NBER WORKING PAPER SERIES

UNDERSTANDING HEALTH DISPARITIES ACROSS EDUCATION GROUPS

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Working Paper 8328
http://www.nber.org/papers/w8328

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
June 2001

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NBER Working Paper No. 8328
June 2001
JEL No. I1

ABSTRACT

Better-educated people are healthier, but the magnitude of the relationship between health and education varies substantially across groups and over time. We undertake a theoretical and empirical study of how health disparities by education vary over time and across the population, according to underlying health characteristics and market forces. One surprising implication of the theory we develop is that health disparities actually increase as the price of health inputs falls. Therefore, government subsidies for health care research or even universal health insurance may *worsen* health inequality. Moreover, technological progress in health care will tend to raise inequality over time. The theory also implies that health disparities will be larger for sicker, older and more vulnerable groups. The first prediction is consistent with significant expansions in health disparities over the last thirty years in the US. The second is consistent with observed patterns in the National Health Interview Survey, the Medicare Current Beneficiary Survey, and the Framingham Heart Study. The returns to schooling are twice as high for the chronically ill and for those out of the labor force, and they tend to rise with age.

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1 Introduction

Better-educated people are healthier. This is one of the most robust empirical findings in health. Farrell and Fuchs (1982) argue that this relationship is "one of the strongest generalizations to emerge from empirical research on health in the United States." Socioeconomic status in general has been shown to affect mortality and morbidity in a number of studies (Marmot, 2000; Smith, 1999). In particular, the association between education and health is pervasive and quantitatively large (Kitagawa and Hauser, 1973; Haan et al, 1987; Feldman et al, 1989; Preston and Taubman, 1994; Pappas, 1993; Schoenbaum and Waidmann, 1997).

Grossman (1972) was among the first to present an explicit theoretical model linking schooling and health.[1] In an earlier paper, Welch (1970) analyzed the more general relationship between education and productive efficiency. The theoretical research has been accompanied by a tremendous amount of empirical evidence substantiating the correlation between schooling and health. Socioeconomic status in general has been shown to affect mortality and morbidity in a number of studies (Marmot, 2000; Smith, 1999). In particular, the association between education and health is pervasive and quantitatively large (Kitagawa and Hauser, 1973; Haan et al, 1987; Feldman et al, 1989; Preston and Taubman, 1994; Pappas, 1993; Schoenbaum and Waidmann, 1997).

However, there has been considerable debate about the source of the relationship. The traditional arguments—that the less well-to-do have access to less or lower quality medical care

[1] For an earlier discussion of the similarities and differences between education investments and health investments, see Mushkin (1962). Muurinen (1982) provides a later, more general formulation of Grossman's model.

or a stronger pattern of deleterious personal behaviors such as smoking and excess drinking—have been rejected as incomplete.[2] For his part, Grossman argues that more educated people are better producers of health. Fuchs (1982), however, responds that the link is not causal, but that unobserved characteristics such as higher ability or lower discount rates make people more disposed towards investments in human capital of all types, be they health investments or education investments. Kenkel's (1991) empirical analysis sheds some light on this debate with its finding that part, but not the majority, of the relationship between schooling and health is explained by real differences in health knowledge. Other researchers have used instrumental variables methods to argue for a causal link between schooling and health.[3] Perhaps not surprisingly, Fuchs (1996) has remained unconvinced by these responses.

Despite this contentious body of work, virtually no research has investigated how health disparities across education groups vary with market forces, across time, and across different groups in the population. There are at least three important reasons to study how health disparities vary across education groups, *given* a fixed distribution of education. First, as a practical matter, public policies of various types often aim to limit these disparities by means other than wholesale changes in the distribution of education. Medicare and Medicaid, two of

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[2] Recently, some intriguing theories have arisen that emphasize long-term impacts of early childhood or even intrauterine environmental factors (Barker, 1993; Wadsworth and Kuh, 1997), the cumulative effects of prolonged exposures to individual stressful events (Seeman et al., 1997), or reactions to macro-societal factors such as rising levels of income inequality (Wilkenson, 1996; Deaton and Paxson, 1999).

[3] Berger and Leigh (1989) use a two-stage selection model to demonstrate this. Arkes (2000) uses state-level variation in unemployment rates as an instrument for schooling, to show that schooling has a causal effect on health. Lleras-Muney (2000) uses compulsory schooling laws as an instrument for schooling attainment, to show that schooling lowers mortality.

the largest public investments in health, have this as an explicit goal. However it is not possible to limit disparities through policymaking unless their economic determinants are well understood. Second, the perennial uncertainty about the true channel of causation from schooling to health makes it important to investigate how health disparities change, *given* fixed disparities in education. It is hard to be sure about how changes in education will affect health disparities, because it has proven to be very difficult to identify the true nature of the causality from schooling to health. A different approach would be to understand how health disparities respond to economic variables when the distribution of education—and thus the various factors that influence education—remains fixed. Third, an analysis of how changes in education affect health disparities may not yield practical implications. Education is determined by many factors other than health; it seems difficult to defend wholesale changes in the education distribution on the basis of health alone.

It is also natural to ask: why study health disparities across *education* groups? A long and distinguished literature has examined wage disparities across education groups (e.g., Katz and Murphy, 1992; Murphy and Welch, 1989), in part because education is one of the best (if not the single best) observable correlates of permanent income. If one cares about disparities in lifetime utility, a natural way to proceed is to examine disparities across education (and thus permanent income) groups.

To be precise, we investigate theoretically and empirically the determinants of health disparities across education groups. We will develop a theoretical model and derive three important sets of testable implications: (1) Reductions in the price of health care expand health disparities across education groups; (2) Groups in the population that benefit more from health investment will exhibit greater disparities; (3) More educated patients will devote relatively more resources to managing their own health, rather than having it managed. One of the most important and attractive features of the model is that its implications do not depend on the specific causal link between schooling and health. The only requirement is that schooling is correlated with a set of characteristics that make people more efficient producers of health.

A simple example helps illustrate the first two implications. Consider a society with two people: person E is an educated and efficient user of health inputs, but person U is an uneducated and inefficient user. Under fairly general conditions, E will use more health care than U, because she is a more efficient user. Accordingly, suppose that E uses 2 units of health care, but U uses only 1. If the price of health care falls by $1 (or the marginal productivity of health care rises by $1) E receives a windfall gain of $2, but U's gain is only $1. E will parlay her disproportionate monetary advantage into a disproportionate gain in health, because on the margin, she spends a larger fraction of her income on health.[4] This example also illustrates why our results do not depend on the specific causal link between schooling and health. It is driven entirely by the fact that better-educated people are better at producing health and will thus invest more in it. It does not matter whether schooling itself makes them better producers, or whether they are better because they are more forward-looking, more able, or because of some other factor.

These two implications help us unravel how new technologies or shocks to health can affect health disparities in different and unexpected ways. First, technological innovation always

[4] On the margin, health care is equally productive for E and U in equilibrium. Therefore, additional health care consumption will not benefit one person more than the other, to a first-order approximation.

lowers the price of health care. This leads to the surprising result that many technological changes can actually expand health disparities. However, we will also consider an important exception to this rule. Certain innovations change the nature of health production by making time inputs much less productive. When the productivity of time investments falls, this especially hurts the educated patients, since they are the heaviest investors of time. As a result, new health care technologies that supplant time investments can in fact contract disparities. For example, the typhoid vaccine made it much easier to prevent typhoid, *without* spending a great deal of time boiling water, washing fresh vegetables, maintaining a high level of hygiene, and so on. By making those time investments much less productive, the advent of the vaccine made it relatively cheaper for the uneducated to prevent typhoid and thus may have contracted health disparities due to typhoid death. In some cases, this countervailing effect of "timesaving innovations" can be large enough to offset the effect of the price reduction.

Similarly, health shocks have different effects on disparities, depending on their nature. An individual who contracts a chronic but treatable disease may suddenly find that health investments are more productive for him. Such a health shock would expand health disparities. Therefore, we expect that people with chronic but treatable conditions would exhibit greater disparities. On the other hand, the advent of a highly untreatable, fatal disease might in fact lower the productivity of health investments. Among people suffering from such conditions, therefore, we might expect fewer disparities in health.

The effects of price and productivity also have important policy implications. Universal health insurance or other blanket price subsidies for health care can actually exacerbate health inequality, as can subsidies for medical research. On the other hand, the prevention of *treatable* conditions will not only improve average health but may also reduce health inequality. Therefore, from the point of view of inequality alone, it is at least as important to prevent treatable disease as untreatable disease.

Our empirical analysis will test our implications for technological change and health shocks. First, we will examine the impact of technological change on health disparities using examples of both "timesaving" innovations and different innovations that are unlikely to have supplanted time investments. Prior to the advent of antihypertensive drugs, the control of hypertension involved substantial investments of time and know-how by patients. Therefore, since these drugs supplanted time investments, they could have substantially limited health disparities. We use data from the Framingham Heart Study (FHS) to show that in fact the emergence of these drugs dramatically reduced disparities in hypertension and hypertensive heart disease over a period of just a few years. The development of Highly Active Antiretroviral Therapy (HAART) for HIV represents a very different example. While the new drugs improve immune function, they also required patients to comply with complicated treatment regimens. They did not supplant time investments and may have even made them more important. Using data from the HIV Cost and Services Utilization Study (HCSUS), we show that HAART substantially expanded the gap in health status across education groups within a few years' time.

