5.6
Birth weight in pounds	At birth	5.96	1.14	5.68	1.11
Monozygotic	1983	0.61	0.49	0.58	0.49
Ever had a disabling injury?	1983	0.32	0.47	0.33	0.47
Years of education	1994	15.1	2.3	14.1	2.2
Physical health problems	1994	0.51	0.50	0.51	0.50
Self-reported health (1-5)	1994	4.42	0.64	4.36	0.66
Overweight	1994	0.66	0.47	0.42	0.49
Alcohol problems	1994	0.045	0.206	0.016	0.124
Died before 2015	1994-2014	0.096	0.295	0.063	0.244
Age at death if died	1994-2014	62.8	7.6	62.9	8.8
(B) Twins Pairs					
Both died before 2015	1994-2014	0.030	0.170	0.020	0.139
At least one died before 2015	1994-2014	0.16	0.37	0.11	0.31
Absolute difference within pairs					
Birth weight, pounds	At Birth	0.68	0.77	0.69	0.61
Ever had a disabling injury?	1983	0.13	0.33	0.12	0.32
Education, years	1994	1.52	1.62	1.19	1.42
Physical health problems	1994	0.42	0.49	0.38	0.49
Self-reported health (1-5)	1994	0.53	0.63	0.51	0.61
Overweight	1994	0.29	0.46	0.30	0.46
Alcohol problems	1994	0.07	0.26	0.03	0.17
Age at death if both died	1994-2014	4.90	5.16	8.00	6.30
Number of individuals		674		1214	

Notes: Estimation sample is conditional on being same-sex white twins and participating in SST survey.

3 Methodology

We apply a linear probability model to within-twin-pair first differences among monozygotic twins in order to determine the effect of education on health outcomes. We then compare results for monozygotic twins to those for dizygotic twins in order to characterize the manner in which families allocate educational resources among siblings with differing health endowments.

3.1 Model of Schooling Decision and Health

Behrman et al. (1994) lay out a model for the determination of schooling and wages for twins. We adapt this model to the case of schooling and health outcomes as follows.

Consider a family j with twin children i and k. The family allots S years of schooling to each twin according to the equations

$$S_{ij} = \alpha_1 a_{ij} + \alpha_2 a_{kj} + \delta h_j + f_j + \boldsymbol{\alpha}_3 \boldsymbol{x}_{ij} + u_{ij} \tag{1}$$

and

$$S_{kj} = \alpha_1 a_{kj} + \alpha_2 a_{ij} + \delta h_j + f_j + \boldsymbol{\alpha}_3 \boldsymbol{x}_{kj} + u_{kj}. \tag{2}$$

Here, a_{ij} and a_{kj} represent individual-specific endowments which are associated with poor health. h_j represents common endowments. f_j represents family environment. $\boldsymbol{x}_{ij}$ and $\boldsymbol{x}_{kj}$ represent vectors of possible confounders—in our case, birth weight and history of disabling injury. u_{ij} and u_{kj} are random shocks to educational attainment.

Mortality outcomes M for each twin are determined by equations:

$$M_{ij} = \beta_1 S_{ij} + a_{ij} + h_j + \gamma f_j + \boldsymbol{\beta}_2 \boldsymbol{x}_{ij} + v_{ij} \tag{3}$$

and

$$M_{kj} = \beta_1 S_{kj} + a_{kj} + h_j + \gamma f_j + \boldsymbol{\beta}_2 \boldsymbol{x}_{kj} + v_{kj}, \tag{4}$$

where v_{ij} and v_{kj} are random shocks to health.

β_1 is a key parameter of interest. $\beta_1 < 0$ would imply that additional years of schooling reduce mortality. Other key parameters are α_1 and α_2, which describe the own- and cross-effects of individual health endowments on the family's distribution of educational resources between twins. If we have $\alpha_1 < 0$ and $\alpha_2 > 0$ (case 1), this would imply that families reinforce differences in health endowments by increasing years of schooling for the better-endowed twin (the twin with the lower value of a) at the expense of the worse-endowed twin (the twin with the higher value of a).[6] If we have $\alpha_1 > 0$ and $\alpha_2 < 0$ (case 2), this would imply that families instead compensate for differences in health endowments.

[6]Note that the signs of these relationships are reversed from those described in Behrman et al. (1994), since we normalize the latent health endowment associated with the adverse outcome of mortality, while they normalize the latent wage-earning endowment associated with the beneficial outcome of wage.

Finally, $\alpha_1 = \delta$ and $\alpha_2 = 0$ (case 3) would imply that the educational investment for each twin is set individualistically and without regard to the other twin's endowment. Other health related outcomes are modeled using the same type of equations that we use for mortality.

