2005

Refundable Tax Credits for Health Insurance: The Sensitivity of Simulated Impacts to Assumed Behavior

David W. Emmons
American Medical Association

Eva Madly
W.E. Upjohn Institute

Stephen A. Woodbury
Michigan State University and W.E. Upjohn Institute, woodbury@upjohn.org

Upjohn Institute Working Paper No. 05-119

Refundable Tax Credits for Health Insurance:
The Sensitivity of Simulated Impacts to Assumed Behavior

David W. Emmons, Eva Madly, and Stephen A. Woodbury

Upjohn Institute Working Paper 05-119
http://www.upjohninst.org/publications/wp
July 2005

David W. Emmons is Director, Center for Health Policy Research, American Medical Association, 515 North State Street, Chicago, Illinois 60610 (David_Emmons@ama-assn.org). Eva Madly is Research Analyst, W.E. Upjohn Institute, 300 South Westnedge Ave., Kalamazoo, MI 49007 (madly@upjohninstitute.org). Stephen Woodbury is Professor of Economics, Michigan State University, East Lansing, MI 48824 (woodbur2@msu.edu) and Senior Economist, W.E. Upjohn Institute, (woodbury@upjohninstitute.org). We are grateful to James Rodgers, Gregory Wozniak, and Kevin Hollenbeck for helpful discussions and comments on an earlier draft. This paper reflects the opinions of the authors and should not be interpreted as representing the views of the organizations with which they are associated.

Refundable Tax Credits for Health Insurance:
The Sensitivity of Simulated Impacts to Assumed Behavior

David W. Emmons, Eva Madly, and Stephen A. Woodbury

Upjohn Institute Working Paper 05-119
July 2005
JEL Codes I18, H23

Abstract

We replicate and extend a simulation model developed by Jonathan Gruber with the goals of illuminating Gruber's modeling of health insurance coverage under a tax credit and examining the sensitivity of the results to changes in the model's key parameters. The replications suggest that a refundable tax credit of $1,000 for a single individual or $2,000 for a family for private health insurance would reduce the number of uninsured individuals by between 17.5 and 28 percent and require new government expenditures of between $16.6 and $44 billion, of which about $7.4–$9.7 billion would be for coverage of previously uninsured individuals. These wide simulated ranges highlight the uncertainty inherent in modeling the effects of health insurance tax credits and suggest that progress on the issue of tax credits for health insurance will require improved evidence on the likely take-up rate of a credit.

Refundable Tax Credits for Health Insurance: The Sensitivity of Simulated Impacts to Assumed Behavior

David W. Emmons, Eva Madly, and Stephen A. Woodbury
July 2005

Dissatisfaction with the level and growth of uninsurance in the U.S. population has spurred interest in alternatives to the existing system of financing health care, which is dominated by employer-provided health insurance among the nonpoor and nonelderly. One approach to reform would be to adopt a refundable tax credit for health insurance under the federal personal income tax. Such a policy would grant a tax credit up to a prespecified maximum—for example, $1,000 for an individual or $2,000 for a family—on a tax return where the filer purchased a private nonemployer health insurance policy. For filers whose tax bill was less than the amount paid for insurance, the difference between the tax bill and the credit would be paid to the filer—hence, the refundable nature of the credit.

The refundable tax credit has been viewed as potentially attractive for at least two reasons. First, it would make the same tax-favored treatment of health insurance available to all individuals, regardless of whether they are employed and regardless of whether their employer provides a health insurance plan. As a result, it should increase the number of insured individuals and decrease uninsurance (Pauly 1999). Second, a tax credit would generate growth in the market for private nonemployer health insurance and increase the population of health care consumers that have an interest in the characteristics and cost of their coverage. These informed, cost-conscious consumers could put a brake on increasing health care costs (Pauly 1999; Hubbard, Cogan, and Kessler 2004).

The extent to which a tax credit for health insurance would reduce the number of uninsured individuals has been controversial. Pauly and Herring (2002), Pauly, Song, and Herring (2001), and Wozniak and Emmons (2000) have simulated a variety of different tax credit policies and have found that a "reasonably generous" credit could reduce the number of uninsured individuals by roughly 50 percent. However, simulations by Gruber (2000a,b) and Gruber and Levitt (2000) suggest that a health insurance tax credit might reduce the number of uninsured by only about 10 percent.[1]

One way to advance understanding of existing simulations of tax credits for health insurance—and of the likely effects of tax credits—is to replicate those simulations and test the extent to which they are sensitive to the assumptions that were maintained to produce them. In this paper, we attempt to replicate Jonathan Gruber and Larry Levitt's simulations of the extent to which tax credits for health insurance would reduce the extent of uninsurance in the United States (Gruber 2000a,b; Gruber and Levitt 2000). The findings from this exercise are most relevant to Gruber's widely discussed findings and to the particular tax credit analyzed. The simulations should not be interpreted as being relevant to proposals that, for example, would cover different populations, would apply tax credits of a different amount, or would eliminate the exclusion of employer contributions for employees' health insurance premiums from employees' taxable income. Nevertheless, we feel that we learn two main lessons from these attempts at replication. First, in writing out and examining Gruber's simulation model, we find that the assumptions underlying the model tend to yield what might be considered lower-bound estimates of the extent to which the credit would be accepted and of the credit's impact on uninsurance. Second, we find that relatively minor changes in assumptions result in quite large changes in simulated results; that is, the simulations are rather sensitive to changes in assumptions. This sensitivity highlights the uncertainty inherent in modeling the effects of tax credits for health insurance.