We will also examine the impact of treatable and untreatable health conditions. We use the National Health Interview Survey (NHIS) to show that health disparities are larger for those with treatable chronic illnesses to health disparities in the rest of the population. To investigate the impact of untreatable disease, we use the Medicare Current Beneficiary Survey (MCBS) to show that disparities are lower among elderly people in their last year of life than among similarly aged people who are not about to die.

2 Schooling and the Determination of Health

It seems reasonable to assume that schooling and its determinants have no effect on the quality of care delivered by a given physician, surgeon, or hospital. That is, a patient's schooling will not help him when he is on the operating table, but it might help him to choose a better doctor or hospital before he enters the operating room. Alternatively, since schooling and its determinants might affect the patient's adherence to a treatment regimen, they might also affect the therapy offered by the physician. However, *holding all these patient investments constant*, they may not have any effect on care. This leads us to distinguish between investments of the patient's own time in her health, and investments in medical goods or services. The first type requires the patient to manage her own care in some way. Examples would be diet, exercise, complex medication regimens, or choosing a health care provider. It is important to recognize that shopping for medical goods or complying with treatment are also investments of the patient's own time. The second type of investment requires no patient management, and is delivered entirely by a physician or other health care provider. Examples would be surgical procedures or physician office visits. An increase in the individual's schooling (or health knowledge) makes own-time investments more productive, but does not affect the productivity of investments in medical goods. Put differently, since our concept of medical care investment holds all patient investments fixed, it reflects a quality-adjusted measure of medical inputs applied to a "standardized" patient.

To understand the distinction more concretely, consider the example of cardiac bypass surgery. We do not view the surgery as consisting entirely of medical care inputs. On the contrary, it involves substantial investments of individual time. For example, the individual spends time choosing a surgeon, a cardiologist, a hospital, as well as rehabilitating from the surgery. To be sure, the patient's skill at performing any of these tasks may influence the doctor's treatment (for example, the two types of inputs may be complementary), but *controlling* for all patient inputs, a given doctor should experience equal rates of success, regardless of how well educated her patients are.

A fair amount of evidence argues for the importance of own-time investments in the production of health. Fuchs (1974) has argued that differences in mortality outcomes bear very little relation to spending on medical inputs. For example, he notes that Utah and Nevada, which have very similar allocations of doctors and hospitals, have vastly different mortality rates. Life expectancy in Utah is almost ten years more, largely because Utah's residents smoke less, drink less, and engage in healthier lifestyles. On the other hand, the RAND Health Insurance Experiment found that increasing medical expenditures, all other things equal, did not improve health outcomes (Newhouse 1993). While medical expenditures seem not to matter much, there is a plethora of evidence that health and mortality are strongly related to education and wealth (Kitagawa and Hauser, 1973; Haan et al., 1987; Feldman et al., 1989; Preston and Taubman, 1994; Pappas, 1993; Schoenbaum and Waidmann, 1997). These points taken together suggest that the inputs under an individual's control are more important than medical goods.

2.1 A Model of Patient-Intensive Therapies

We denote the two types of health investments as t for own-time investments, and M for medical goods. These investments are complementary, because higher levels of patient investments are assumed to make physicians more productive. The productivity of own-time investments rises with schooling, S. More generally, we allow for the possibility that productivity depends on a third factor, a, that also determines schooling; this could represent ability, rate of time preference, or similar unobserved factors.

Formally, health is produced according to the technology $F(t,M;a)$. To emphasize the effect of health knowledge on relative productivities, we assume that ability raises the output elasticity of t, $\frac{F_t t}{F}$, but leaves the elasticity of M, $\frac{F_M M}{F}$, unaffected.[5] Finally, we assume complementarity between t and M. Higher levels of patient investment make physicians more productive on the margin, or $F_{tM} > 0$, and in percentage terms, so that own-time investments raise the output elasticity of medical goods: $\frac{\partial}{\partial t}\left(\frac{F_M}{F}\right) \geq 0$.[6] Total health is equal to initial health plus the health that is produced: $H_0 + F(t,M;a)$.

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[5] The restriction on the elasticity of M implies that $\frac{F_{Ma}}{F_M} = \frac{F_a}{F}$, or that a unit change in ability raises output and the marginal product of M proportionately. The other restriction implies that $\frac{F_{ta}}{F_t} > \frac{F_a}{F}$, or that a unit change in ability raises the marginal product of own-time by a greater percentage than output.

[6] This condition would be satisfied, for example, by a Cobb-Douglas health production function.

To simplify, we consider a pure investment model, where health does not enter the utility function, but time available for labor is a concave, increasing function of total health, $l(H_0 + F(t,M;a))$. Schooling depends on ability, according to $S(a)$, and the wage rate is $w(S(a))$, which rises in schooling and ability. An individual who faces the medical goods price π_M solves the problem:

$$\max_{t,M}[w(S(a))]\{l(H_0 + F(t,M;a)) - t\} - \pi_M M \tag{1}$$

This problem has two first order conditions:

$$\begin{aligned} F_t l' &= 1 \\ w(S(a))F_M l' &= \pi_M \end{aligned} \tag{2}$$

An increase in ability always raises the equilibrium health, because it raises the marginal revenue of health by more than the marginal cost.[7] However, the key to understanding how health disparities change over time and across groups is to understand how the demand for health *inputs* varies. As our earlier example demonstrated, health disparities will be higher among populations that demand more health inputs.

Ability will raise input usage, provided that it raises the marginal revenue of input usage by more than marginal cost. To ensure this marginal revenue condition, it is necessary to assume that a one percent increase in health investment lowers its marginal revenue by less than one percent:

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[7] Suppose that growth in ability pushes up the wage by one percent. To a first-order approximation, the marginal revenue of health investment, $w(S(a))l'(h)$, rises by exactly one percent. In contrast, the marginal cost of health, $w(S(a))t_h + \pi_M M_h$, rises by less than one percent, so long as $M > 0$.

$$\frac{-l''}{l'} F < 1 \tag{3}$$

Given our previous assumptions about the effects of ability on output elasticities, this condition is enough to imply that ability raises the marginal revenue of time investments, $F_t l'$, and of medical care investments, $F_M l'$.[8]

The impacts of changes in other parameters are similar. When the price of medical care M rises, the individual invests less in both types of inputs. The own-price effect on medical goods is standard, and reduction in the use of medical goods makes own-time investments less productive.[9] The implications for initial health are essentially the reverse of those for ability: increases in initial health lower the usage of both inputs, because they make them less productive.[10] Finally, growth in the monetary returns to schooling raises both types of health

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[8] A unit change in ability raises F_M and health by the same percentage, but raises F_t by a greater percentage (see footnote 5). Moreover, equation 3 guarantees that l' falls more slowly than health grows. These facts taken together imply that ability raises $F_t l'$ and $F_M l'$. A formal proof is provided in Appendix A.

[9] If we denote the Hessian of the objective function as Det, comparative statics implies that:

$$\frac{\partial t}{\partial \pi_M} = \frac{-F_{tM} l' - F_t F_M l''}{Det}$$
$$\frac{\partial M}{\partial \pi_M} = \frac{F_{tt} l' + F_t^2 l''}{Det}.$$

The first numerator is negative as a result of equation 3 and of the fact that own-time investments do not lower the elasticity of M. The second is negative by concavity.

[10] This follows from comparative statics, as long as equation 3 holds, and l is concave.

inputs. Suppose that $w(S(a)) = wS(a)$ and that w rises. In this case, the marginal revenue from health investment of either type rises.[11]

These results imply that health investments will be higher among groups that: face lower prices of medical care; face greater shocks to underlying health; or face higher returns to schooling. There are two empirically important qualifications to these results. New medical care technologies can lower the price of M and will thus tend to expand health disparities. However, innovations that are "timesaving" can actually have the opposite result. In particular, suppose a new technology lowers the output elasticity of t. To return to our earlier example, the advent of a typhoid vaccine makes it much less productive for people to spend time boiling water, cleaning fresh vegetables, and the like. As a result, people may invest less time than they did previously. The second qualification concerns health shocks. Certain kinds of health shocks—such as untreatable, terminal conditions—can actually lower the productivity of both types of inputs. People hit with these kinds of shocks may thus invest less in their health than healthy people.

[11] Denoting the Hessian of the objective function as Det, comparative statics implies that:

$$\frac{\partial t}{\partial w} = \frac{S(a)F_M l'(F_{tM} l' + F_t F_M l'')}{Det}$$
$$\frac{\partial M}{\partial w} = \frac{-S(a)F_M l'(F_{tt} l' + F_t^2 l'')}{Det}$$

The first numerator is positive, assuming that equation 3 obtains and that own-time investments do not lower the output elasticity of M. The second is positive by concavity.