3.2 Within-Twin-Pair First Differences

Monozygotic twins have identical genetic endowments, and so, for monozygotic twin pairs in our model, $a_{ij} = a_{kj}$. Taking the difference between Equations (1) and (2) yields the following equations for the difference in years of schooling and for the difference in mortality among monozygotic twin pairs:

$$\Delta S_j^M = \boldsymbol{\alpha}_3 \Delta \boldsymbol{x}_j^M + \Delta u_j^M \tag{5}$$

and

$$\Delta M_j^M = \beta_1 \Delta S_j^M + \boldsymbol{\beta}_2 \Delta \boldsymbol{x}_j^M + \Delta v_j^M, \tag{6}$$

from which we can identify β_1.

Dizygotic twins have different genetic endowments, so the analogous equations for dizygotic twin pairs are:

$$\Delta S_j^D = (\alpha_1 - \alpha_2)\Delta a_j + \boldsymbol{\alpha}_3 \Delta \boldsymbol{x}_j^D + \Delta u_j^D \tag{7}$$

and

$$\Delta M_j^D = \beta_1 \Delta S_j^D + \Delta a_j + \boldsymbol{\beta}_2 \Delta \boldsymbol{x}_j^D + \Delta v_j^D. \tag{8}$$

In the system of equations represented by Equations (5)–(8), α_1 and α_2 are not individually identified. However, as shown by Behrman et al. (1994), if we impose two restrictions—β_1 is identical for both MZ and DZ twins, and the individual-specific stochastic components v_{ij} and u_{ij} are drawn from the same distribution for both MZ and DZ twins—then the difference $(\alpha_1 - \alpha_2)$ is identified and can be calculated in the following way:

$$\alpha_1 - \alpha_2 = \frac{1 - R}{\beta_1^D - \beta_1^M}, \tag{9}$$

where $0 < R = \frac{var(\Delta S^M)}{var(\Delta S^D)} < 1$, and β_1^D and β_1^M represent the estimates from Equation (6) for the DZ and MZ twin subsamples, respectively. As $R < 1$, the sign of $(\alpha_1 - \alpha_2)$ matches the sign of $(\beta_1^D - \beta_1^M)$. Identification of this difference is sufficient to determine whether families engage in compensating behavior versus the two alternatives. As follows from cases 1–3 discussed in the previous section, $\alpha_1 - \alpha_2 > 0$ implies compensation (case 2). $\alpha_1 - \alpha_2 < 0$ implies either reinforcement or allocation without regard for the other twin (cases 1 and 3). Here we assume that, in case 3, $\delta < 0$, given the well-known strong complementarity between education and health in the individualistic case (e.g., Becker (2007)).

3.3 Addressing Measurement Error through Instrumental Variables

As Griliches (1979) points out, measurement error bias is particularly troublesome in estimates derived from twins data, like ours. Although birth weights as well as dates of death and birth for the twins in our sample are drawn from official records, years of schooling are reported by the twins themselves and are likely subject to sizable measurement error. Ashenfelter and Krueger's (1994) elegant instrumental variables approach eliminates measurement error bias resulting from any individual's tendency to over- or under-report education levels. The Ashenfelter-Krueger approach uses one twin's report of the intra-twin-pair difference in education as an instrument for the other twin's report of the same difference. We apply this IV approach in our analysis, using the 1994 SST survey data in which each twin reported both own and twin's education backgrounds.

Consider twins 1 and 2 from same-sex pair j. Let S_k^i represent twin i's report of twin k's years of schooling, and let $\Delta_{Si} = (S_1^i - S_2^i), i = 1, 2$, which is how many more years of schooling twin 1 had than twin 2 based on twin i's reports. Then the first stage regression for each gender in this two-stage least squares framework can be written as

$$\Delta_{S1} = a_0 + b\Delta_{S2} + \boldsymbol{c}\Delta\boldsymbol{x}_j + \epsilon_j. \tag{10}$$

In the second stage of this IV approach, the observed difference in mortality outcomes is regressed on the predicted value of the difference in education $\widehat{\Delta_{S1}}$ as calculated in the first stage regression:

$$\Delta M_j = \beta_1 \widehat{\Delta_{S1}} + \boldsymbol{\beta}_2 \Delta \boldsymbol{x}_j + \Delta v_j, \tag{11}$$

Ashenfelter and Krueger demonstrate that this approach generates unbiased estimates of β_1, the coefficient of interest, even when a twin's reports of her own education and of her twin's education have measurement errors that are correlated with one another. We estimate bootstrapped standard errors for the estimate of β_1.

