Infant deaths: Notes toward a behavioral model

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Abstract

A woman may choose to become more educated, partly because she wishes to emulate those around her. A behavioral model suggests that she is less likely to lose her baby than the less educated by flouting basic rules of health. Estimates of a three-equation model suggest that low-weight births are most likely where youths (as well as the adults around them) are most likely to have dropped out of high school. The impact of the dropout rate on low-weight births varies from state to state, however. Preliminary estimates suggest a high marginal cost of health information. [JEL I12, I29]

1 Introduction

Many economic studies of infant death focus on factors that the mother ostensibly must take as given: Medicaid, paid maternity leave, community health centers, and access to abortions as well as to neonatal intensive care.[1] Generally, environmental — as opposed to behavioral — theories of infant death seem to have dominated its economic study since the early 1800s, when Malthus posited it as a positive check on population growth.[2]

The incidence of low-weight birth greatly influences the rate of infant death. Indeed, a traditional regression analysis may thereby discount the importance of social and economic factors. Among the 50 states in 1992, a simple linear regression on the incidence of low-weight birth accounts for over half of the variance in the rate of infant death. Adding household income and the incidence

[1]For studies of these factors, see respectively Currie, Gruber and Fischer (1995), Winegarden and Bracy (1995), Goldman and Grossman (1988), and Corman, Grossman and Joyce (1988).

[2]In "A summary view of the principle of population," Malthus writes that the pressures on resources due to population growth would "render the children unhealthy from bad and insufficient nourishment, which would check the rate of increase by occasioning a greater proportion of deaths" (Malthus, page 243). Elsewhere, Malthus also seems to regard infant death as a preventive check on population growth. His first essay on the principle of population asserts that, among North American Indians, the miserable toils of women must "prevent any but the most robust of infants from growing to maturity....Misery is the check that represses the superior power of population and keeps its effects equal to the means of subsistence" (Malthus, page 82).

of teenage births as independent variables little enhances the explanatory power of the equation: That unrestricted form of the model does not pass an F-test at a level of significance of 1 percent.[3]

Although environmental factors surely matter, some evidence suggests that the mother's decisions during and after pregnancy may also affect the prospects of an infant death. For example, Corman, Joyce and Grossman (1987) find that beginning prenatal care early is the most cost-effective way to cut the neonatal death rate for blacks and whites. It would be valuable to extend our understanding of how and why the mother makes such decisions as whether to seek out prenatal care. In particular, the impact of her education on her decisions is of interest, given the general linkage, in cross-country studies, of a high level of education to a low rate of infant death (Barro and Jong, 1993).

For instance, it remains possible that the incidence of low-weight birth itself depends on social and economic factors - especially those that shape the woman's decisions concerning her pregnancy. This paper explores that possibility.

The paper develops and tests a model of infant death as an event due in part to the mother's decisions about education. In the model, the mother influences the chance for a healthy birth by deciding how much health information to acquire. If she is poorly educated, then acquiring health information will cost her a lot, and so she will probably acquire just a bit of it.

Section 2 presents the model. Section 3 reports the results of testing the model. Section 4 gives rough estimates, derived from the tests, of the marginal cost of health information. Section 5 concludes with reflections.

2 The model

The paper is to test this idea: Women choose the probability of a healthy birth in the same way that they make other decisions about the future – by choosing the course of action that seems likely to satisfy them the most. To put it simply, when they try to secure a healthy birth, they consider costs. More precisely, the model posits that the woman seeks to maximize the sense of welfare, or utility, that she expects from a healthy birth, net of the costs of acquiring and using relevant information. Notation follows.

2.1 Basic functions

2.1.1 Probability of an infant death

The chance of an infant death is M, where $0 \leq M \leq 1$. This chance depends, in part, on the mother's access to doctors for prenatal care. The more information that she has, the more likely it is that she can avoid a low-weight birth, the probability of which is W, $0 \leq W \leq 1$. Denote the information set as I, where

[3] See Appendix B for details.

$0 \leq I < \infty$. The model posits that $\frac{\partial W}{\partial I} < 0$. This derivative links to the chance of an infant death, for M depends directly on the chance of a low-weight birth. Low-weight infants are more likely to die than high-weight infants. So $\frac{\partial M}{\partial W} > 0$.

The model also posits that $\frac{\partial^2 M}{\partial W^2} > 0$, because a lower-weight birth correlates with both a greater prior belief of a low-weight birth and with a much greater probability of infant death. The assertion may bear some explanation. The incidence of a low-weight birth may be the most conspicuous determinant of infant death, in the sense that one can estimate a negative correlation between birth weight (of 500 to 4,500 grams) and the probability of infant death more precisely than one can estimate correlations of other factors with infant death. Indeed, for this range of birth weight, the rate of infant deaths seems generally to increase more sharply as weight decreases (MacDorman and Atkinson (1998), Figure 1).[4] I postulate that the *ex ante* probability of a low-birth weight correlates negatively with the *ex post* birth weight. That is, I posit that the lower the actual weight, the greater the prior belief that the birthweight would be below 2,500 grams. To a degree, health specialists can predict birthweights – and prematurity, which correlates with low birth weights – through sonography. The woman may also expect a low birthweight because she has observed the births given by women around her who have followed practices similar to hers.

The more easily that the pregnant woman can reach doctors, the lower the probability that her baby will die. One may measure her medical access in terms of the number of doctors in her area. Denote the number of doctors as D, where $0 \leq D < \infty$. Then $\frac{\partial M}{\partial D} < 0$. Adding another doctor to the area's supply will have greater value in an area that has just a few doctors than in an area that has many doctors. And so every increase in D will reduce the chance of an infant death, M, by less and less. Thus $\frac{\partial^2 M}{\partial D^2} > 0$.

Summing up these ideas,

$$
\begin{aligned}
M &= M(W, D), \\
\frac{\partial M}{\partial W} &> 0, \frac{\partial^2 M}{\partial W^2} < 0, \\
\frac{\partial M}{\partial D} &< 0, \frac{\partial^2 M}{\partial D^2} > 0, \\
\frac{\partial^2 M}{\partial W \partial D} &\leq 0. \qquad (1)
\end{aligned}
$$

One can interpret the cross-partial above in this way: Ready access to doctors may dampen the rise in the likelihood of an infant death that is due to a greater likelihood of a low-weight birth. This is because doctors can recommend ways to avert the death of the baby in the event that it would weigh little.

[4] For birth weights below 500 grams, infant death is virtually certain; the rate exceeds 90 percent. For birth weights above 4,500 grams, the rate of infant death increases with weight.

2.1.2 Probability of a low-weight birth

The likelihood of a low-weight birth, W, depends negatively on the data that the would-be mother has for avoiding such a birth. Given her level of education, however, as she acquires more and more information, she will find the new data harder and harder to assimilate; for education is the technology that enables her to acquire information more easily, and that is held constant. As a result, every additional bit of information is less and less effective at lowering the likelihood of a low-weight birth. Thus $\frac{\partial^2 W}{\partial I^2} > 0$.

The likelihood of a low-weight birth also depends on the access of the would-be mother to doctors for prenatal care. If she can reach a doctor more easily, than a low-weight birth is less likely. Thus $\frac{\partial W}{\partial D} < 0$. The value of adding another doctor to the area supply, however, is smaller when doctors abound than when doctors are scarce. So $\frac{\partial^2 W}{\partial D^2} > 0$.

The model thus posits that

$$\begin{aligned} W &= W(I, D), \\ \frac{\partial W}{\partial I} < 0, &\quad \frac{\partial^2 W}{\partial I^2} > 0, \\ \frac{\partial W}{\partial D} < 0, &\quad \frac{\partial^2 W}{\partial D^2} > 0, \\ \frac{\partial^2 W}{\partial D \partial I} &\leq 0. \end{aligned} \tag{2}$$

The cross-partial posits this: As the would-be mother learns more about health from sources other than her doctor, she may duplicate what her doctor knows. This will reduce his impact on the chance for a low-weight birth.

2.1.3 Health information

The amount of health information that the would-be mother obtains and uses depends on her general education. When I say that she "obtains" information about health, I mean that she assembles and assimilates a list of rules to follow in pregnancy. To assemble the list, she must know where to turn for information. To assimilate the list, she must know how to identify good rules – i.e., rules that, once executed, are most likely to lead to the results that are claimed for them. The selection, assimilation and retrieval of information are broad skills that one may acquire in formal education. When I say that she "uses" information about health, I mean that she follows good rules. To do this, she must have discipline. That she has an education is evidence that she has discipline since, to acquire education, one must be able to collect and follow good rules.

Her decision of how much education to acquire depends on the net benefits that she expects from it. Here, however, she is in a quandary. Lacking education, she will find it costly to obtain information about the net benefits of education. So she will rely on folk rules: She will estimate the benefit and the cost of additional education by observing the amount of education acquired by the youths and adults that she knows. That few of them bothered with high school degrees suggests to her that the degrees are worth little. The lack of education among people she knows also suggests to her a psychic cost of obtaining education – social disapproval. By acquiring an education, she sets herself apart from her group and risks its censure.