2.2 Implications for Health Disparities

To show how these comparative static results translate into implications for health disparities, let us return to the example we presented earlier: E is an educated patient, and U is an uneducated one. We have just shown that E consumes more of both types of health inputs than U. To take an example, suppose that E consumes 2 units of each input, while U consumes 1 of each. Now suppose that the net marginal revenue product of one health input rises. Both agents receive a windfall gain from this increase in productivity. Moreover, since we showed previously that gains in net marginal productivity raise input usage, both agents will use at least part of their gains to finance additional health investment. However, since E uses more of each input, he receives a larger windfall gain. In addition, since better-educated people use more health inputs *ceteris paribus*, E spends a larger fraction of his income on health inputs at the margin. Therefore, E will choose to invest a larger fraction of his larger gain on health. Since E will spend more additional resources on health than U, his health will rise by more.

This is a heuristic description of the key result that health disparities rise with the net marginal productivity of health investments. Health disparities will be larger for: (1) Those who face lower medical care prices π_M; (2) Those who enjoy higher marginal products of time, F_t, or medical care, F_M; and (3) Those who face higher monetary returns to schooling. It is important to note that when we refer to health disparities, we are focusing on absolute differences in health, rather than percentage differences in health, because the former are more relevant for making welfare comparisons. Some of our results for absolute differences do carry over for percentage differences, although this tends to depend on the form of the production function.

To derive these implications formally, we impose a few simplifications. In particular, suppose that $l(H_0 + F(t,M;a,H_0)) = \left\{H_0 + t^{\alpha(a)}M^{\beta}\right\}^{\delta}$, where $\delta < 1$, and $\alpha + \beta \leq 1$. The previous assumptions we made about the output elasticities imply that $\alpha_a > 0$. This Cobb-Douglas type production function embeds all the restrictions we imposed in the previous section. In Appendix A, we show formally how our results follow from this model.

2.2.1 Testable Implications

Our results have important implications for technological change in medical care. The effects of technological change depend on whether or not an innovation is "timesaving." Any innovation that is not timesaving—i.e., does not lower the marginal product of time investments—will always expand health disparities by lowering the price of medical care. On the other hand, an innovation that is timesaving can contract health disparities, because the reduction in the productivity of time investments hurts the educated more than the less educated. In particular, we define a timesaving innovation as one that makes medical care cheaper (and possibly raises the output elasticity of medical care), but lowers the complementarity between medical care and time investments. This would have the effect of lowering the marginal productivity (and output elasticity) of time investments. Formally, $F_t(t,M;a)$ would fall for every input combination if F_{tM} fell. Assuming that the technological change shifts out the production possibilities frontier, $\frac{F_t}{F}$ would also fall for all input combinations.

Similarly, the effects of health shocks on disparities depend on the precise nature of the shock. Consider first a chronic, treatable illness. This would have the effect of lowering initial health and making health investments more beneficial. As a result, chronic illness would tend to raise health disparities. At the other extreme, consider an acute, untreatable illness. A health shock like that would make health investments less productive and would tend to contract health disparities. This seems relevant at older ages, where individuals are hit with health shocks that may often result in death. As a result, health disparities may contract with age among very old populations.

Finally, the model yields implications for treatment choices. Even though their time is more valuable, more educated patients are predicted to invest more in time-intensive treatments. Among the chronically ill, for example, we would expect more educated patients to spend more time monitoring their health, adhering to their physician's orders, controlling their diet, and exercising.

2.2.2 Normative Implications

Health care policy is informed by a variety of motives other than inequality, but the behavior of policymakers does suggest that the desire to limit inequality is a powerful one. For example, major public health programs, such as Medicaid and Medicare, are explicitly designed to guarantee health care for those who might otherwise not be able to afford it. In the interests of informing policy, therefore, it is crucial to understand the real effects of economic variables and health care policy on inequality. The model presented above provides some useful guidance for limiting inequality.

Our results for the impact of wage and price changes have normative implications. First, the usual concern over wage inequality should be magnified somewhat, since wage inequality also leads to health disparities. More surprising is our implication for the effect of medical care price reductions. Some have argued that high medical care prices promote an unfair distribution of resources by impeding access to care for the poor.[12] Our results imply exactly the opposite conclusion. Reductions in the price of medical care actually raise inequality along educational (and thus permanent income) lines. Government policies that seek to lower the overall price of health care—such as universal health care coverage—are likely to be particularly blunt instruments for improving the health of the poor. A better approach to limiting disparities would emphasize subsidies that are targeted towards the poor. This would argue in favor of US-style Medicaid programs, rather than European or Canadian-style National Health Systems. Another approach might emphasize investments in pre-natal and early childhood health. The latter kinds of investments could help limit lifetime health disparities by limiting chronic, treatable disease.

Clearly, government policy should not be targeted solely at limiting disparities; it should also focus on improving the absolute health of the population. However, policymakers are likely to prefer actions that both improve absolute health and reduce inequality. Investments that improve underlying health and prevent chronic illness can help accomplish both goals much more effectively than price subsidies or federally funded medical research. Public health investments—in sanitation, or pollution prevention—represent particularly compelling examples of policies that can improve average health and promote a fairer distribution of health.

[12] In "A National Health Program for the United States: A Physicians' Proposal," Himmelstein et al (1989) argue that "financial barriers to care" represent a serious injustice of the present health care system.

The model also provides some justification for targeting health care subsidies towards the aged, because they tend to be sicker. The actual effect of Medicare in the US, however, is somewhat more complicated, because it is unclear whether or not it targets subsidies towards the poor elderly. Everyone over the age of 65 receives Part A Medicare coverage, and nearly everyone over the age of 65 in the US is enrolled in Part B.[13] Since Medicare is not means-tested, the entire population over 65 faces uniform prices for medically intensive inputs. At first glance, it would appear that Medicare lowers prices and raises inequality among the elderly, but this ignores important policies that affect the below 65 population. The federal government subsidizes the purchase of employer-based health insurance. It tends to be the richer and well-educated segment of the population that benefits from these tax incentives. In other words, π_M is lower for the better educated among the population under the age of 65. Therefore, Medicare has two opposing effects on health disparities. First, it lowers the price of medical care for everyone over the age of 65. This raises disparities. Second, however, it equalizes the price of medical care across educational groups. This benefits the less educated and lowers disparities.[14] The overall effect of Medicare is theoretically ambiguous and is thus a subject we later propose for empirical study.

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[13] In 2000, for example, 96% of the eligible population over age 65 enrolled in Part B. (House Committee on Ways and Means, *Green Book 2000*.)

[14] It is worth pointing out that these results hold true, even though more educated people over age 65 may receive supplementary Medigap insurance from their (current or previous) employers on a tax-free basis. Since Medigap covers a much smaller portion of total health care costs than health insurance for the young, the subsidy received by more educated workers is much smaller over age 65 than under it. Therefore, even though health care prices may not be perfectly uniform over age 65, the disparity may be substantially reduced.

3 Empirical Analysis

The theoretical model clarified the key econometric issues with our analysis. In the model, schooling is endogenous, but we derived implications for how disparities across education groups change with technology and health shocks, conditional on a fixed relationship between schooling and ability, $S(a)$. Therefore, we do not need to know how changes in the distribution of schooling affect disparities in health. This simplifies our econometric problem somewhat. To estimate the true effect of schooling changes on health disparities, it would be necessary to ensure that $S(a) = S$, or that all variation in schooling is exogenous. This would require a traditional instrumental variables approach. However, to estimate the effects of technological change or health shocks on health disparities, given a fixed distribution of schooling and ability, it is necessary only to ensure that $S(a)$ is stable across the relevant comparison groups. Intuitively, suppose we find that a new technology does increase health disparities among a particular population. This is consistent with our predictions *only* if we can show that the result is not driven by a concurrent expansion in the ability-schooling relationship $S(a)$ among the chronically ill. This weaker condition is definitely satisfied if we have a valid instrument for schooling, but it can also be satisfied without one. In the empirical work that follows we suggest various approaches, including the traditional instrumental variables approach, to solve this identification problem. At the end of each subsection, we explain how this condition for identification will be met for each specific piece of analysis.

3.1 Technological Change and Health Disparities

Technological change can have different effects on health disparities, depending on the nature of the innovation. An innovation that is not timesaving—in that it does not lower the marginal productivity of time investments—will always raise health disparities. However, by simplifying health care, or lowering the relative productivity of patient time, certain new technologies could contract health disparities. We propose to examine the impact of each type of technology. Antihypertensive drugs, perhaps the single biggest medical breakthrough of the past fifty years, greatly simplified the treatment of hypertension. Instead of exercising, watching their diet, and controlling their weight, hypertensive patients were able to take two pills in the morning to control their blood pressure. On the other hand, new HIV treatments have greatly improved immune function among HIV patients, but have not simplified its treatment. The theory predicts that the breakthroughs in hypertension would have limited health disparities in hypertension and related ailments, while the breakthroughs in HIV may have had the opposite effect on HIV patients.

3.1.1 Breakthroughs in Hypertension Treatment: Beta Blockers

Perhaps the most important set of innovations in medical care over the past fifty years occurred in the treatment of heart disease. In 1960, roughly two-thirds of deaths were attributed to heart-related conditions, while by 1986 this had fallen to one-third.[15] In particular, since 1970 there has been a substantial decline in mortality from conditions that are directly linked to hypertension. From 1970 to 1994, mortality from stroke fell by at least 50% across sex and race lines, while mortality for coronary heart disease fell by roughly the same amount (Joint National Committee on Prevention, Detection, Evaluation, and Treatment of High Blood Pressure, 1997).