We estimate versions of (10) and (11) under each of two alternative specifications: (1) with no control for $\Delta \boldsymbol{x}_j$; and (2) controlling for $\Delta \boldsymbol{x}_j$, with missing values for $\Delta \boldsymbol{x}_j$ imputed using Markov chain Monte Carlo multiple imputation as described in Rubin (1987) and Schafer (1997), a method that preserves the variance-covariance matrix of variables in the data. Results from estimating approaches (1) and (2) are close to one another. We report results for specification (2) in the main text and show a comparison with specification (1) in Table A-1.[7]

As evidenced by Behrman and Rosenzweig (2002) and follow-ups to that work (Antonovics and Goldberger, 2005; Behrman and Rosenzweig, 2005), there

[7]Twins from the same pair were likely weighed on the same hospital scale at birth, so differencing birth weights, Δx_j, cancels out any possible systematic additive measurement error that may result from miscalibration of scales.

is no single, straightforward way to translate each individual's responses to the array of SST questions into a count of total years of schooling. We follow the same procedure used by Antonovics and Goldberger (2005) for coding years of schooling from the raw SST responses, in which years of schooling are defined based on the highest degree achieved as well as any additional reported schooling beyond the highest degree.[8]

4 Results

4.1 Health Outcomes

Results from estimation of the first stage regression in Equation (10) separately for monozygotic (MZ) twins and dizygotic (DZ) twins are shown in Table 2. Unsurprisingly, one twin's report of the intra-pair difference in years of schooling is a strong instrument for the other twin's report of the same difference: F-statistics are no smaller than 160.

Applying the 2SLS approach described above to the samples of MZ twins of each sex allows us to identify β_1 from Equation (11), the effect of education on health outcome M. Specifically, we consider the outcomes of mortality (death

[8] For example, a high school degree is coded as 12 years of schooling or a college degree as 16. A twin who reports a high school degree plus one year of college will be coded 13 years of schooling. However, a twin who has not completed a particular degree can be coded with at most one less year than is associated with that degree, regardless of how many years they report. Thus a twin who reports a high school degree plus five years of college but no college degree will be coded with 15 years rather than 17.

Table 2: First Stage Results, Intra-Pair Difference in Years of Schooling as Reported by Twin One

		Pooled genders		Males		Females	
Monozygotic	coefficient	0.780	***	0.860	***	0.710	***
	standard error	*(0.040)*		*(0.068)*		*(0.049)*	
	F-statistic	*380*		*160*		*210*	
	# of twin pairs	558		204		354	
Dizygotic	coefficient	0.854	***	0.855	***	0.850	***
	standard error	*(0.029)*		*(0.039)*		*(0.039)*	
	F-statistic	*867*		*481*		*475*	
	# of twin pairs	386		133		253	

Notes: We use specification (10) for each gender. For the pooled sample we additionally control for a gender dummy. Asterisks represent statistical significance levels: *** 1%, ** 5%, * 10%.

within 20 years after the 1994 SST survey), any report of physical health problems in the SST, and overall health as self-reported in the SST.

In light of consistent evidence in the literature that the effects of education on health, longevity, and a number of health behaviors are non-harmful,[9] we use one-sided tests for the estimated coefficients on years of schooling in our regressions.

Second stage results for β_1 are shown in Table 3. The estimate for males indicates that each additional year of schooling yields a 3.1 percentage point (pp) drop in the probability of death during the 20 years immediately following the 1994 SST survey. Each additional year of schooling is associated with 3.4 pp

[9] See, for example, Grossman (2006) and Grossman and Kaestner (1997), in addition to the discussion of the literature in this paper.

Table 3: Second Stage Results, Effects of Education on Mortality and Health

		Pooled genders		Males		Females		Gender Difference
Mortality	coefficient	-0.023	**	-0.031	**	-0.015		-0.015
	standard error	*(0.012)*		*(0.018)*		*(0.015)*		*(0.024)*
	# of twin pairs	558		204		354		
Physical Health Problems	coefficient	-0.029	**	-0.022		-0.034	*	0.012
	standard error	*(0.019)*		*(0.028)*		*(0.025)*		*(0.038)*
	# of twin pairs	694		244		450		
Self-reported Health	coefficient	0.029	*	0.040		0.015		0.025
	standard error	*(0.022)*		*(0.032)*		*(0.033)*		*(0.046)*
	# of twin pairs	680		241		439		

Notes: Bootstrapped standard errors reported from 300 replications. One-sided p-values reported for estimated coefficients on years of education, two-sided for difference in coefficient estimates across genders. Asterisks represent statistical significance levels: *** 1%, ** 5%, * 10%.

decline in the probability of reported physical health problems among women. Other estimates by gender are not precisely determined, but the sings of these noisy estimated coefficients are all in the direction of health improvement.