The young woman may also infer the value of education from what her acquaintances decide to do in lieu of an education. Since the uneducated are less likely to find a job, they are more likely to make choices that center on the home. Observing such choices suggests to the young woman that an education is worth little in the sense that it would not benefit her as much as a simple home life would. Suppose, for instance, that many teens that the young woman knows have become pregnant. Then she may infer that she would benefit more from activities related to pregnancy – such as unconstrained sex and the anticipation of parenting – than from education as an alternative use of her time. Indeed, she may infer that the returns to education are particularly low if she sees that many women that she knows decided to have children, or to risk having them, even though they would likely have to raise them alone. One cost of single parenting is that the parent has less time for work or hobbies in which she would have gained directly from her education. A woman who chooses to rear a child on her own may thus attach little value to education – and, by implication, to work or to hobbies. Observing the choice of her friends to become single parents, the young woman in school concludes that education would not do her much good, either – for she considers herself to be like her friends.

More formal expression may aid testing of these ideas. Denote the share of births to teen mothers out of all births as T, where $0 \leq T \leq 1$. Denote the share of births to single mothers out of all births as S, where $0 \leq S \leq 1$. Denote the share of nongraduates out of all adults as N, where $0 \leq N \leq 1$. In a given area and at a given time, a rise in T, S or N will discourage a young woman from getting more education. This lack of education, in turn, will make it more costly to her to acquire and use a little more information about health.

Thus the marginal cost of information, $\frac{\partial C}{\partial I}$, increases as the share of all births to teens (T) increases. That is, $\frac{\partial^2 C}{\partial I \partial T} > 0$. Moreover, as the share of all births to teens increases, the young woman feels more and more confirmed in her belief that an education would not be worth much to her. And so she is more and more likely to drop out of school – and to later find that health information is costly to acquire. Then $\frac{\partial^3 C}{\partial I^2 \partial T} > 0$.

Similarly, a rise in the share of all births to single mothers (S) will boost the cost of acquiring a little more information at an increasing rate. Thus $\frac{\partial^2 C}{\partial I \partial S} > 0$ and $\frac{\partial^3 C}{\partial I^2 \partial S} > 0$.

A rise in the share of nongraduates out of all adults has the same sort of impact on the cost of acquiring a little more information. Thus $\frac{\partial^2 C}{\partial I \partial N} > 0$ and

$\frac{\partial^3 C}{\partial I^2 \partial N} > 0$.

In sum, the model posits the cost of health information as the function

$$\begin{aligned} C &= C(I;T,S,N), \\ \frac{\partial C}{\partial I} &> 0, \frac{\partial^2 C}{\partial I^2} > 0, \\ \frac{\partial^2 C}{\partial I \partial T} &> 0, \frac{\partial^3 C}{\partial I^2 \partial T} > 0, \\ \frac{\partial^2 C}{\partial I \partial S} &> 0, \frac{\partial^3 C}{\partial I^2 \partial S} > 0, \\ \frac{\partial^2 C}{\partial I \partial N} &> 0, \frac{\partial^3 C}{\partial I^2 N} > 0. \end{aligned} \tag{3}$$

The amount of health information used by the woman may influence the probability that her baby lives or dies. Let U_h denote her utility value in the event that her baby lives; let U_m denote her utility value in the event that her infant dies. U_h and U_m are parameters, not functions.

2.2 Optimization problem

Given the amount of education that she already has chosen, the would-be mother decides how much health information (I) to acquire and use. Her goal is to act in a way that will leave her feeling as good as possible after the birth. So she chooses I to maximize her expected welfare from the birth. She will thus choose I to maximize

$$L = (1 - M[W,D])U_h + M[W,D]U_m - C(I;T,S,N) \tag{4}$$

Rearranging the first-order condition yields one way to interpret any solution to the mother's problem:

$$\frac{\partial M}{\partial W}\frac{\partial W}{\partial I}(U_m - U_h) = \frac{\partial C}{\partial I}. \tag{5}$$

The condition says this about the would-be mother: To optimize, she will use information up to the point that the cost of using just a little more will equal its expected benefit to her in helping her avoid a low-weight birth.[5]

In other words, the amount of information that she will choose to use is a function of its benefits and costs to her. Let us express this optimal amount of information – the solution to her problem – as the function $I^*(D,T,S,N)$. Simple comparative statics characterize the function:[6]

[5] The appendix shows that a solution satisfying the first-order condition will also satisfy the second-order condition. It thus solves the mother's problem.

[6] The appendix has derivations.

$$
\begin{aligned}
\frac{\partial I^*}{\partial D} &\leq 0, \\
\frac{\partial I^*}{\partial T} &< 0, \\
\frac{\partial I^*}{\partial S} &< 0, \\
\frac{\partial I^*}{\partial N} &< 0.
\end{aligned} \tag{6}
$$

These results are simple to interpret if one begins with the earlier decision of the would-be mother about how much education to acquire. She will forgo education if a large share of her adult acquaintances have dropped out of high school (N); or if a large share of the births in her locale occurred to single or teen mothers (S and T, respectively). In turn, the lack of education will make it costly for her to gather and use health information. So, she will choose to use little health information if many of her adult acquaintances are dropouts ($\frac{\partial I^*}{\partial N} < 0$); or if many local births were to single or teen mothers ($\frac{\partial I^*}{\partial S} < 0$ and $\frac{\partial I^*}{\partial T} < 0$, respectively). She might also forgo learning about health if she can easily reach doctors ($\frac{\partial I^*}{\partial D} \leq 0$). That is, she might believe that medical treatment and medication would achieve the same ends as learning health rules on her own. She would substitute the expertise of her doctor for her own knowledge of health rules.

2.2.1 Optimal functions

In this simple model, the amount of health information that the would-be mother chooses to acquire (I^*) will help set both the likelihood of a low-weight birth to her (given by the function $W(I, D)$) and the likelihood of an infant death (given by the function $M(W, D)$). Solving the model, then, leads to the three optimal functions

$$I^* = I^*(D, T, S, N), \tag{7}$$

$$W^* = W^*(I^*, D), \tag{8}$$

and

$$M^* = M^*(W^*, D). \tag{9}$$

The model in (7) - (9) is behavioral. It presumes that the mother can affect the chances of a low-weight birth and of an infant death. But perhaps she cannot really do much about these chances one way or the other. In that case, a nonbehavioral model will explain them better. The amount of health information that she chooses to use will not greatly affect the chances that her baby will have a low weight or that it will die. She must take those chances as given. In sum, the nonbehavioral model reduces to

$$W = W(D) \tag{10}$$

and

$$M = M(W, D). \tag{11}$$

because the amount of health information, I, is not relevant to this approach.

An empirical test of the behavioral model (in (7) - (9)) against the nonbehavioral model (in (10) - (11)) hinges on the sign of the derivative $\partial W^*/\partial I^*$. The behavioral model predicts a positive value for the derivative; the nonbehavioral model predicts the value of zero.

3 Tests of the model

I turn to the estimation. In the system given by (7) through (9), two independent variables – W and I – also serve as dependent variables. They are thus likely to correlate with error terms. Hausman tests suggest that simultaneity is especially present in the equation to estimate W.[7] Ordinary estimation through least squares could produce biased and inconsistent estimators of the coefficients (Kelejian and Oates (1981)). Multi-stage estimation seems appropriate. I will present estimates for the system of three simultaneous equations in (7) through (9).

3.1 Data

The dataset draws upon the 50 states of the United States in order to satisfy two conditions that arise from the model. First: The probability that a young woman will drop out of school may depend to some degree on the policies adopted by the public schools. This suggests that observations should be taken at the same level as the one at which school decisions are made – either the district level or the state level. Second: The area embraced by each observation should be large enough to include, for a typical woman in that area, the adults who will most influence her educational decisions. The state is more likely to satisfy this restriction than the district.

[7] I regressed an included endogenous variable, DROPOUTS, on the predetermined variables DOCS, TEEN, NOGRADS and SINGLE. I then included the fitted errors from this equation in an OLS estimate of the structural equation for LOWT. The T-value for the coefficient on the fitted error was -7.04, suggesting the presence of simultaneity in the structural equation. I also regressed LOWT on the predetermined variables and then included the fitted errors in an OLS estimate of the structural equation for DEAD. The T-value for the coefficient on the fitted error was -1.45, $p = .155$.