[15] 1960 data based on Kitagawa and Hauser (1972). 1986 data based on the 1986 National Mortality Followback Survey (NMFS).

While the prevalence of uncontrolled hypertension actually rose from 1960 to 1971, it has declined steadily ever since then. During the 1960s, prevalence rose from 30% to 36%, but by 1988, it had declined to 20% (Burt et al., 1995). Much of the decline that began in 1972 was probably the result of new antihypertensive drugs. In 1965, a new drug called propranolol, a member of the class of drugs now called beta-blockers, was introduced in Europe. However, in the US, the FDA was slow to approve this drug. While propranolol was approved for a few minor uses in 1968, it was approved for the treatment of angina only in 1973, and for hypertension in 1976 (Ruwart, 2002). At roughly the same time, in 1967 and 1970, there emerged evidence from two clinical trials that diuretics and vasodilators could also treat high blood pressure effectively (Veterans Administration Cooperative Study Group on Antihypertensive Agents, 1967, 1970). Not coincidentally, mortality from heart disease began to fall from 1973 onwards and continued to fall until the early '90s, when mortality rates reached a plateau at about 50% below their initial level (Joint National Committee on Prevention, Detection, Evaluation, and Treatment of High Blood Pressure, 1997). In terms of mortality reduction, it is possible that these rank as the most significant medical breakthroughs of the past 50 years. We propose to study their effects on health disparities.

The introduction of new drugs for the treatment of hypertension supplanted the former treatment of diet, exercise, and weight control (occasionally supplemented by the use of diuretics). The previous treatment regimen placed significant emphasis on the patient's ability to spend time monitoring subtle variations in her health. The advent of the new drugs, however, made these time investments much less important in determining the effectiveness of treatment. As a result, complementarity between time and treatment likely fell, as did the productivity of time investments. This would suggest that these breakthrough drugs would have contracted disparities in the severity of hypertension. Previously, the educated would have been better able to control their blood pressure, but the decreased productivity of time investments would have lessened their advantage.

To analyze the effect of antihypertensive drugs, we will use the Framingham Heart Study (FHS). The FHS tracked the health of a cohort of 5209 white men and women, aged 28 to 59 in 1948, and who resided in the town of Framingham, Massachusetts.[16] From 1948 onwards, this cohort received biennial medical exams, which also included interviews about health history and behavior. We will use data from the ninth exam, conducted in 1966, through the seventeenth exam, conducted in 1982. We have chosen only exams that post-date the enactment of Medicare, in order to net out the effects of Medicare on health disparities. We break up this period into two segments: 1966-72, the pre-beta blocker period; and 1976-82, the post-beta blocker period. In 1976, beta-blockers were finally approved for the treatment of hypertension specifically. We will examine health disparities during the 1966-72 period for the 2005 respondents who are aged 58 through 75 in 1966. These will be compared to disparities during the 1976-82 period for the 1983 respondents who are aged 58 through 75 in 1976. This represents the widest age interval present during both time periods. Moreover, the age distribution for respondents in the pre-period cohort is essentially identical to the distribution for the post-period cohort.

[16] Since the FHS is a local study, it is unable to track migrants from Framingham. However, we study 58 to 75 year-olds, for whom migration is a much less important possibility.

At baseline, all individuals reported their age and educational attainment, which was broken down into six groups: less than 8th grade, some high school attended, high school graduate, some college attended, college graduate, and those who attended graduate school, nursing school, art school, music school, or business school. Since they seem to behave similarly empirically, we group college graduates with those who attended some college. The last educational group is extremely heterogeneous, and should not necessarily be interpreted as a group of postgraduates: over this time period in the US, nursing school or art school, for example, was sometimes conducted at an early college or high school level. Indeed, this group does not seem healthier than those who simply graduated from college.

The FHS does not ask a question about general health status, but there are several objective measures of health that can be correlated with education: whether an individual has high blood pressure, hypertensive cardiovascular disease (HCVD)--defined as the presence of high blood pressure and an enlarged heart--or heart disease. Each biennial exam contains three blood pressure readings. We define an individual as having high blood pressure if all of his systolic readings exceed 160 mm/Hg, *or* if all of his diastolic readings exceed 95 mm/Hg. This corresponds to the World Health Organization definition of high blood pressure as a systolic pressure exceeding 160 or a diastolic pressure exceeding 95. (An alternative definition we will explore is if all systolic readings exceed 140 mm/Hg, or all diastolic readings exceed 90 mm/Hg. This has been proposed as a better measure of hypertension.) HCVD is diagnosed by the examining physician, based on blood pressure readings, X-Rays of the heart, and Electro-Cardiograms (ECG). While this is no longer a commonly used diagnosis category, HCVD is a subset of congestive heart failure, which is a commonly used diagnosis today. Heart disease is also diagnosed by the examining physician, who identifies the individual as being in one of six functional classes: no definite heart disease, class 1, class 2, class 3, class 4, or class 5. We define an individual without heart disease as one diagnosed with "no definite heart disease."

Table 1 summarizes the characteristics of the pre-period and post-period cohorts. By design, the age and sex composition of the pre- and post-cohorts is quite similar. Observe, however, the dramatic decline in hypertension and hypertensive cardiovascular disease. Much of this decline has been attributed to the emergence of beta-blockers and other antihypertensives (Joint National Committee on Prevention, Detection, Evaluation and Treatment of High Blood Pressure, 1997). There was not a coincident reduction in heart failure. While uncontrolled hypertension is a risk factor for heart failure, it is possible that the prevalence of heart failure rose, because more heart patients survived to the point where they would experience heart failure. It is also important to understand changes in the educational distribution between the two cohorts. To identify the effect of technology, we must rule out changes in the ability-schooling relationship as an alternate cause. The post-period cohort shows a substantial increase in high school attendance and graduation—there is a shift in the distribution out of "no high school" and into the some high school and high school graduate groups. Presumably, therefore, the average ability of the "no high school" group would have fallen. However, the proportion of people with post-high school education barely moved. If anything, therefore, the ability gap between the no high school and post-high school groups would have grown. This would bias us against finding that technology contracted health disparities across education groups.

Using these measures of health, along with dummy variables for education groups and age categories, we will estimate the following regression for the pre- and post-antihypertensive periods:

$$Health_{it} = \beta_0 + \beta_1 Ed_i + \beta_2 Age_{it} + \varepsilon_{it} \quad (4)$$

These regressions will allow us to investigate whether health disparities changed after the introduction of antihypertensive drugs. If beta-blockers were indeed timesaving, one would expect a lessening of health disparities in the severity of hypertension.

The results of the regression are shown in Table 2. In the post-period, there is no statistically significant gradient in hypertension, while in the pre-period, college attendees were ten percentage points less likely to be diagnosed with it. The mean prevalence of hypertension fell by about eight percentage points, according to Table 1, and so did disparities across education groups. The same can be seen by hypertensive heart disease, although the effects are less dramatic. The gradient is about half the size in the post-period. The effects were robust to the inclusion of age category variables, rather than the age and age-squared specification reported in the table. Finally, notice that the gradient in heart failure did not change, just as its prevalence did not go down. This could be because hypertensive treatments did not have such immediate effects on the prevalence of heart failure, as shown in Table 1. This finding is also significant, because it shows that there was not a generic decline in health disparities from one period to the next. This provides further evidence against the argument that a contraction in the schooling-ability relationship explains our results. It is also worth noting that there is relatively little evidence in the labor economics literature to support the contention that the ability-schooling relationship has changed across cohorts (see, e.g., Katz and Murphy, 1992). In particular, changes in the wage premium seem to occur within cohorts rather than between cohorts.

An important issue to consider is the generalizability of the FHS results, since after all they are based on a cohort of whites in the single town of Framingham, MA. Without question, the town of Framingham is wealthier than average. Data from the 1990 Census Summary Tape File, for example, show that median household income was about 43 percent above the national average. The poverty rate in Framingham was 6%, compared to the national average of 13%. Only 5% of residents in Framingham were receiving public assistance, compared with 7.5% of Americans nationwide. The fact that the Framingham population is richer and healthier does not alter our predictions for how technology will affect health disparities, but it does affect how *quickly* technology will have an effect. It is likely that the very rapid response of the Framingham population to the introduction of new drugs is unique to a highly educated and healthy population.

To investigate this hypothesis, we exactly repeated our calculations using the National Health and Nutrition Examination Surveys, Waves 1, 2, and 3. Wave 1 took place from 1971 to 1975, wave 2 from 1976 to 1980, and wave 3 from 1988 to 1993. We examined the education gradient in physician-assessed hypertension for white 58-75 year-olds in each wave of the NHANES, using the same regression specification used for the FHS. We found that education gradients in waves one and two were significant and essentially identical. However, we found virtually no education gradient in wave three. This suggests that it may have taken up to ten years longer for the new treatment technology to diffuse out to the overall population, although in the end, it had the same effect on health disparities.