When we increase statistical power by pooling genders, effects on all three health outcomes become statistically significant. One year of schooling decreases mortality by 2.3 pp, decreases reporting physical health problems by 2.9 pp, and increases self-reported health by 0.03 standard deviations.

Given the lack of a strong relationship between education and mortality among women, the presence of a stronger connection between education and physical health problems may seem puzzling. This pattern of results could be related to the established fact that at any given age women tend to report worse health than men but are also less likely to die than men (Case and Paxson, 2005).

On the other hand, prior research established that individuals with higher income and education levels consume more health care, all else equal (Strauss and Thomas, 1998). Some health conditions, like high blood pressure or heart conditions, are not likely to be known to the respondent in the absence of a diagnosis from a medical professional. Accordingly, our coefficient estimates for the physical health problem outcome, which describe the protective effect of education on the probability of reporting *awareness* of having experienced a physical health problem, likely understate education's effect on the probability of truly *experiencing* a physical health problem. Indeed, if the more educated had the same amount of health issues as the less educated but were more aware of them, we would find a positive effect of education on the probability of reporting health problems. Despite this expected bias, we find a negative effect, suggesting a substantial true effect of education on the probability of experiencing health problems. While health problems are self-reported by twins and measure awareness rather than objective health status, mortality is an objective measure and is not susceptible to the same type of bias.

4.2 Mediators

We have data on alcohol problems and overweight, which are possible mediators that drive the effects of education on health and longevity. Twins indicated their height and weight at the time of the SST, from which we generate a dummy variable for overweight based on a body mass index of 25 or above. The twins also indicated whether they had ever experienced "family, job, or health problems due to alcohol use," which can be viewed as a proxy for alcohol addiction or abuse.

2SLS estimates for the effects of education on overweight and alcohol problems are presented in Table 4. Among men, each additional year of education yields a statistically significant 4.5 pp decrease in the likelihood of being overweight. We find no statistically significant relationship between education and overweight for women. We also find a 1% reduction in alcohol-related problems for the pooled sample of men and women, a result statistically significant at the 10% level. [10]

Table 4: Effects of Education on Potential Mediators of Health

		Pooled genders	Males	Females	Gender Difference
Overweight	coefficient	-0.010	-0.045 **	0.025	-0.070 **
	standard error	*(0.014)*	*(0.022)*	*(0.017)*	*(0.028)*
	# of twin pairs	670	240	430	
Alcohol	coefficient	-0.012 *	-0.016	-0.009	-0.007
	standard error	*(0.007)*	*(0.013)*	*(0.008)*	*(0.015)*
	# of twin pairs	694	244	450	

Notes: Bootstrapped standard errors reported from 300 replications. One-sided p-values reported for coefficient estimates for overweight, two-sided for alcohol and for gender differences. Asterisks represent statistical significance levels: *** 1%, ** 5%, * 10%.

[10] Because of the lack of a consensus in the health economics literature regarding the sign of the relationship between educational attainment and alcohol use, we apply a two-sided test of statistical significance to the coefficient estimates for alcohol problems.

The overweight dependent variable is based on the twins' self-reported height and weight, and the alcohol problem dummy variable is based on twins' answers to the question of whether they ever experienced "family, job, or health problems due to alcohol use." Neither of these two measures would involve any specific diagnosis from a medical professional, unlike some of the physical health measures considered in Table 3.

4.3 Intra-Household Allocation of Resources

We can determine whether parents compensate for or reinforce endowment differences in siblings by estimating the value of $(\beta_D - \beta_M)$. Our estimates of this difference are shown in Table 5. The statistically significant positive numbers that we find are indicative of compensating behavior, in which the less healthy twin receives more education, and the healthier twin less education. Our estimation results provide some evidence of compensating behavior when health is measured in terms of eventual mortality, and strong evidence of compensating behavior when health is measured in terms of physical health problems. The outcome of self-reported health provides no precisely determined estimate of the difference, but this outcome is arguably the noisiest. Our finding of compensating behavior with respect to health endowments complements results by Behrman et al. (1994), who find that families reinforce ability endowments.