A third reason for using state data may also matter, although possibly less than the other two reasons, since it does not stem directly from the theory to be tested. Such variables as the dropout rate among late teens and the nongraduation rate among adults are estimated with an error that may grow, relative to the mean of the estimates, as the observation unit shrinks. The measurement error may thus be relatively larger for data drawn from the level of the county or the tract than for data drawn from the level of the state. Where both the dependent and independent variables involve such measurement errors, the OLS estimator of the response coefficient may yield estimates that are inconsistent (Pindyck and Rubinfeld, 1991). In the present instance, it is conceivable that the probability limit of the estimator may be half of the true value of the response coefficient, when one measures the variables as deviations from their means.[8] Where no suitable instrument is evident, one may well prefer a small data set that involves small errors for both variables to a large data set that involves large errors.

The data come from the early 1990s. This gives all schools enough time to put into effect three sets of federal requirements: First, from Title IX of the Educational Amendments of 1972, that they let pregnant girls or mothers attend class in public schools; second, from the Adolescent Pregnancy Act of 1978, that they provide for comprehensive services to pregnant teens (McCarthy and Radish, 1983); third, that all state Medicaid programs cover the cost of pregnancy and child birth for women in households with income up to 133 percent of the poverty line (Currie and Gruber (1997)).

I cannot observe directly the acquisition and use of health information. So I use, as a proxy for I, the dropout rate among high-school students by state (DROPOUTS). I posit that, where youths tend to drop out of school, would-be mothers tend to acquire and use little health information. The two decisions – to drop out and to get health data – relate to the earlier decision about how much education to get. They relate in opposite ways: In an area where the average person decides to acquire a lot of education, she is both unlikely to drop out and likely to inform herself keenly about health. So the decisions to drop out and to get health data respond to the same factors that affect the earlier decision to get education: the dropout rate among adults (N), the percentage of local births that occurred to single or teen mothers (S and T); and the local supply of doctors (D). Since the decisions to drop out and to get health data respond to these factors in opposite ways, I posit that $\partial DROPOUTS/\partial x = -\partial I/\partial x$, where $x \in \{D, T, S, N\}$.

Tables 1 and 2 describe the data. In the three equations estimated, the dependent variables are the percentage of births below 2,500 grams in 1992 (LOWT); the infant mortality rate (DEAD) in the early 1990s; and the percentage of those aged 16 to 19 who dropped out of high school in 1990 (DROPOUTS). Tables 7 through 11 suggest the prudence of estimating simultaneous equations.

[8]See appendix F for derivations.

Table 1: Description of variables

Variable	*Year*	*Description*
DEAD	1992	Deaths of infants, younger than 1 yr, per 1,000 births
DOCS	1992	Number of doctors per 100,000 civilian residents
DROPOUTS	1990	% of 16-to-19 year-olds dropping out of high school
INCOME	1992	Median household money income
LOWT	1992	% of births below 2,500 grams
MDPHC	1993	Medicaid spending on personal health care per household
NOGRADS	1990	% of those 25 or older who weren't high school grads
SINGLE	1992	% of births that were to unmarried mothers
TEEN	1992	% of births that were to teen mothers

Of 50 correlations, 23 exceed .5 in absolute value.

The independent variables are the number of doctors per 100,000 residents in 1993 (DOCS); the percentage of births to teen mothers (TEEN) in 1992; the percentage of adults 25 or older in 1990 who never graduated from high school (NOGRADS); and the percentage of births that were to unmarried mothers (SINGLE) in 1992.

3.2 Estimates

Table 3 sums up linear estimates of the system in (7)-(9). Generally, the disparity in coefficient estimates between the 2SLS and 3SLS versions of the equation for DROPOUTS suggests some correlation of errors across equations. Of the two estimation procedures, 3SLS is better suited to removing that correlation (Pindyck and Rubinfeld, 1991).

In Table 3, Model 3 (*MOD 3*) is the full model. Model 1 drops the variable that expresses the abundance of doctors (DOCS) from one equation, and Model 2 drops it from two equations; for — compared to other independent variables in these equations — the effects of DOCS were relatively paltry and ambiguous.

Table 2: Descriptive statistics

Variable	*Mean*	*Std Dev*	*Min*	*Max*	*Obs*
DEAD	8.3880	1.3986	5.600	11.900	50
INCOME	31509.0400	5300.7474	20878.000	43374.000	50
DOCS	206.1000	51.6417	130.000	361.000	50
DROPOUTS	10.3320	2.3857	4.600	15.200	50
NOGRADS	23.7140	5.6309	13.400	35.700	50
TEEN	12.6800	3.4081	6.700	21.400	50
SINGLE	28.5980	5.7721	15.100	42.900	50
MDPHC	1107.9828	369.5900	646.616	2697.115	50
LOWT	6.8740	1.2535	4.900	9.900	50

Table 4 includes estimates of second-order effects in the 2SLS and 3SLS models.

3.3 Interpretations

The tests confirm the importance of nonbehavioral factors. In all runs of the models, the infant death rate relates negatively to the abundance of doctors. It also relates positively to the share of all births that are low-weight. The t-statistics in Table 4, however, suggest that we cannot reject the possibility that the incidence of low-weight births has no effect on the rate of infant death when one controls for second-order effects.

Holding constant the incidence of a low-weight birth, a slight rise in the number of doctors per 100,000 residents leads to a steep drop in the infant death rate. Conceivably, this may reflect the success of hospitals that have specialists in postnatal care.

Consideration of the second-order effects in Table 4 suggests that adding doctors may lower the incidence of infant death at a diminishing rate – again, holding constant the incidence of a low-weight birth. One can speculate that there may be diminishing returns to the use of medical technology, assuming that the use correlates positively with the density of doctors in a given population. This speculation might help explain why increasing the incidence of low-weight birth appears to raise the rate of infant death at an increasing rate. The additional babies of low weight may have less access than the others to technology, diminishing their chances for postnatal survival.[9]

Using the estimates in Table 4, one can infer that an increase in the supply of doctors may lower the incidence of low-weight birth, but at a diminishing rate. One cannot place much confidence in the results, however.

[9]Indeed, consider the marginal impact, on the rate of infant death, of increasing the supply of doctors. This impact is more likely to be greater than to be lesser if the incidence of low-weight birth is high. In the equation for *Dead* in Table 4, the coefficient on *LowDocs* is positive, although the t-statistic suggests that we cannot be sure of that.

Table 3: Estimates of linearized models

	Two-stage least squares			Three-stage least squares		
	MOD1	**MOD2**	**MOD3**	**MOD1**	**MOD2**	**MOD3**
Depvar: Dead						
Indvars						
Constant	3.558	3.558	3.558	3.570	3.054	3.560
t-ratio	3.473	3.473	3.473	3.485	3.035	3.475
Lowt	0.913	0.913	0.913	0.913	0.947	0.913
t-ratio	7.119	7.119	7.119	7.114	7.422	7.116
elasticity	.748	.748	.748	.748	.776	.748
Docs	-0.007	-0.007	-0.007	-0.007	-0.006	-0.007
t-ratio	-2.792	-2.792	-2.792	-2.807	-2.318	-2.792
elasticity	-12.01	-12.01	-12.01	-12.01	-10.373	-12.101
Depvar: Lowt						
Indvars						
Constant	0.584	0.584	-0.418	0.581	-0.336	-0.422
t-ratio	0.456	0.456	-0.251	0.454	-0.272	-0.253
Dropouts	0.609	0.609	0.630	0.609	0.698	0.631
t-ratio	4.971	4.971	4.998	4.973	5.919	5.001
elasticity	.915	.915	.947	.915	1.049	.948
Docs			0.004			0.004
t-ratio			0.960			0.961
elasticity			1.334			1.334
Depvar: Dropouts						
Indvars						
Constant	0.428	2.596	0.428	-0.442	3.062	0.595
t-ratio	0.203	1.925	0.203	-0.255	2.463	0.293
Teen	0.445	0.275	0.445	0.387	0.153	0.378
t-ratio	2.606	2.409	2.606	3.616	2.050	3.609
elasticity	.546	.337	.546	.475	.188	.464
Nograds	-0.032	0.011	-0.032	0.026	0.078	0.027
t-ratio	-0.420	0.161	-0.420	0.647	1.943	0.690
elasticity	-.073	0.025	-.073	.060	.179	.062
Single	0.105	0.139	0.105	0.093	0.122	0.090
t-ratio	1.753	2.550	1.753	2.715	3.441	2.730
elasticity	.291	.385	.291	.257	.338	.249
Docs	0.010		0.010	0.013		0.008
t-ratio	1.320		1.320	2.958		1.401
elasticity	.199		.199	.259		.16