3.1.2 Breakthroughs in HIV Treatment: Highly Active Antiretroviral Therapy

The treatment of HIV presents a useful example of technological change that did not reduce the complementarity between time and medical care; indeed, it may have even increased it. During the mid-1990s, Highly Active Antiretroviral Treatments (HAART) became available for the treatment of HIV. These treatments substantially improved the health statusof HIV patients, but they often involved highly complex medication regimens that required substantial patient adherence (Goldman and Smith, 2002). As a result, the new therapy was highly complementary with patient investments, and made it substantially cheaper to survive HIV. This makes it a perfect candidate for our purposes. Moreover, since it was introduced very rapidly during the mid-1990s, it is possible to identify periods with relatively low and relatively high exposure to HAART.

The data on the HIV positive population come from the HIV Cost and Services Utilization Study (HCSUS). HCSUS employs a multi-stage national probability sample design, described in detail elsewhere (Frankel et al 1999). The HCSUS sample is representative of the 18 and older HIV positive population, which made at least one visit for regular care in the contiguous United States in early 1996.[17] Women and patients of private, staff-model HMOs are over-sampled. HCSUS is a panel data set with three rounds of interviews. The first round of 2864 interviews was conducted between January 1996 and April 1997, the period during which HAART were first coming into broad use. The second round of 2466 interviews was conducted between December 1996 and July 1997, and the last round of 2267 interviews was between August 1997 and

[17] The HCSUS sample does not include patients whose only contact with the health care system was through military, prison, or emergency department facilities.

January 1998.   The first wave covers the period prior to the introduction of HAART, and the latter the period post-introduction.

In addition to other covariates, HCSUS collects data on educational attainment, health insurance status (Medicare, Medicaid, Private Insurance, or other Public Insurance), income, and whether or not a respondent was using HAART. Individuals can be placed into one of three groups that differ in the severity of the disease: asymptomatic patients, symptomatic patients, or patients with full-blown AIDS. HCSUS also reports an individuals CD4 T-lymphocyte cell count, a critical measure of the function of the patient's immune system. A depletion of these cells correlates strongly with the worsening of HIV disease and the risk of developing acquired immunodeficiency syndrome-defining opportunistic infection (Harrison et al., 1997). Other demographic data on income, sex, race, sexual orientation, exposure route(s), and age are also available.

Table 3 displays the characteristics of the HCSUS population. The average educational make-up of the HCSUS population does not change over time. The population does become sicker, as more people move out of the asymptomatic and symptomatic categories into the full-blown AIDS category. People also tend to move out of the uninsured group into the publicly insured groups. However, immune function goes up.

At baseline, only about 30 percent of respondents with AIDS had ever been exposed to HAART treatment. However, just six months later, over 60 percent of respondents had been exposed. At a minimum, physicians' cost of acquiring information about and prescribing HAART seems to have gone down precipitously during this period, as its dissemination suddenly became widespread. The wide dissemination of HAART in the second follow-up suggests that health disparities among HIV patients would have risen post-baseline.

Our theory predicts that the introduction of HAART should have increased health disparities, controlling for initial health. Consider the following linear probability model for individual i and time t:

$$Died_{it+1} = \beta_0 + \beta_1 Sch_i + \beta_2 Insurance_{it} + \beta_3 CD4_{it} + \beta_5 Sex_i + \beta_6 Black_i + \beta_7 Age_{it} + \beta_8 Age_{it}^2 + \varepsilon_{it} \tag{5}$$

The results are presented in Table 4. The most important finding, shown in the first two columns, is the expansion in health disparities from baseline (the early HAART period) to second and third periods (the late HAART period). The gap between high school dropouts and high school graduates (which includes those who attended college but did not receive a degree) expands dramatically. Our results are robust to the inclusion of insurance status, as well as measures of log income and income category (not shown in the table).

One problem with this analysis is its lack of statistical power. In spite of the apparently large estimated increase in health disparities, there is not enough power to reject the hypothesis that health disparities are constant, simply because there are relatively few observations and even fewer deaths. It is thus important to explore whether or not the change in health disparities is consistent with random variation. If it were generated by random noise, the expanding health gradient should not be affected by adding controls for whether or not a respondent was on HAART therapy. On the other hand, if the introduction of HAART caused the larger gradient, adding this variable would reduce the expansion.

The effect we have estimated is in fact the effect of the new technology, provided that the ability-schooling relationship $S(a)$ did not change between waves in HCSUS. Since no one in the HCSUS cohort is acquiring schooling, this will be mechanically true, so long as ability is fixed for each individual. Of course, some of this may be due to mortality, which is the primary source of attrition between waves. There are two reasons to believe that this is not driving our results. This effect, if anything, is likely to induce a contraction in health disparities over time. Empirically, differential mortality tends to contract health disparities. Indeed, among very old populations, uneducated people are less likely to die than more educated people (Hurd, McFadden, and Merrill, 2001). Similar patterns can be observed for other risk factors: among the elderly, having smoked in the past is positively correlated with survival, even though it is negatively correlated with survival for the young.[18] This is because the average uneducated decedent is likely to be healthier than the average educated one. Differential mortality lowers the average health of the less educated by relatively more and would thus contract health disparities.

3.2 Health Disparities and Chronic Illness

The theory also implies that a health shock that comes in the form of a chronic, treatable illness will raise health disparities, while one that represents an untreatable, fatal illness may contract them. If true, it demonstrates the value of preventing *treatable* illnesses; doing so can improve average health and reduce health inequality. We examine directly whether populations with treatable chronic conditions exhibit larger health disparities. The major econometric issue is whether the ability-schooling relationship changes with illness status. Since there is no clear

[18] Based on authors' analysis of the Medicare Current Beneficiary Survey (MCBS) data.

theoretical answer to this question, we employ an instrumental variables strategy, by using quarter of birth as an instrument for schooling. This is a particularly appropriate instrument in our context, as we discuss below. We will also attempt to assess the effect of non-treatable, fatal conditions by examining very old populations. We propose to use data on the elderly from the Medicare Current Beneficiary Survey (MCBS) to compare disparities among people in their last year of life, to disparities among other people.

3.2.1 Treatable Illnesss

We will use individual-level data from the National Health Interview Surveys (NHIS). The NHIS is an annual survey, conducted every year since 1957, in which individual respondents are asked various questions about their health, economic, and demographic conditions. We pool the surveys for every year from 1982 to 1996, incorporating year-specific fixed-effects.[19]

To separate the NHIS sample along the lines of chronic illness, we identify five major chronic, treatable illnesses: hypertension, diabetes, asthma, arthritis, and heart disease (defined as the presence of any of the following: ischemic heart disease, heart rhythm disorders, congenital heart disease, or other non-hypertensive diseases of the heart). Unfortunately, while the NHIS asks respondents about a variety of chronic illnesses, not every respondent is asked about every illness. There are six non-overlapping lists of illnesses; each list is asked of a one-sixth sub-sample. Each individual is thus asked about conditions on one of the six lists. We can identify a set of individuals that definitely have a particular condition, but we cannot identify the complete

[19] Prior to 1982, the NHIS used a different general health measure. After 1996, it used a different scheme for identifying the chronically ill.

set of individuals that do not have the condition, because we cannot rule out the possibility that some sick people were not asked about their particular condition. To separate the population along illness lines, therefore, we adopt the following conservative procedure: we define as chronically ill people who definitely report having at least one of the five conditions. All other people in the sample are taken to be the "not chronically ill" population, which *could* include people with one of these five illnesses. This will bias us against finding a difference in health disparities across these populations.

From the NHIS, we will use data on years of schooling, age, sex, and self-reported general health status. General health is measured on a 5-point scale: each individual in the NHIS sample is asked whether her health is excellent, very good, good, fair, or poor. From these variables, we construct a binary variable called $GoodHealth$, which is one if the individual reports good, very good, or excellent health. We will explore whether or not our results are sensitive to restricting this definition to, say, very good or excellent health, or just excellent health. (It does not make sense to expand the definition further, since there are relatively few people who report poor health.) From the years of schooling variables, we construct three dummy variables: $HighSchool$, which is one if the individual has exactly 12 years of schooling; $SomeCollege$, which is one if she has more than 12 years, but less than 16; $College$, which is one if she has at least 16 years of schooling. In general, we estimate the within-year health returns to schooling by regressing $GoodHealth$ on age, sex, and our three educational dummies:[20]

$$GoodHealth = \beta_0 + \beta_1 HighSchool + \beta_2 SomeCollege + \beta_3 College + \beta_4 Age + \beta_5 Sex + \varepsilon \quad (6)$$

[20] By "within-year," we mean that year-specific fixed-effects are included in the regression.

In most cases, these regressions will be run separately for 5-year age intervals. In these cases, we will enter age linearly. In other cases, data from all age groups will be pooled, and we will use dummy variables for narrow (five years or less) age categories, or age splines.