Since wages affect longevity, our estimates of $(\alpha_1 - \alpha_2)$ may be biased due to

Table 5: Difference in Education Coefficients between DZ and MZ Twins, $(\beta_1^D - \beta_1^M)$

		Pooled genders	Males	Females
Mortality	coefficient	0.026 *	0.036	0.019
	standard error	*(0.015)*	*(0.022)*	*(0.018)*
Physical Health Problems	coefficient	0.066 ***	0.060 *	0.073 **
	standard error	*(0.024)*	*(0.036)*	*(0.032)*
Self-reported Health	coefficient	0.020	0.022	0.029
	standard error	*(0.030)*	*(0.044)*	*(0.044)*

Notes: Bootstrapped standard errors calculated from 300 replications. Two-sided p-values reported for difference in coefficient estimates between DZ and MZ twins. Asterisks represent statistical significance levels: *** 1%, ** 5%, * 10%.

the omission of an unobserved earning ability endowment. The data available for our sample of twins does not include early-life measures of ability which would allow us to model such a multi-dimensional endowment framework. We do, however, have quality data from the SST on the wages of male respondents.[11] We leverage this wage data by re-estimating the DZ-MZ differences in estimates of β_1 as shown in Table 5 with wage as an added regressor. In this way, wage proxies for earning ability. Though wage itself is an endogenous outcome, we argue that this approach provides a helpful robustness check. If the DZ-MZ differences are robust to the inclusion of the wage control, then we have evidence that our results are not driven by the wage-earning endowment.

[11] Wage data were gathered for women as well as men, but an insufficient number of female twin pairs have wage information provided for both twins.

Results from estimating models that include wage as a background control are shown in Table 6. The implied effect of education on mortality is not greatly affected by the inclusion of a wage control (and, in fact, the result is strengthened). There is little change in the implied effect of education on self-reported health and a modest decrease for the effect on physical health problems. Taken together, we interpret these results as evidence that the single-dimensional measure of child's endowment a_1 which we consider in our analysis is not dominated by non-health-related wage-earning potential.

Table 6: Robustness Check: Difference in Education Coefficients between DZ and MZ Twins, $(\beta_1^D - \beta_1^M)$, with and without Wage Controls, Males

		No wage control	Wage control
Mortality	coefficient	-0.036	-0.039 *
	standard error	*(0.024)*	*(0.023)*
Physical Health Problems	coefficient	0.060 *	0.051
	standard error	*(0.036)*	*(0.036)*
Self-reported Health	coefficient	0.022	0.021
	standard error	*(0.044)*	*(0.066)*

Notes: Bootstrapped standard errors calculated from 300 replications. Two-sided p-values reported for difference in coefficient estimates between DZ and MZ twins. Asterisks represent statistical significance levels: *** 1%, ** 5%, * 10%.

It is possible that parents respond to differences in children's health endowments by reinforcing some of the resulting gaps in outcomes while simultaneously compensating for other gaps. As mentioned, this is precisely the finding of Yi et al. (2015), who use Chinese twins data to show that when one twin experiences a negative health shock in childhood, the parents divert educational resources toward the healthier twin (reinforce) but divert health resources toward the less healthy twin (compensate). Parents compensate more than they reinforce, so the authors find that families' overall behavior is compensatory. We do not observe information about childhood health investments, e.g. physician visits, for our twin sample, so we are unable to identify this kind of multidimensional response to differences in health endowments. However, our findings for US twins indicate that parents divert educational resources toward the less healthy twin, which is the opposite of the finding by Yi et al. for Chinese twins, suggesting differences in the representative household objective function for the Chinese versus US families sampled. Apart from the differences in countries considered in these papers, there are also differences in the types of educational investments and health differences considered. Yi et al. analyze payments for schooling at age 11, while we analyze total years of schooling. They consider responses to early life health shocks, while we consider health endowments identified by observed longevity.

5 Conclusions

Using newly collected mortality data for the largest survey of US twins, we provide new evidence that education affects health-related outcomes for both men and women and that parents compensate for health endowments gaps between children by using educational investments.

Our results are relevant not only for theory but also for economic policy. The existence of a causal effect of education on health makes education a useful health policy variable in cases of sub-optimal educational investments due to market failure. The compensation result should be taken into account when modeling intrafamily allocation of additional resources provided by government programs.

A Appendix

Table A-1: Effects of Education on Mortality, Omitting Background Controls

		With controls		With No controls	
Pooled	coefficient	-0.023	**	-0.021	**
	standard error	*(0.012)*		*(0.010)*	
	# of twin pairs	558		558	
Males	coefficient	-0.031	**	-0.030	**
	standard error	*(0.018)*		*(0.019)*	
	# of twin pairs	204		204	
Females	coefficient	-0.015		-0.011	
	standard error	*(0.015)*		*(0.014)*	
	# of twin pairs	354		354	

Notes: Bootstrapped standard errors reported from 300 replications. One-sided p-values reported for estimated coefficients on years of education. Asterisks represent statistical significance levels: *** 1%, ** 5%, * 10%.

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