Table 4: Estimates of full models

	2SLS	3SLS		2SLS	3SLS
Depvar: Dead			**Depvar: Dropouts**		
Indvars			*Indvars*		
Constant	17.705	14.7377	*Constant*	0.428	0.1716
t-ratio	1.374	1.155	t-ratio	0.203	0.082
Lowt	-1.507	-0.6799	*Teen*	0.445	0.3687
t-ratio	-0.447	-0.204	t-ratio	2.606	2.220
elasticity	-1.235	-.557	elasticity	.546	.452
Docs	-0.061	-0.0587	*Nograds*	-0.0322	0.0116
t-ratio	-2.397	-2.348	t-ratio	-0.420	0.160
elasticity	-1.499	-1.442	elasticity	-.074	-.0266
$Docs^2$	0.00005	0.00005	*Single*	0.1046	0.1272
t-ratio	1.446	1.448	t-ratio	1.753	2.225
elasticity	.253	.253	elasticity	.2895	.352
$Lowt^2$	0.1045	0.0501	*Docs*	.0099	0.0076
t-ratio	0.534	0.258	t-ratio	1.32	1.032
elasticity	.589	.282	elasticity	.197	.152
LowDocs	0.004	0.00399			
t-ratio	1.156	1.083			
elasticity	.676	.674			
Depvar: Lowt					
Indvars					
Constant	-40.463	-29.150			
t-ratio	-2.044	-1.502			
Dropouts	6.586	4.871			
t-ratio	2.537	1.907			
elasticity	9.899	7.321			
Docs	0.1398	0.0999			
t-ratio	1.758	1.295			
elasticity	4.192	2.995			
$Docs^2$	-0.000067	-0.000050			
t-ratio	-0.842	-0.660			
elasticity	-.414	-.30897			
$Drop^2$	-0.1989	-0.1417			
t-ratio	-2.465	-1.784			
elasticity	-3.089	2.201			
DocsDrop	-0.0114	-0.0079			
t-ratio	-2.012	-1.428			
elasticity	-3.531	-2.447			

One may be more confident that the share of low-weight births relates positively to the share of youths that drop out of high school. The effect is rather moderate in the linear model: A 1 percent increase in the percentage of dropouts leads to roughly a 1 percent increase in the percentage of low-weight births. Judging from the second-order effects in Table 4, a rise in the incidence of dropping out may increase the incidence of low-weight births at a diminishing rate. One can speculate that additional dropouts may be less likely to have babies.

The share of youths that drop out of high school relates positively to the share of mothers who are teens. It also relates positively to the share of mothers who are not married. The "teen" effect is the more direct of the two effects. In an area where many mothers are teens, a female teen in high school may well feel pressure to drop out herself – more pressure, in fact, than she would feel if she simply saw that many mothers were single, for a teen relates more easily to someone of the same age than to someone of the same marital status. Since, in this sense, the "teen" effect is more direct than the "unmarried" effect, one would also expect it to be the stronger effect – and, in most runs, it is. An increase of 1 percent in the percentage of teen mothers leads to an increase of roughly one-half percent in the percentage of dropouts. The "unmarried" effect, however, also seems to matter: An increase of 1 percent in the percentage of single mothers leads to an increase of roughly one-third percent in the percentage of dropouts.

The direction of the effect on the percentage of dropouts due to the share of adults who did not graduate from high school is not robust across the models. In any event, the effect is small. This suggests that potential dropouts may relate more strongly to their peers in age than to adult role models.

The share of youths that drop out of high school may relate positively to the supply of doctors. But the coefficient is not estimated as precisely as those for teen or single mothers, and the effect is not as large. This is to be expected. It seems unlikely that teens would attach much weight to their access to doctors when deciding whether to stay in school.[10]

3.4 Impact of low-weight birth

The main order of business in the testing is to see how factors affect the probability of low-weight birth and of infant death. Table 4 gives estimates for second-order approximations of the system in (7) through (9). From the second equation of the 2SLS model, the total impact of the dropout rate on the rate of low-weight births is positive:

$$\partial Lowt/\partial Dropouts = 6.586 - 1.34 * 10^{-4} Dropouts. \tag{12}$$

Even when the *Dropouts* rate is a theoretical 100 (percent), the derivative

[10]The supply of doctors might proxy here for the supply of low-skill service jobs in the state economy. When such jobs abound, teens may want to drop out of school and go to work.

remains positive. As the *Dropouts* rate increases, the derivative does diminish, but only slightly. An increase in the rate of dropouts of one standard deviation (2.3857) leads to a decrease in the rate of low-weight births of $3.1968 * 10^{-4}$. That is a decline in the low-birth rate of about 3 in 10,000.

In comparison, the supply of doctors may have a more substantial impact on the effect of the dropout rate on the rate of low-weight births. Judging from the coefficients of the second equation in the 2SLS model, when the number of doctors drops by a standard deviation (51.6), the derivative $\partial Lowt/\partial Dropouts$ increases by .589. That is, as we move from one state that abounds in doctors to another that lacks them, an increase in the dropout rate of one percentage point leads to an additional increase in the rate of low-weight births of nearly one percentage point.

Broadly, these results suggest that programs to encourage young women to stay in school, or to complete their general equivalency degrees, may be most effective in cutting the rate of low-weight births by an absolute amount in states that already have low rates of low-weight births and that lack many doctors.

3.5 Summary of estimates

Table 5 presents point estimates of derivative values for second-order approximations of the system (7) through (9), evaluated at the means for variables reported in Table 2. These calculations use the estimates of the coefficients from the full specifications of the 2SLS and 3SLS models, reported in Table 4. Table 5 presents sign estimates for second derivatives in equations (7) and (8) only, since the comparative statics do not require the signing of second derivatives in equation (9). In scanning the table, the reader should bear in mind that, for some of these coefficient estimates, the T-tests suggest that the actual coefficients may not, in fact, differ much from zero. The precision of the estimates of derivative values should thus be taken as provisional.

Table 5 also compares the signs of the estimated values of the derivatives to the signs predicted for them. The most striking "misses" involve the second-order impact of the supply of doctors on the rate of low-weight births.

Table 5: Coefficient signs

Coefficient	Estimate	Predicted sign?
Two-stage least squares		
$\partial Dead/\partial Lowt$	.761	Yes
$\partial^2 Dead/\partial Lowt^2$	.209	Yes
$\partial Dead/\partial Docs$	-.0096	Yes
$\partial^2 Dead/\partial Docs^2$	.0215	Yes
$\partial^2 Dead/\partial Lowt\partial Docs$	.0043	No
$\partial Lowt/\partial Drop$	.122	Yes
$\partial^2 Lowt/\partial Drop^2$	-.011	Yes
$\partial Lowt/\partial Docs$	-.0058	Yes
$\partial^2 Lowt/\partial Docs^2$	-.00013	No
$\partial^2 Lowt/\partial Drop\partial Docs$	-.0114	No
$\partial Drop/\partial Docs$	2.040	Yes
$\partial Drop/\partial Teen$	5.643	Yes
$\partial Drop/\partial Nograds$	-.7636	No
$\partial Drop/\partial Single$	2.991	Yes
Three-stage least squares		
$\partial Dead/\partial Lowt$	.831	Yes
$\partial^2 Dead/\partial Lowt^2$	.100	Yes
$\partial Dead/\partial Docs$	-.0107	Yes
$\partial^2 Dead/\partial Docs^2$	.0001	Yes
$\partial^2 Dead/\partial Lowt\partial Docs$	.00399	No
$\partial Lowt/\partial Drop$	.315	Yes
$\partial^2 Lowt/\partial Drop^2$	-.2834	Yes
$\partial Lowt/\partial Docs$	-.0023	Yes
$\partial^2 Lowt/\partial Docs^2$	-.0001	No
$\partial^2 Lowt/\partial Drop\partial Docs$	-.0079	No
$\partial Drop/\partial Docs$	1.566	Yes
$\partial Drop/\partial Teen$	4.675	Yes
$\partial Drop/\partial Nograds$	2.751	No
$\partial Drop/\partial Single$	3.638	Yes

Table 6: Simple correlations: Part 1

	DEAD	INCOME	DOCS	DROP	NOGR	TEEN
DEAD	1.0000	-0.4561	-0.2497	0.3237	0.6380	0.6594
INCOME	-0.4561	1.0000	0.5051	-0.2515	-0.6618	-0.7435
DOCS	-0.2497	0.5051	1.0000	-0.1202	-0.1425	-0.5620
DROPOUTS	0.3237	-0.2515	-0.1202	1.0000	0.5114	0.5960
NOGRADS	0.6380	-0.6618	-0.1425	0.5114	1.0000	0.7461
TEEN	0.6594	-0.7435	-0.5620	0.5960	0.7461	1.0000
SINGLE	0.5540	-0.2978	0.0476	0.5656	0.5686	0.5439
MDPHC	-0.0406	0.0426	0.5429	-0.0769	0.1918	-0.2173
LOWT	0.7158	-0.3089	0.0116	0.4749	0.6693	0.6465

Table 7: Simple correlations: Part 2

	SINGLE
DEAD	0.5540
INCOME	-0.2978
DOCS	0.0476
DROPOUTS	0.5656
NOGRADS	0.5686
TEEN	0.5439
SINGLE	1.0000
MDPHC	0.2047
LOWT	0.6617