Table 5 compares health disparities for the chronically ill and healthy populations. Within the "Not Chronically Ill" and "Chronically Ill" panels, each row shows the results of a single regression for the given age group of good health on the three listed education dummies, a linear age term, and a dummy for sex. Within nearly every age group, health disparities are roughly twice as high for the chronically ill than for the healthy. Not surprisingly, the magnitude of the difference is declining with age—one would expect the prevalence of unobserved chronic illness among the healthy population to rise with age. Among the youngest populations, however, disparities are about two and a half times as high for the chronically ill than for the healthy.

To explore the robustness of these results, we must confront two potential problems. First, it is possible that variation in the educational gradient reflects "diagnosis bias." Suppose that more educated people are diagnosed with chronic illnesses earlier and in milder forms. Among the chronically ill, therefore, the educated would tend to be relatively healthier. To rule out this explanation, we use another measure of health from the NHIS: whether or not an individual reports that he is able to work. The bias with this measure will be in the opposite direction, since educated people will have the most incentive to stay in the labor force, even if they are ill. On the basis of their responses to a series of questions about their ability to work, the NHIS classifies respondents aged 18-69 in one of four categories: unable to work because of a health condition, limited in the kind or amount of work because of a health condition, limited in non-work activities only, and not limited at all by health conditions. We classify an individual in either of the first two categories as being "unable to work" because of a health condition. Once again, we are adopting the conservative procedure of including people who might be only slightly impaired in our "unable to work" category.

Table 6 presents the results of this breakdown. The results are essentially the same as for the chronic illness analysis. At every age and level of schooling, health disparities are greater for those unable to work than those who are. For the younger age groups, the gradient is about three times as steep for those that are unable to work; for the older age groups, it is nearly twice as steep. It is sensible that the difference between the two groups is more pronounced for the young, because the actual difference in health across groups is probably most pronounced among the young. Among the elderly, even those who pronounce themselves "able to work" may not be in perfectly robust health.

The second problem requires us to rule out the possibility that the ability-schooling gradient is steeper for the chronically ill. To address this problem, we will use an instrument for schooling that we believe is uncorrelated with ability, time preference, or other plausible factors that jointly determine health and schooling. In particular, we use an individual's quarter of birth, whose use was first suggested by Angrist and Krueger (1991) in the context of estimating the wage returns to schooling. Angrist and Krueger argue that children start school at different ages, depending on their season of birth, but compulsory schooling laws cease to bind at a particular age. As a result, the number of compulsory schooling years varies with a child's quarter of birth. In particular, children born earlier in the year tend to end up with less educational attainment than those born later in the year.

This instrument requires us to confront two issues. First, samples above 100,000 observations are required in order to identify the correlation between quarter of birth and educational attainment with the required precision. Therefore, we pool our data across age groups, and estimate the effect of age as a piecewise linear spline. We are also limited to estimating the effect of years of schooling attained, rather than the effect of three educational dummies, because the instrument lacks the power to identify all three categorical variables. Second, since age affects health, and quarter of birth influences age, this could invalidate the instrument. However, this is unlikely to be a problem here. A simple regression of good health on sex, education dummies, and single-year age dummies for the population aged 25 to 99 reveals that health significantly declines at adjacent age groups only 3 out of 74 times. In other words, even though health declines with age, it does not decline at the frequency of one quarter; indeed, it does not even decline at the frequency of one year.

Table 7 presents these results. The table shows the coefficients on sex, highest grade attained, and the coefficients on the piecewise linear age spline. The first two columns present the OLS estimates, while the second two present the IV estimates. In both cases, health disparities are about twice as large for the chronically ill. The IV estimates are also consistently larger than the OLS estimates; this is consistent with the findings of many other researchers. Card (1995) reports that nearly all researchers who estimate IV models of the monetary return to schooling find that the IV estimates are larger than the OLS estimates. Lleras-Muney (2001) uses state-level compulsory schooling laws as an instrument for the effect of schooling on mortality and also finds that the IV estimates are considerably and consistently larger than the IV estimates.

This may be because the effect of schooling is larger at lower levels of schooling, where the schooling instruments derive their explanatory power.

3.2.2 Untreatable Illness

The effects of chronic, treatable illnesses are predicted to differ from those of diseases that respond less to treatment. It is not straightforward to identify an "untreatable" disease, because many diseases that can be treated often become untreatable at the end of life, and because diseases that seem treatable may not turn out to be (Garber, MaCurdy, and McClellan, 1999). The best we can do, it would seem, is to analyze whether health disparities contract for people who are in their last year of life. While people in their last year of life clearly do not know this *ex ante*, on average they will probably be facing conditions that are less treatable than elderly people who will live longer than one year.

We can perform these comparisons using individual-level data from the Medicare Current Beneficiary Survey (MCBS). The MCBS is a rotating panel survey, available from 1992 through 1998, designed to be representative of the Medicare population in the given year. It contains data on age, sex, education, self-reported health status (also on a scale of one to five), and most importantly, whether the respondent died in the year of the survey. Among the oldest segments of the MCBS population, deaths are common enough for us to construct reasonable samples. For example, pooling the 1992-8 samples, 2085 people over age 80 died during the survey year.

The data we use are summarized in Table 8. Among those in their last year of life, only about 30% report that they are in good health, while the proportion is about twice as high for other respondents. It is also not surprising that men are at greater risk of death, although the gap narrows with age. Finally, those in their last year of life are slightly less educated than other respondents, but these differences are not very large. Using Kolmogorov-Smirnov tests for the equality of distributions, we cannot reject at the 10% level that the distributions are equal for 85-90 year-olds and those over 90. We can reject this hypothesis for 80-85 year-olds, but not at the 5% level. This is consistent with other research that finds mortality gradients narrowing among the very old (Hurd, McFadden, and Merrill, 2001). The rough similarities of the education distribution provide us with some comfort that the ability-schooling distribution does not vary dramatically for those in their last year of life.

Table 9 compares health disparities for those in their last year of life to disparities for other respondents. Disparities among those in their last year of life are about 40 to 50 percent smaller than disparities among other respondents. The standard errors for the survivors regression are clustered by respondent, to account for the fact that some people enter this regression twice.

4 Conclusions

We have developed a theory that helps us understand how and why health disparities vary over time and across population groups. The theory predicts that most technological innovations in health care, by lowering the price of health, will expand health disparities. However, certain innovations can contract health disparities, if they simplify the production of health and reduce the importance of time investments. In addition, the advent of a chronic, treatable illness will tend to widen health disparities, while the advent of an untreatable illness will contract them. The data bear out our predictions for the effects of different types of technological changes and different types of health shocks. The development of new HIV drugs that involved complicated medication regimens widened health disparities, while the development of hypertension drugs that lessened the need to undertake diet control, weight control, and exercise had the opposite effect. Similarly, people with chronic, treatable conditions exhibit wider health disparities than healthy people, while people in their last year of life—who presumably suffer from less treatable conditions—exhibit narrower disparities.

This paper suggests the importance of an empirical research agenda designed to understand how health disparities vary across the population and over time. We have identified a few important dimensions along which the returns vary, but there are likely to be many other dimensions that require further empirical and theoretical investigation. In addition, this paper has relied on advances in technology as a source of change over time in health disparities. While we have taken these types of innovations as exogenous, it is possible that health disparities themselves have a role to play in the development of technological change. Timesaving technologies may be more likely to arise when large numbers of uneducated people suffer from a disease; conversely, timesaving technologies are less likely when a disease is confined to the educated or the rich. Alternatively, economy-wide growth in schooling may encourage certain types of technological change that involve more own-time investments. Growth in schooling raises the payoff to developing such technologies. Future work could examine the theoretical linkage between the growth in the educated population and the incentives for patient-intensive technology.

Hopefully, our paper has laid the groundwork for a research agenda aimed at understanding the cross-sectional variation in the health returns to schooling. Understanding this variation seems crucial for gaining further insight into the relationship between socioeconomic status and health, the relationship at the heart of many discussions about health and economic inequality.

Appendix

First, we will prove that $\frac{\partial t}{\partial a}, \frac{\partial M}{\partial a} > 0$ for the model in equation 1. We made the following four assumptions: ability raises the output elasticity of t; the output elasticity of M is invariant to ability and does not fall with own-time investments; and, the condition in equation 3 is met. Comparative statics imply that:

$$\frac{\partial t}{\partial a} = \frac{w(a)}{Det}\left\{(-F_{ta}l' - F_t F_a l'')(F_{MM}l' + F_M^2 l'') + (\frac{w'(a)}{w(a)} F_M l' + F_{Ma}l' + F_M F_a l'')(F_{tM}l' + F_t F_M l'')\right\}$$

The term Det, the determinant of the Hessian matrix, is positive if the second order conditions hold. The first term in parentheses is negative as long as equation 3 holds and schooling raises the output elasticity of own-time. The second term is negative by concavity. The third term in parentheses is positive if equation 3 holds, and schooling leaves the output elasticity of M unchanged. The last term in parentheses is positive if own-time investments do not lower the elasticity of M. These arguments imply that $\frac{\partial t}{\partial a} > 0$.

Similarly, comparative static analysis implies that:

$$\frac{\partial M}{\partial a} = \frac{w(a)}{Det}\left\{(-F_{tt}l' - F_t^2 l'')(\frac{w'(a)}{w(a)} F_M l' + F_{Ma}l' + F_a F_M l'') + (F_{ta}l' + F_t F_a l'')(F_{Mt}l' + F_M F_t l'')\right\}$$

Concavity implies that the first term in parentheses is positive. The second term is positive, given equation 3 and given that ability leaves the elasticity of M unchanged. The third term in parentheses is positive given equation 3 and given that ability raises the elasticity of own-time.

The last term in parentheses is positive given equation 3, and given that own-time investments do not lower the output elasticity of M. These arguments imply that $\frac{\partial M}{\partial a} > 0$.

To prove the model's implications for health disparities, it is helpful to observe the following decomposition:

$$\frac{dH}{da}|_{H_0,\pi_p,\pi_M} = \frac{\partial F}{\partial a} + \frac{\partial F}{\partial t}\frac{\partial t}{\partial a} + \frac{\partial F}{\partial M}\frac{\partial M}{\partial a} \tag{7}$$

Consider first changes in F_a across groups. Computation reveals that $F_a = F\alpha_a \ln t$. Since t and M are complementary, all groups that use more t also engage in more health investment h. Therefore, they exhibit higher levels of F_a. This applies to groups with lower initial health, higher monetary returns to schooling, or a lower price of medical goods.

The effect of ability on input usage can be characterized as:

$$\begin{aligned} \frac{\partial t}{\partial a} &= \frac{t}{1-\alpha\delta-\beta\delta}\left(\alpha_a\delta\ln t + \frac{\alpha_a}{\alpha}(1-\beta\delta) + \beta\delta\frac{w'(a)}{w(a)}\right) \\ \frac{\partial M}{\partial a} &= \frac{M}{1-\alpha\delta-\beta\delta}\left(\delta\alpha_a\left(1+\ln t\right) + (1-\alpha\delta)\frac{w'(a)}{w(a)}\right) \end{aligned} \tag{8}$$

Calculating the marginal products, we have the expressions:

$$\begin{aligned} F_t\frac{\partial t}{\partial a} &= \frac{\alpha\delta F}{1-\alpha\delta-\beta\delta}\left(\alpha_a\delta\ln t + \frac{\alpha_a}{\alpha}(1-\beta\delta) + \beta\delta\frac{w'(a)}{w(a)}\right) \\ F_M\frac{\partial M}{\partial a} &= \frac{\beta\delta F}{1-\alpha\delta-\beta\delta}\left(\delta\alpha_a\left(1+\ln t\right) + (1-\alpha\delta)\frac{w'(a)}{w(a)}\right) \end{aligned} \tag{9}$$

The equations in 9 prove the results. First, consider the effect of a reduction in π_M. This raises F, t, and M. It is thus clear that it must also raise $F_t \frac{\partial t}{\partial a}$ and $F_M \frac{\partial M}{\partial a}$. Second, consider the effect of raising the monetary return to ability and schooling, $\frac{w'(a)}{w(a)}$. This also raises both $F_t \frac{\partial t}{\partial a}$ and $F_M \frac{\partial M}{\partial a}$. Third, consider the effect of a reduction in initial health, H_0. This has the effect of raising α, β, F, M, t, and α_a. (Its effect on α_a follows, because $\frac{\partial}{\partial H_0}\left(\frac{F_a}{F}\right) < 0$.) By inspection, it is clear that it must then raise $F_t \frac{\partial t}{\partial a}$, since $\frac{1-\beta\delta}{1-\alpha\delta-\beta\delta}$ is rising in β. It will also raise $F_M \frac{\partial M}{\partial a}$, because $\frac{1-\alpha\delta}{1-\alpha\delta-\beta\delta}$ is rising in α. Finally, observe that a reduction in the productivity of time investments in health—by means of a reduction in α, would contract health disparities.

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Table 1: Characteristics of pre- and post-Beta Blocker Cohorts in the Framingham Heart Study.

	Pre-Beta Blockers, 1966-72			Post-Beta Blockers, 1976-82		
	Mean	Std Dev.	Median	Mean	Std Dev.	Median
Age	67.6	5.4	67	67.8	5.3	67
Male	41.6%	0.49	0	41.0%	0.49	0
Hypertension	60.1%	0.49	1	52.8%	0.50	1
Hypertensive Heart Disease	36.8%	0.48	0	26.6%	0.44	0
Heart Failure	27.9%	0.45	0	32.0%	0.47	0
Never Attended High School	32.6%	0.47	0	22.5%	0.42	0
Attended High School	14.4%	0.35	0	13.0%	0.34	0
Graduated from High School	24.0%	0.43	0	33.3%	0.47	0
Attended College	29.1%	0.45	0	31.3%	0.46	0
Person-Years		5775			7337	

Note: The pre-Beta Blockers group includes all respondents aged 58 to 75 in 1966. The post-Beta Blockers group includes all respondents aged 58 to 75 in 1976.

Table 2: Effects of Beta-Blockers on Health Disparities in Heart Disease.

	Physician-Assessed Hypertension		Hypertensive Heart Disease		Heart Failure	
	1966-72	1976-82	1966-72	1976-82	1966-72	1976-82
High School Attendee	-0.009	0.027	-0.090 *	-0.039	-0.045 **	-0.031
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
High School Graduate	-0.037 **	0.026	-0.097 *	-0.030	-0.054 *	-0.064 *
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
College Attendee	-0.103 *	-0.016	-0.121 *	-0.066 *	-0.055 *	-0.067 *
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Male	-0.083 *	0.009	-0.108 *	-0.054 *	0.003	0.079 *
	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)
Age	0.042	0.050 **	0.069 *	-0.012	0.015	-0.004
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Age-Squared	-0.0003	-0.0002	-0.0004 **	0.0002	0.0000	0.0001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	-0.995	-1.720 **	-2.241 *	0.187	-0.559	-0.027
	(1.04)	(0.98)	(1.10)	(0.89)	(1.07)	(0.90)
R-Squared	0.0244	0.0296	0.0433	0.0497	0.0212	0.0381
Observations	5992	7338	5788	7339	5788	7336

*Significant at 95% level.
**Significant at 90% level.
Note: The reference education group is people who did not attend high school. Standard errors, clustered by individual, appear in parentheses. Propranolol, the first beta-blocker available, was approved by the FDA for angina treatment in 1973, and for hypertension treatment in 1976. The 1966-72 regressions include only those who were between 58 and 75 in 1966. 1976-82 regressions include only those between 58 and 75 in 1976.

Table 3: Characteristics of the HCSUS Population.

High School Degree	0.27	0.27	0.28
	(0.45)	(0.45)	(0.45)
Some College	0.28	0.28	0.28
	(0.45)	(0.45)	(0.45)
College Graduate	0.19	0.20	0.20
	(0.39)	(0.40)	(0.40)
Black	0.33	0.33	0.32
	(0.47)	(0.47)	(0.47)
Female	0.23	0.23	0.23
	(0.42)	(0.42)	(0.42)
Medicaid	0.44	0.46	0.47
	(0.50)	(0.50)	(0.50)
Medicare	0.19	0.22	0.25
	(0.39)	(0.41)	(0.43)
Private Insurance	0.35	0.35	0.34
	(0.48)	(0.48)	(0.47)
No Insurance	0.20	0.18	0.16
	(0.4)	(0.38)	(0.36)
Asymptomatic	0.10	0.06	0.05
	(0.31)	(0.24)	(0.21)
Symptomatic	0.51	0.52	0.51
	(0.5)	(0.50)	(0.50)
AIDS	0.38	0.41	0.44
	(0.49)	(0.49)	(0.50)
Immune Function (CD4)	315	351	373
	(254)	(280)	(260)
On HAART	0.24 [a]	0.40 [b]	0.61 [c]
	(0.43)	(0.49)	(0.49)
Observations	2864	2466	2267

Note: Standard deviations appear in parentheses below means.

[a]Based on 2828 observations.

[b]Based on 2405 observations.

[c]Based on 2216 observations.