Table 8: Simple correlations: Part 3

	MDPHC	LOWT
DEAD	-0.0406	0.7158
INCOME	0.0426	-0.3089
DOCS	0.5429	0.0116
DROPOUTS	-0.0769	0.4749
NOGRADS	0.1918	0.6693
TEEN	-0.2173	0.6465
SINGLE	0.2047	0.6617
MDPHC	1.0000	0.0172
LOWT	0.0172	1.0000

Table 9: Probability of no correlation: Part 1

	DEAD	INCOME	DOCS	DROP	NOGR	TEEN
DEAD	0.0000	0.0009	0.0803	0.0218	0.0000	0.0000
INCOME	0.0009	0.0000	0.0002	0.0780	0.0000	0.0000
DOCS	0.0803	0.0002	0.0000	0.4056	0.3235	0.0000
DROPOUTS	0.0218	0.0780	0.4056	0.0000	0.0001	0.0000
NOGRADS	0.0000	0.0000	0.3235	0.0001	0.0000	0.0000
TEEN	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
SINGLE	0.0000	0.0357	0.7429	0.0000	0.0000	0.0000
MDPHC	0.7793	0.7692	0.0000	0.5957	0.1821	0.1296
LOWT	0.0000	0.0291	0.9362	0.0005	0.0000	0.0000

Table 10: Probability of no correlation: Part 2

	SINGLE
DEAD	0.0000
INCOME	0.0357
DOCS	0.7429
DROPOUTS	0.0000
NOGRADS	0.0000
TEEN	0.0000
SINGLE	0.0000
MDPHC	0.1538
LOWT	0.0000

3.6 Simulations

Simulations of the estimated system in (7) through (9) suggest that a drop of one percentage point in the dropout rate would lead, on average, to a short-run drop of .15 in the rate of infant death (or 15 deaths avoided per 100,000 live births) in a state. The precise change, however, varies from state to state. The predicted drop in the rate of infant death is greatest for North Dakota (-1.21, or 121 deaths averted per 100,000 live births). The precise change is also sensitive to the number of stages in the least-squares estimation. Under 2SLS, the predicted mean change in the rate of infant death is positive (.118, or an additional 11.8 deaths per 100,000 live births). Tables 12 and 13 present the predicted changes, by state, in the rate of low-weight birth as well as in the rate of infant death.[11]

[11] Appendix E gives the equations used in the simulations.

Table 11: Probability of no correlation: Part 3

	MDPHC	LOWT
DEAD	0.7793	0.0000
INCOME	0.7692	0.0291
DOCS	0.0000	0.9362
DROPOUTS	0.5957	0.0005
NOGRADS	0.1821	0.0000
TEEN	0.1296	0.0000
SINGLE	0.1538	0.0000
MDPHC	0.0000	0.9054
LOWT	0.9054	0.0000

Table 12: Short-run changes in low-weight, death rates

	2SLS		3SLS	
State	Δ *Lowt*	Δ *Dead*	Δ *Lowt*	Δ *Dead*
Alabama	0.364	0.346	0.043	0.036
Alaska	-0.631	-0.054	-0.660	-0.249
Arizona	1.354	0.821	0.743	0.546
Arkansas	-0.204	-0.175	-0.360	-0.284
California	1.799	1.234	1.049	0.912
Colorado	-0.157	-0.181	-0.340	-0.359
Connecticut	0.654	0.797	0.216	0.278
Delaware	-0.066	-0.061	-0.273	-0.250
Florida	1.554	1.398	0.880	0.809
Georgia	1.098	1.095	0.563	0.505
Hawaii	-0.821	-0.799	-0.818	-0.830
Idaho	-0.955	-0.159	-0.889	-0.350
Illinois	0.253	0.258	-0.050	-0.050
Indiana	-0.136	-0.077	-0.313	-0.207
Iowa	-2.148	-0.688	-1.744	-0.917
Kansas	-1.016	-0.580	-0.944	-0.660
Kentucky	0.745	0.470	0.312	0.224
Louisiana	0.678	0.855	0.259	0.276
Maine	-1.095	-0.335	-1.002	-0.588
Maryland	1.569	2.460	0.865	1.287
Massachusetts	0.911	1.085	0.390	0.531
Michigan	-0.385	-0.324	-0.497	-0.422
Minnesota	-1.395	-0.709	-1.224	-0.939
Mississippi	-0.410	-0.444	-0.500	-0.415

Table 13: Short-run changes in low-weight, death rates, Part 2

	2SLS		3SLS	
State	Δ *Lowt*	Δ *Dead*	Δ *Lowt*	Δ *Dead*
Missouri	0.309	0.261	-0.005	-0.004
Montana	-1.437	-0.608	-1.240	-0.739
Nebraska	-1.647	-0.691	-1.394	-0.886
Nevada	1.148	0.653	0.606	0.377
New Hampshire	-0.441	-0.196	-0.540	-0.374
New Jersey	0.231	0.243	-0.073	-0.079
New Mexico	0.234	0.178	-0.054	-0.043
New York	1.160	1.644	0.573	0.811
North Carolina	0.644	0.670	0.236	0.224
North Dakota	-2.613	-0.812	-2.082	-1.210
Ohio	-0.686	-0.595	-0.713	-0.633
Oklahoma	-0.705	-0.356	-0.715	-0.430
Oregon	0.502	0.211	0.132	0.090
Pennsylvania	-0.070	-0.071	-0.285	-0.301
Rhode Island	0.919	0.821	0.416	0.429
South Carolina	0.040	0.043	-0.189	-0.172
South Dakota	-1.745	-0.356	-1.456	-0.675
Tennessee	1.139	1.263	0.586	0.591
Texas	0.563	0.374	0.183	0.133
Utah	-0.993	-0.409	-0.928	-0.582
Vermont	-0.451	-0.315	-0.558	-0.510
Virginia	-0.157	-0.141	-0.339	-0.311
Washington	0.139	0.067	-0.129	-0.094
West Virginia	-0.175	-0.127	-0.344	-0.264
Wisconsin	-1.504	-0.779	-1.295	-0.908
Wyoming	-2.279	-1.292	-1.833	-1.097
State average	-0.126	0.118	-0.315	-0.156

Table 14: Marginal cost of health information

Model	$\frac{\partial DEAD}{\partial LOWT}$	$\frac{\partial LOWT}{\partial DROPOUTS}$	Income	$\approx \frac{\partial C}{\partial I}$
Model 1, 2SLS	.913	.609	\$31,509	\$17,520
Model 1, 3SLS	.913	.609	\$31,509	\$17,520
Model 2, 2SLS	.913	.609	\$31,509	\$17,520
Model 2, 3SLS	.947	.698	\$31,509	\$20,828
Model 3, 2SLS	.913	.630	\$31,509	\$18,124
Model 3, 3SLS	.913	.631	\$31,509	\$18,152
Full Model, 2SLS	.761	.122	\$31,509	\$2,925
Full Model, 3SLS	.831	.315	\$31,509	\$8,248

4 Marginal cost of health information

Specifying the first-order condition in (5) yields crude and preliminary estimates of the marginal cost and value of health information to the pregnant woman. The estimates use $\partial DEAD/\partial LOWT$ for $\partial M/\partial W$; and $\partial LOWT/\partial DROPOUTS$ for $\partial W/\partial I$. To approximate $U_h - U_m$, the estimates use median household money income. U_h and U_m are values; no utility function is assumed.

Computations are in Table 14. Estimates of marginal cost are sensitive to the specification of the model, but all amounts are considerable. The estimates suggest that the would-be mother acquires health information up to the point that she would be willing to pay more than \$2,900 – an eleventh of the annual income of her household – to forgo acquiring a little more. It seems that the marginal cost of health information is quite high. Since the optimizing mother acquires health information until the marginal value equals the marginal cost, its marginal value – the gain to the would-be mother in reducing the chance of an infant death – is also more than \$2,900.

While one must be cautious about drawing conclusions from such a simple model, the high marginal value of information suggests that education would also be valuable to the woman but that she finds it costly to acquire. The strength of the peer effects suggests that perhaps the woman drops out of school because she finds education costly in social terms, not because she lacks motivation to learn. Though she highly values education, social pressures powerfully constrain her from completing her degree. This speculation, while highly tenuous, is somewhat supported by the statistical results: The share of youths that dropped out of high school related positively to the share of mothers who were teens and to the share of mothers who were single.

5 Conclusions and reflections

While highly tentative, the empirical results suggest two issues for policy research. First, the results fit the idea that the woman bases her estimates of the net returns to education on what she sees others do. For example, she is more likely to drop out of school if she observes that many peers and adults dropped out, too. But the decisions of adults to drop out, when they were youths, may have stemmed in part from observing that the peers and adults of their day had dropped out. And so the impact of an individual decision may be transmitted over time, from generation to generation.

The empirical results also fit the idea that raising the perceived returns to education could lower the incidence of infant mortality.