Table 4: Effect of HAART on Health Disparities among HIV Patients

	CD4+ lymphocyte count (cells per mm3)	
Variable	Baseline	1st and 2nd followup
Education (excluded=less than high school):		
High school degree	24.28	52.885
	(13.913)*	(13.859)***
Some college or more	10.665	53.666
	(15.894)	(17.935)***
Age	-10.23	-11.459
	(3.578)***	-6.861
Age squared/1000	111.367	115.772
	(44.968)**	-78.129
Black	15.451	15.692
	-10.799	-16.336
Female	55.593	47.341
	(12.655)***	(13.063)***
Used intravenuous drugs	1.22	4.413
	(11.150)	(12.534)
Had sex with men (0 if female)	-13.037	-6.293
	(9.404)	(15.983)
Region (excluded=Midwest):		
Northeast	69.708	46.347
	(26.949)**	-29.749
West	101.608	77.819
	(29.086)***	(29.958)**
South	43.666	53.779
	(28.335)	(31.412)*
Insurance (excluded=None):		
Medicaid	-75.796	-66.818
	(13.813)***	(26.598)**
Medicare	-80.576	-118.521
	(25.321)***	(21.924)***
Private Insurance	-38.601	-43.213
	(19.519)*	(15.425)***
Medicaid and Medicare	-108.683	-89.951
	(17.455)***	(28.380)***
Self-reported general health at baseline (excluded=Poor):		
Excellent/Very Good	103.644	97.418
	(17.778)***	(16.788)***
Good	96.885	104.272
	(17.709)***	(21.262)***
Fair	27.065	22.888
	(12.569)**	(17.722)
Observations	2457	3889
R-squared	0.09	0.07

Standard errors in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 5: Health Returns to Schooling, by Age and Chronic Illness Status.[a]

	Not Chronically Ill					Chronically Ill				
Age Group	High School	Some College	College	# Obs	R^2	High School	Some College	College	# Obs	R^2
25-34	0.074	0.093	0.108	244,664	0.03	0.188	0.233	0.319	11,384	0.07
	(35.69)	(44.87)	(54.23)			(13.81)	(16.32)	(23.55)		
35-44	0.101	0.123	0.144	212,428	0.03	0.239	0.308	0.398	18,540	0.09
	(38.94)	(47.01)	(57.87)			(22.82)	(27.13)	(37.01)		
45-54	0.123	0.150	0.172	139,868	0.04	0.270	0.342	0.436	26,345	0.11
	(40.69)	(46.8)	(57.52)			(34.79)	(35.88)	(49.01)		
55-59	0.131	0.162	0.180	53,389	0.04	0.255	0.303	0.406	17,696	0.09
	(28.5)	(31.37)	(37.85)			(28.1)	(24.51)	(35.05)		
60-64	0.134	0.167	0.181	46,594	0.04	0.238	0.304	0.368	21,540	0.08
	(27.9)	(30.12)	(34.41)			(29.04)	(26.29)	(33.22)		
65-69	0.109	0.142	0.158	39,536	0.03	0.199	0.258	0.315	23,209	0.06
	(21.57)	(23.46)	(27.82)			(25.26)	(23.14)	(28.64)		
70-74	0.110	0.148	0.147	31,991	0.03	0.163	0.216	0.251	19,278	0.04
	(19.4)	(20.99)	(20.71)			(18.32)	(17.03)	(20.07)		
75+	0.074	0.105	0.088	42,412	0.02	0.107	0.165	0.127	31,179	0.02
	(13.9)	(14.97)	(13.35)			(14.22)	(15.84)	(12.57)		

Note: Table shows the difference in the probability of reporting good health between the listed education group and those with less than a high school education, using a linear probability model. Regressions are run separately for each age group and illness status, and also control for gender and year. The chronically ill are those who report having either: hypertension, diabetes, asthma, arthritis, or heart disease. Data are from the 1982-1996 NHIS.

[a] Absolute values of T-statistics appear below coefficients.

Table 6: Health Returns to Schooling, by Age and Work-Limitation Status.[a]

	Unable to work due to health condition					Able to work				
Age Group	High School	Some College	College	# Obs	R^2	High School	Some College	College	# Obs	R^2
25-34	0.162	0.210	0.302	44,869	0.07	0.055	0.071	0.081	195,427	0.01
	(14.65)	(16.49)	(21.87)			(28.12)	(36.08)	(42.73)		
35-44	0.159	0.225	0.306	36,632	0.12	0.077	0.095	0.108	182,371	0.02
	(16.46)	(20.28)	(25.95)			(31.62)	(38.76)	(45.85)		
45-54	0.193	0.266	0.326	33,195	0.13	0.103	0.127	0.141	125,005	0.03
	(23.03)	(24.24)	(27.25)			(35.21)	(41.85)	(49.17)		
55-59	0.176	0.218	0.259	23,509	0.12	0.115	0.143	0.156	44,472	0.03
	(17.13)	(14.33)	(15.66)			(26.19)	(30.17)	(35.44)		
60-64	0.168	0.219	0.271	37,179	0.08	0.109	0.140	0.145	28,733	0.03
	(18.11)	(15.59)	(18.48)			(24.41)	(28.14)	(30.64)		
65-69	0.151	0.211	0.241	48,720	0.06	0.095	0.122	0.133	12,827	0.02
	(16.67)	(15.19)	(16.64)			(20.44)	(22.35)	(26.12)		

Note: Table shows the difference in the probability of reporting good health between the listed education group and those with less than a high school education, using a linear probability model. Regressions are run separately for each age group and work-limitation category, and all contain dummies for gender and year, and a linear term for age. Data are from the 1982-1996 NHIS.

[a]Absolute values of T-statistics appear below coefficients.

Table 7: Instrumental Variables Estimates of Health Disparities by Illness Status.

	OLS		Instrumental Variables		Education Instruments[a]	
	Chronic	Healthy	Chronic	Healthy	Chronic	Healthy
Female	0.005 ***	-0.001	0.017 **	0.001	-0.305 *	-0.182 *
	1.86	-1.16	2.10	0.38	-17.61	-27.07
Highest Grade Attained	0.033 *	0.015 *	0.072 *	0.022 *	.	.
	94.42	113.78	2.96	3.06		
Age, 25 to 34	-0.008 *	-0.002 *	-0.008 *	-0.002 *	0.014 ***	0.027 *
	-7.97	-15.94	-7.86	-9.19	1.79	17.18
Age, 35 to 44	-0.007 *	-0.002 *	-0.005 *	-0.002 *	-0.061 *	-0.008 *
	-9.67	-15.10	-2.85	-13.42	-11.14	-5.25
Age, 45 to 54	-0.005 *	-0.002 *	-0.002	-0.002 *	-0.087 *	-0.076 *
	-7.47	-12.90	-0.84	-3.23	-17.46	-40.95
Age, 55 to 59	-0.007 *	-0.004 *	-0.005 *	-0.003 *	-0.049 *	-0.050 *
	-4.88	-6.75	-2.61	-5.06	-5.08	-10.47
Age, 60 to 64	0.005 *	-0.002 *	0.007 *	-0.001 ***	-0.052 *	-0.055 *
	3.46	-2.56	3.59	-1.71	-5.31	-9.64
Age, 65 to 69	0.003 **	-0.004 *	0.005 **	-0.003 *	-0.041 *	-0.080 *
	2.10	-4.74	2.55	-3.27	-4.27	-12.79
Age, 70 to 74	-0.001	-0.005 *	0.001	-0.005 *	-0.054 *	-0.094 *
	-0.60	-6.08	0.65	-4.12	-6.01	-15.15
Age, 75+	0.001	-0.003 *	0.003 **	-0.003 *	-0.063 *	-0.063 *
	1.25	-7.58	1.96	-4.49	-16.25	-21.94
Birth Quarter 2	.	.	.	.	0.013	0.029 *
					0.55	3.02
Birth Quarter 3	.	.	.	.	0.106 *	0.120 *
					4.47	12.91
Birth Quarter 4	.	.	.	.	0.118 *	0.063 *
					4.85	6.52
Constant	0.55 *	0.81 *	0.07	0.72 *	12.26 *	12.19 *
	16.99	187.43	0.22	8.02	48.28	237.90
R-Squared	0.082	0.058	0.006	0.052	0.073	0.060
Observations	169171	810882	169061	810421	169061	810421

*Significant at 99% level.
**Significant at 95% level.
***Significant at 90% level.
Note: All Regressions Include Year Dummies.
[a]Joint F-statistics for the Quarter of Birth Instruments were 12.23 (3, 169941) for the Chronically ill, and 64.00 (3, 814125) for the Healthy.

Table 8: Characteristics of MCBS Respondents Over Age 80, by Mortality Status.

	Age Group					
	80-85		85-90		90+	
	Survivors	Last Year of Life	Survivors	Last Year of Life	Survivors	Last Year of Life
Good Health	0.61	0.33	0.59	0.37	0.56	0.35
	(0.49)	(0.47)	(0.49)	(0.48)	(0.5)	(0.48)
Male	0.35	0.45	0.30	0.37	0.23	0.27
	(0.48)	(0.5)	(0.46)	(0.48)	(0.42)	(0.45)
Less than HS	0.48	0.50	0.53	0.58	0.58	0.60
	(0.5)	(0.5)	(0.5)	(0.49)	(0.49)	(0.49)
High School	0.28	0.30	0.23	0.22	0.18	0.19
	(0.45)	(0.46)	(0.42)	(0.42)	(0.39)	(0.4)
Some College	0.25	0.20	0.24	0.20	0.23	0.21
	(0.43)	(0.4)	(0.43)	(0.4)	(0.42)	(0.4)
Observations	12,498	1,064	7,051	1,002	3,557	967

Note: Numbers in parentheses are standard deviations.

Table 9: Determinants of Good Health among MCBS Respondents, by Mortality Status.

	Survivors		Last Year of Life	
High School	0.08	*	0.04	
	(0.01)		(0.03)	
Some College	0.15	*	0.09	*
	(0.01)		(0.03)	
Age 80-85	0.03	**	-0.03	
	(0.01)		(0.03)	
Age 85-90	0.02		0.02	
	(0.02)		(0.03)	
Male	0.03	*	0.05	*
	(0.01)		(0.02)	
R-Squared	0.018		0.009	
Observations	15888		2085	

Note: Robust Standard Errors, clustered by respondent, in parentheses.
*Significant at 95% level.
**Significant at 90% level.