If these provisional interpretations are correct, then one may ask: How can a family, community or government raise the returns to education that are perceived by the uneducated?

The results may also suggest that the would-be mother acquires education – and, by extension, health information – to the point that she would find it quite costly to acquire more. If that interpretation is correct, then one may ask: How can one lower the cost – especially in terms of social pressure – of acquiring education?

6 Appendix A: Derivations

6.1 Second-order conditions

The second derivative of the function to be maximized (L), with respect to the choice variable, health information (I), is

$$\frac{\partial^2 L}{\partial I^2} = -\frac{\partial M}{\partial W}\frac{\partial^2 W}{\partial I^2}(U_h - U_m) - \frac{\partial^2 M}{\partial W^2}(\frac{\partial W}{\partial I})^2(U_h - U_m) - \frac{\partial^2 C}{\partial I^2} < 0.$$

The strict inequality follows in part from the assumptions that $\partial^2 W/\partial I^2 > 0$and $\partial^2 C/\partial I^2 > 0$.

6.2 Comparative statics

The mathematics draw upon Chiang (1974). Rewrite $\partial L/\partial I$ as the function

$$F(D, T, S, N) = -\frac{\partial M}{\partial W}\frac{\partial W}{\partial I}(U_h - U_m) - \frac{\partial C}{\partial I} \equiv 0.$$

From (**??**), we have that $\partial F/\partial I < 0$. Using the implicit function theorem, we have that

$$\frac{\partial F}{\partial D} = -(\frac{\partial^2 M}{\partial W \partial D}\frac{\partial W}{\partial I} + \frac{\partial M}{\partial W}\frac{\partial^2 W}{\partial I \partial D})(U_h - U_m) \leq 0$$

so

$$\frac{\partial I^*}{\partial D} = -\frac{F_D}{F_I} \leq 0.$$

Also,

$$\frac{\partial F}{\partial S} = -\frac{\partial^2 C}{\partial I \partial S} < 0$$

so

$$\frac{\partial I^*}{\partial S} = -\frac{F_S}{F_I} < 0.$$

Also,

$$\frac{\partial F}{\partial N} = -\frac{\partial^2 C}{\partial I \partial N} < 0$$

so

$$\frac{\partial I^*}{\partial N} = -\frac{F_N}{F_I} < 0.$$

Finally,

$$\frac{\partial F}{\partial T} = -\frac{\partial^2 C}{\partial I \partial T} < 0$$

so

$$\frac{\partial I^*}{\partial T} = -\frac{F_T}{F_I} < 0.$$

7 Appendix B: One-equation models

A linear regression of *Dead* on *Lowt* yields results reported in Table 15, where $s = 0.9868$, $R^2 = .512$ and adjusted $R^2 = .502$. The Durbin-Watson statistic is 1.64.

Table 15: Infant death and low weight

Predictor	*Coefficient*	*Standard Deviation*	*T-ratio*	*p*
Constant	2.8980	0.7855	3.69	0.001
Lowt	0.7987	0.1125	7.10	0.000

The model makes clear that the rate of low-weight birth shapes the rate of infant death. Still, caveats are in order. First, Mississippi's influence on the model is palpable; the state had both the highest rate of infant death (11.9 deaths in every 1,000 live births) and the highest rate of low-weight birth (9.9 percent of all registered births were below 2,500 grams). Second, the model seriously mis-predicts the rate of infant death for three states. For Colorado and Hawaii, it predicts rates that are too high. For Colorado, the model predicts 9.7; the rate is actually 7.6. For Hawaii, the model predicts 8.6; the rate is actually 6.3. For South Dakota, the model predicts a rate that is too low. The model predicts 7.1; the rate is actually 9.3.

A slightly more complex model yields intriguing results. Consider

$$Dead_i = a_0 + a_1 Income_i + a_2 Teen_i + a_3 Lowt_i + \epsilon_i \tag{13}$$

where i indexes the states. The results in Table 16 show that the impact of income is so small, relative to the imprecision of its estimation, that one cannot discard the possibility that the impact is zero. For the model, $s = 0.9294$, $R^2 = .585$ and adjusted $R^2 = .558$. The Durbin-Watson statistic is 1.87.

Table 16: Infant death: A fuller model

Predictor	*Coefficient*	*Standard Deviation*	*T-ratio*	*p*	*VIF*
Constant	4.227	1.804	2.34	0.024	
Income	-0.00003414	0.00003978	-0.86	0.395	2.5
Lowt	0.5976	0.1474	4.05	0.000	1.9
Teen	0.08905	0.07713	1.15	0.254	3.9

The standardized form of the model also suggests that income is relatively unimportant, compared to the impacts of the other independent variables. The results are in Table 17, where $s = 0.6574$. Since standardization reduces the constant to zero, I have suppressed it here – and, consequently, I report no R^2.

Table 17: Infant death: A standardized model

Predictor	*Coefficient*	*Standard Deviation*	*T-ratio*	*p*
Income	-0.1294	0.1491	-0.87	0.390
Lowt	0.5356	0.1307	4.10	0.000
Teen	0.2170	0.1859	1.17	0.249

Despite the statistical and relative insignificance of income in such simple models, which treat independent variables as little influenced by income, its impact on infant health may be noticeable. The standardized model indicates that an increase in median household income by one standard deviation ($5,300) leads to a reduction in the rate of infant mortality of about .13 of a standard deviation, or 18 additional lives saved in every 100,000 live births.

I return now to the regular regressions. As the Variance Inflation Factors indicate in Table 16, collinearity is not likely to account for the statistical insignificance of the coefficient on *Income*, although its simple correlation with *Teen* is somewhat strong (-.744). So one may wish to test the hypothesis that, in (13), $a_1 = a_2 = 0$. Calculating the F-statistic for the two models yields

$$F_{2,47} = \frac{(R^2{}_{UR} - R^2{}_R)/2}{(1 - R^2{}_{UR})/47} = \frac{(.585 - .512)/2}{(1 - .585)/47} = 4.13.$$

Critical F-values are 3.23 at the 5 percent level of significance and 5.18 at the 1 percent level. It is hard to reject the idea that a model based on low-weight birth alone is effective.

The puzzling results concerning income may stem in part from the high incomes – and the higher-than-average rates of infant death – in Alaska and South Dakota. Omitting those observations from the dataset improves the fit of the model considerably at the expense of a slight loss of relevant information. Excluding *Teens* from the model, because of its negative covariance with *Income*, also improves the fit, at the expense of a slight downward bias in the *Income* coefficient and a slight upward bias in the *Lowt* coefficient. Results are reported in Table 18, where $s = 0.8233$. Also, $R^2 = .679$ and adjusted $R^2 = .665$.

Table 18: Infant death: Omitting a control for teens

Predictor	*Coefficient*	*Standard Deviation*	*T-ratio*	*p*	*VIF*
Constant	5.162	1.199	4.30	0.000	
Income	-0.00007802	0.00002460	-3.17	0.003	1.1
Lowt	0.8129	0.1028	7.91	0.000	1.1

Standardized error terms appear to be distributed normally. Under the Anderson-Darling test, $p = .18$.

Inspection of a graph of the standardized residuals against the fitted values for the equation revealed no obvious pattern of heteroscedasticity. A more precise analysis is provided by a linear regression of the error variances, normalized by their mean, on *Income* and *Lowt*. Given the normality of the error terms, an application of the Breusch-Pagan test seemed appropriate here. The test suggested that the error term was homoscedastic (Pindyck and Rubinfeld (1991)).[12]

The standardized version of the model suggests that a change in income would have only 41 percent of the impact on the rate of infant death as a commensurate change in the incidence of low-weight birth. Results are in Table 19, where $s = 0.5864$.

[12] Half of the regression sum of squares was 2.807, well below the χ^2 critical value at the 5 percent level for two degrees of freedom (5.99).

Table 19: Standardized model without a control for teens

Predictor	*Coefficient*	*Standard Deviation*	*T-ratio*	*p*
Income	-0.29482	0.09288	-3.17	0.003
Lowt	0.72428	0.09163	7.90	0.000

Omitting *Teen* from this standardized model introduces a downward bias in the *Income* coefficient and an upward bias in the *Lowt* coefficient. Including *Teen* produces the results in Table 20, where $s = 0.5929$.

Table 20: Standardized model with a control for teens

Predictor	*Coefficient*	*Standard Deviation*	*T-ratio*	*p*
Income	-0.2844	0.1584	-1.80	0.079
Lowt	0.7168	0.1303	5.50	0.000
Teen	0.0155	0.1890	0.08	0.935

With the inclusion of *Teen*, the ratio of coefficients for *Income* to *Lowt* drops from -.4070 to -.3968, a relative change of -2.5 percent. The bias due to excluding *Teen* from the standardized model is thus small.

Generally, the models suggest that if one treats the share of low-weight births as an exogenous determinant of the rate of infant death, then the impact of socioeconomic variables may appear to be relatively small.

8 Appendix C: Data sources

DEAD: Deaths of infants under 1 year old, excluding fetal deaths. Excludes deaths of nonresidents of the U.S. Source: Table 123 of the 1995-96 version of *The statistical abstract of the United States*. Cited sources: U.S. National Center for Health Statistics, *Vital statistics of the United States*; and unpublished data.

DOCS: The number of physicians per 100,000 civilian population. Active non-federal physicians as of January 1, 1993. Excludes doctors of osteopathy, federal employees, and physicians with unknown addresses. Source: Table 177 of the 1995-96 version of *The statistical abstract of the United States*. Cited source: American Medical Association, *Physician characteristics and distribution in the United States*, Chicago, annual.

DROPOUTS: Of all persons 16 to 19 years old, the percentage of those who were not in regular school and had neither completed the 12th grade nor received a general equivalency degree. Source: Table 242 of the 1995-96 version of *The statistical abstract of the United States*. Cited source: U.S. Bureau of the Census, *1990 census of population*, CPH-L-96.

INCOME: Median money income of households for 1992, in 1993 dollars. The deflator used is a variant on the consumer price index. Source: Table 730 of the 1995-96 version of *The statistical abstract of the United States*. Cited source: U.S. Bureau of the Census, *Current population reports*, P60-188. The census bureau cautions that the Current Population Survey is designed to gather data primarily on the national level and secondarily on the regional level. State-level data may be less reliable.

LOWT: Of all registered births, the percentage of births that are less than 2,500 grams (5 pounds, 8 ounces). Excludes births to nonresidents of the United States. Source: Table 95 of the 1995-96 version of *The statistical abstract of the United States*. Cited source: U.S. National Center for Health Statistics, *Vital statistics of the United States*, annual; and *Monthly vital statistics report*.

MDPHC: Medicaid spending for personal health care per household. Source: Derived from Table 153 of the 1995-96 version of *The statistical abstract of the United States*.

NOGRADS: Of all persons 25 years old and over, the percentage who were not high school graduates. Source: Table 242 of the 1995-96 version of *The statistical abstract of the United States*. Cited source: U.S. Bureau of the Census, *1990 census of population*, CPH-L-96.

SINGLE: Of all registered births, the percentage of births to unmarried mothers. Excludes births to nonresidents of the United States. Source: Table 95 of the 1995-96 version of *The statistical abstract of the United States*. Cited source: U.S. National Center for Health Statistics, *Vital statistics of the United States*, annual; and *Monthly vital statistics report*.

TEEN: Of all registered births, the percentage of births to teenage mothers. Excludes births to nonresidents of the United States. Source: Table 95 of the 1995-96 version of *The statistical abstract of the United States*. Cited source: U.S. National Center for Health Statistics, *Vital statistics of the United States*, annual; and *Monthly vital statistics report*.

9 Appendix D: Data

Datasets are in Tables 21 through 24 on following pages.

Table 21: Dataset, Part 1

State	*Dead*	*Income*	*Docs*	*Dropouts*
Alabama	10.5	26581	170	12.6
Alaska	8.6	43053	142	10.9
Arizona	8.4	30237	194	14.4
Arkansas	10.3	24597	162	11.4
California	7	35948	240	14.2
Colorado	7.6	33456	222	9.8
Connecticut	7.6	42064	321	9
Delaware	8.6	36746	209	10.4
Florida	8.8	28168	215	14.3
Georgia	10.3	29659	182	14.1
Hawaii	6.3	43374	244	7.5
Idaho	8.8	28533	131	10.4
Illinois	10.1	32496	230	10.6
Indiana	9.4	29384	168	11.4
Iowa	8	29603	159	6.6
Kansas	8.7	31254	185	8.7
Kentucky	8.3	24188	179	13.3
Louisiana	9.4	26201	201	12.5
Maine	5.6	30504	192	8.3
Maryland	9.8	38317	335	10.9
Massachusetts	6.5	37447	361	8.5
Michigan	10.2	33233	195	10
Minnesota	7.1	31908	232	6.4
Mississippi	11.9	21186	130	11.8

Table 22: Dataset, Part 2

State	*Dead*	*Income*	*Docs*	*Dropouts*
Missouri	8.5	28180	207	11.4
Montana	7.5	27319	169	8.1
Nebraska	7.4	30948	189	7
Nevada	6.7	32863	148	15.2
New Hampshire	5.6	40617	211	9.4
New Jersey	8.4	40168	263	9.6
New Mexico	7.6	26634	190	11.7
New York	8.8	31981	334	9.9
North Carolina	10	28602	198	12.5
North Dakota	7.8	27766	188	4.6
Ohio	9.4	32344	207	8.9
Oklahoma	8.8	26041	153	10.4
Oregon	7.1	32883	210	11.8
Pennsylvania	9	30777	254	9.1
Rhode Island	7.4	31343	271	11.1
South Carolina	10.4	28404	173	11.7
South Dakota	9.3	27045	156	7.7
Tennessee	9.4	25046	210	13.4
Texas	7.8	28790	177	12.9
Utah	5.9	35276	187	8.7
Vermont	7.2	33736	259	8
Virginia	9.5	39341	215	10
Washington	6.8	34915	220	10.6
West Virginia	9.2	20878	182	10.9
Wisconsin	7.2	34305	198	7.1
Wyoming	8.9	31113	137	6.9

Table 23: Dataset, Part 3

State	*Nograds*	*Lowt*	*Teen*	*Single*	*Mdphc*
Alabama	33.1	8.5	18.2	32.6	811.1888
Alaska	13.4	4.9	10.9	27.4	1325.243
Arizona	21.3	6.4	15	36.2	869.2676
Arkansas	33.7	8.2	19.4	31	1095.756
California	23.8	5.9	11.8	34.3	1047.038
Colorado	15.6	8.5	12	23.8	697.6912
Connecticut	20.8	6.9	8	28.7	1627.036
Delaware	22.5	7.6	12.4	32.6	950.3817
Florida	25.6	7.4	13.5	34.2	870.9438
Georgia	29.1	8.5	16.2	35	1087.712
Hawaii	19.9	7.2	10	26.2	936.5079
Idaho	20.3	5.5	13	18.3	734.1772
Illinois	23.8	7.7	12.9	33.4	1071.611
Indiana	24.4	6.7	14.1	29.5	1292.229
Iowa	19.9	5.7	10.2	23.5	885.6089
Kansas	18.7	6.4	12.4	24.3	797.7178
Kentucky	35.4	6.8	16.5	26.3	1176.101
Louisiana	31.7	9.4	18.1	40.2	1732.12
Maine	21.2	5	10.2	25.3	1520
Maryland	21.6	8.3	9.8	30.5	1058.306
Massachusetts	20	6	7.7	25.9	1630.858
Michigan	23.2	7.5	13	26.8	1104.917
Minnesota	17.6	5.2	8.1	23	1309.636
Mississippi	35.7	9.9	21.4	42.9	1108.395

Table 24: Dataset, Part 4

State	*Nograds*	*Lowt*	*Teen*	*Single*	*Mdphc*
Missouri	26.1	7.3	14.5	31.5	823.1768
Montana	19	6	11.9	26.4	1003.115
Nebraska	18.2	5.6	9.9	22.6	913.6808
Nevada	21.2	7.1	12.4	33.3	646.6165
New Hampshire	17.8	5.3	6.7	19.2	1064.439
New Jersey	23.3	7.2	8	26.4	1358.577
New Mexico	24.9	7.2	17	39.5	1000
New York	25.2	7.6	9	34.8	2697.115
North Carolina	30	8.4	15.4	31.3	970.8444
North Dakota	23.3	5.1	9.3	22.6	1111.57
Ohio	24.3	7.4	13.6	31.6	1113.631
Oklahoma	25.4	6.7	16.8	28.4	820.9076
Oregon	18.5	5.2	12.4	27	810.6961
Pennsylvania	25.3	7.2	10.5	31.6	1122.176
Rhode Island	28	6.3	9.8	29.6	2103.448
South Carolina	31.7	9	16.6	35.5	999.2453
South Dakota	22.9	5.2	11.4	26.6	1000
Tennessee	32.9	8.5	16.9	32.7	1124.099
Texas	27.9	7	15.9	17.5	919.3222
Utah	14.9	5.6	10.5	15.1	815.3846
Vermont	19.2	5.6	8.5	23.4	1059.361
Virginia	24.8	7.4	11	28.3	671.7779
Washington	16.2	5.3	10.6	25.3	1070.862
West Virginia	34	7.2	17.2	27.7	1524.823
Wisconsin	21.4	5.9	10.2	26.1	1135.422
Wyoming	17	7.3	13.2	24	778.4091

10 Appendix E: Simulations

10.1 Basic equations and tentative results

For predictions of the short-run change in the rate of infant death due to a reduction in the dropout rate of one percentage point, the 2SLS equations were

$$\Delta Lowt = \Delta Dropouts * [6.586 - .3978 Dropout - .0114 Docs]$$

and

$$\Delta Dead = \Delta Lowt * [-1.507 + .209 Lowt + .004 Docs].$$

The 3SLS equations were

$$\Delta Lowt = \Delta Dropouts * [4.871 - .2834 Dropout - .0079 Docs]$$

and

$$\Delta Dead = \Delta Lowt * [-.6799 + .1002 Lowt + .00399 Docs].$$

To calculate the long-run rates of low-weight birth and infant death, I assumed that, in a steady state, the *Nograds* rate would equal the *Dropout* rate. This, in turn, presumes a steady-state distribution of ages in the population. Tables 25 through 28, below, present the values predicted by the simulations. On average, the simulations predict that the dropout rate would fall from 10.3 percent to 9.93 percent but that the rate of infant death would rise from 8.4 to 8.52 per 1,000 live births. The puzzling results probably stem from the attempt to hold constant the teen share of all births (*Teen*), a variable that correlates somewhat strongly with the nongraduate share of all adults, *Nograds* ($r = .746$).

11 Appendix F: Stochastic errors

11.1 Errors on both sides of the equation

The treatment here follows that of Pindyck and Rubinfeld (1991). Let the observed independent variable be

Table 25: Infant death rate in long-run equilibrium, Part 1

	Early 1990s			Long run (2SLS)		
State	*Drop*	*Lowt*	*Dead*	*Drop*	*Lowt*	*Dead*
Alabama	12.6	8.5	10.5	13.20	8.07	8.91
Alaska	10.9	4.9	8.6	9.25	6.97	8.58
Arizona	14.4	6.4	8.4	12.41	7.79	8.40
Arkansas	11.4	8.2	10.3	13.47	8.17	9.09
California	14.2	5.9	7	11.28	7.35	7.57
Colorado	9.8	8.5	7.6	10.13	7.94	8.30
Connecticut	9	6.9	7.6	9.85	7.04	6.88
Delaware	10.4	7.6	8.6	11.07	7.99	8.45
Florida	14.3	7.4	8.8	11.76	7.62	8.03
Georgia	14.1	8.5	10.3	12.69	7.98	8.70
Hawaii	7.5	7.2	6.3	9.72	7.85	8.06
Idaho	10.4	5.5	8.8	9.13	6.62	8.64
Illinois	10.6	7.7	10.1	11.57	7.39	7.69
Indiana	11.4	6.7	9.4	11.09	8.47	9.29
Iowa	6.6	5.7	8	8.72	6.57	8.06
Kansas	8.7	6.4	8.7	10.00	7.99	8.67
Kentucky	13.3	6.8	8.3	11.91	8.34	9.06
Louisiana	12.5	9.4	9.4	14.22	5.78	6.89
Maine	8.3	5	5.6	9.22	7.54	8.21
Maryland	10.9	8.3	9.8	10.95	5.31	4.94
Massachusetts	8.5	6	6.5	9.82	6.35	6.01
Michigan	10	7.5	10.2	10.61	8.15	8.73
Minnesota	6.4	5.2	7.1	8.46	7.47	7.75
Mississippi	11.8	9.9	11.9	15.23	8.17	9.53

Table 26: Infant death rate in long-run equilibrium, Part 2

	Early 1990s			Long run (2SLS)		
State	*Drop*	*Lowt*	*Dead*	*Drop*	*Lowt*	*Dead*
Missouri	11.4	7.3	8.5	11.84	7.76	8.24
Montana	8.1	6	7.5	9.84	7.84	8.73
Nebraska	7	5.6	7.4	8.79	7.15	7.93
Nevada	15.2	7.1	6.7	10.55	8.31	9.38
New Hampshire	9.4	5.3	5.6	7.27	5.94	6.81
New Jersey	9.6	7.2	8.4	9.06	7.85	7.99
New Mexico	11.7	7.2	7.6	13.57	7.03	7.84
New York	9.9	7.6	8.8	11.03	5.21	4.85
North Carolina	12.5	8.4	10	12.13	7.84	8.40
North Dakota	4.6	5.1	7.8	8.52	6.86	7.75
Ohio	8.9	7.4	9.4	11.47	7.91	8.39
Oklahoma	10.4	6.7	8.8	12.00	8.82	9.78
Oregon	11.8	5.2	7.1	10.51	8.03	8.48
Pennsylvania	9.1	7.2	9	10.58	7.50	7.64
Rhode Island	11.1	6.3	7.4	10.24	7.45	7.50
South Carolina	11.7	9	10.4	12.83	8.17	8.97
South Dakota	7.7	5.2	9.3	9.52	7.46	8.63
Tennessee	13.4	8.5	9.4	13.03	6.79	7.39
Texas	12.9	7	7.8	10.74	8.30	9.04
Utah	8.7	5.6	5.9	8.27	6.56	7.57
Vermont	8	5.6	7.2	8.94	7.84	7.99
Virginia	10	7.4	9.5	10.09	7.97	8.38
Washington	10.6	5.3	6.8	9.66	7.88	8.26
West Virginia	10.9	7.2	9.2	12.38	8.12	8.83
Wisconsin	7.1	5.9	7.2	9.36	7.68	8.26
Wyoming	6.9	7.3	8.9	9.85	7.62	9.05
State average	10.3	6.9	8.4	10.76	7.50	8.13

Table 27: Infant death rate in long-run equilibrium, Part 3

	Long run (3SLS)		
State	*Drop*	*Lowt*	*Dead*
Alabama	12.18	8.34	9.67
Alaska	8.65	5.86	8.47
Arizona	11.64	8.01	9.20
Arkansas	12.35	8.46	9.84
California	10.58	7.56	8.49
Colorado	9.20	7.25	8.30
Connecticut	9.10	7.28	8.08
Delaware	10.35	7.69	8.80
Florida	11.00	7.77	8.83
Georgia	11.84	8.16	9.42
Hawaii	8.94	7.24	8.14
Idaho	8.19	4.99	8.37
Illinois	10.80	7.64	8.62
Indiana	10.28	7.68	9.17
Iowa	8.03	5.37	7.87
Kansas	9.13	6.94	8.41
Kentucky	10.83	7.95	9.27
Louisiana	13.33	7.50	8.69
Maine	8.51	6.47	7.96
Maryland	10.09	6.73	7.37
Massachusetts	8.94	7.12	8.02
Michigan	9.74	7.43	8.68
Minnesota	7.75	6.37	7.41
Mississippi	14.34	8.98	10.54

Table 28: Infant death rate in long-run equilibrium, Part 4

	Long run (3SLS)		
State	*Drop*	*Lowt*	*Dead*
Missouri	10.97	7.83	8.94
Montana	9.09	6.74	8.48
Nebraska	8.04	5.94	7.64
Nevada	9.99	7.38	9.21
New Hampshire	6.61	4.69	6.44
New Jersey	8.38	7.12	7.93
New Mexico	12.76	7.96	9.18
New York	10.33	6.58	7.17
North Carolina	11.20	7.93	9.10
North Dakota	7.81	5.66	7.47
Ohio	10.65	7.78	8.89
Oklahoma	11.01	8.11	9.66
Oregon	9.66	7.43	8.55
Pennsylvania	9.87	7.47	8.34
Rhode Island	9.49	7.40	8.21
South Carolina	11.98	8.28	9.60
South Dakota	8.84	6.31	8.43
Tennessee	12.02	7.76	8.86
Texas	9.49	7.16	8.67
Utah	7.30	5.00	7.09
Vermont	8.15	6.98	7.80
Virginia	9.35	7.29	8.39
Washington	8.86	7.05	8.12
West Virginia	11.29	8.07	9.35
Wisconsin	8.65	6.67	8.04
Wyoming	9.03	6.25	8.76
State average	9.93	7.15	8.52

$$x_i{}^* = x_i + v_i$$

where x_i is the true value and v_i is a measurement error that is approximately normal with zero mean and constant variance $\sigma_v{}^2$. Similarly, let the observed dependent variable be

$$y_i{}^* = y_i + u_i$$

where y_i is the true value and u_i is approximately normal with zero mean and constant variance. Assume that neither measurement error correlates with x_i; with each other; or with itself, in a serial sense. Finally, let the true equation be

$$y_i = \beta x_i.$$

Then the probability limit of the OLS estimator for β – denote that estimator as $\hat{\beta}$ – is

$$plim\ \hat{\beta} = \frac{\beta}{1 + \frac{\sigma^2{}_v}{Var(x)}}.$$

In this paper, x_i and $x_i{}^*$ are both rates bounded by 0 and 1. These variables may represent, for example, the true and observed values of the nongraduation rate. If

$$\frac{\sigma_v^2}{Var(x)} \approx 1,$$

then $plim\ \hat{\beta} \approx \beta/2$.

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