Section 1 outlines the structure of the simulations, and Section 2 sets out the equations

[1] Glied, Remler, and Zivin (2001) present a useful guide to the various methods of simulating the impacts of tax credits for health insurance but do not present their own simulations. Helms (2001, pp. 135–141) further reviews several efforts to simulate the impact of tax credits. Burman et al. (2003) offer a critique of the policy.

that drive the simulations. The equations amount to rules for assigning a probability of accepting the tax credit (that is, a take-up probability) to each observation in the sample. Section 3 describes the data we use—the 1999 Current Population Survey (which is the basis of the simulations) and the 1999 Survey of Employer-Sponsored Health Benefits (which we use to "stretch" the CPS and make imputations of data missing from the CPS). Section 4 describes three imputations we make in order to implement the simulations. Specifically, for each person covered by employer-provided group health insurance, we impute the health insurance premium and employee contribution. Also, we impute the premium that each person in the sample would pay if he or she switched to private nonemployer health insurance (the so-called market premium). Section 5 presents and describes the results and sensitivity tests, and Section 6 offers concluding remarks.

1. Structure of the Simulation

Gruber's (2000a) simulation model is essentially a set of rules for determining whether a given individual (or family) would accept a federal refundable tax credit of $1,000 (for a single individual) or $2,000 (for a family) for privately purchased health insurance. Gruber began by identifying four groups, each of which faces different circumstances with respect to health insurance:

1) those currently covered by employer-provided group health insurance,

2) those covered by private nonemployer insurance,

3) those covered by Medicaid,

4) those currently uninsured.

The decision whether to accept a refundable tax credit must be modeled separately for each group. Accordingly, an equation is specified for each group that yields a "take-up probability"—that is, the probability of a person accepting the tax credit—for each person in that group. (The equations are described in the next section.)

For individuals currently covered by private nonemployer health insurance, accepting the refundable tax credit implies no change in health insurance status because the tax credit is applied to health insurance that already covers them. For individuals in the other three groups—covered by employer-provided group health insurance, covered by Medicaid, and currently uninsured—accepting the tax credit does imply a change in health insurance status: Those covered by employer-provided insurance and Medicaid move to credit-subsidized private health insurance and remain insured. Those who are uninsured become insured under a private nonemployer plan.

The goal of the simulation is to model take-up of the credit (which, for three of the groups, implies a change of insurance status) and then to determine the implications of a given pattern of take-up for the total cost of the tax credit and its impact on aggregate health insurance coverage. A main goal of our replication is to make clear the implications of assumptions about take-up for the simulated results. In particular, we examine the sensitivity of the simulated results to variation in the model's key parameters.

2. Take-up Rates

Predictions about the probability of accepting the refundable tax credit are central to the simulations because they predict the number of individuals who would accept the credit, the cost of the credit, and the extent to which the credit would reduce uninsurance. This section describes and notes the implications of the equations Gruber developed to predict take-up rates for each of the four groups being considered.

2.1. Currently covered by employer-provided group health insurance

The probability that a worker who is currently covered by group insurance in his or her name will take up the credit is simulated as

$$P(accept) = 0.625\left(\frac{E(group) - E(priv)}{C(group)}\right), \tag{1}$$

where *E*(*group*) denotes the worker's contribution to (or expenditures on) employer-provided group health insurance, *E*(*priv*) denotes the worker's expenditure on private insurance after receiving the tax credit, and *C*(*group*) denotes the total cost (employer's and worker's shares combined) of the group health plan. Accordingly, equation (1) says that the probability of a worker switching from group health insurance to a tax-subsidized private plan is a constant (0.625) times the proportional difference between the individual's current contribution to group insurance and the individual's anticipated expense for private insurance (after receiving a subsidy). The constant (0.625) can be interpreted as an elasticity of the probability of accepting the credit with respect to the savings from accepting the credit. Note that this elasticity is assumed to be less than one, implying relatively unresponsive behavior.

Note also that the simulation assumes that employer-provided insurance and private insurance offer identical coverage, deductibles, co-payments, and so on. As a result, the difference between the current contribution to employer-provided insurance and the post-subsidy private insurance premium is assumed to represent the full difference in expenditures incurred by the individual from accepting the tax credit.

We calculate *P*(*accept*) for each worker who has group coverage in his or her name (see Section 4.1), then apply the same *P*(*accept*) to dependents who are covered by the same policy. As a result, the simulations account for the impact of the tax credit on both the primary insured and his or her dependents.

The implications of equation (1) will be clearer if we consider some examples. Table 1 shows the probability of accepting the tax credit in 11 cases where individuals are currently covered by employer-provided health insurance. These cases draw on the nationally representative data we use in the simulations below. In the first six cases, we take the 20th, 50th, and 80th percentiles of $E(group)$, $E(priv)$, and $C(group)$ from those data—first for families with group health insurance coverage, then for single household heads with group coverage—and apply them to equation (1). For example, Case 1 represents a worker from a family covered by group health insurance at the 20th percentile of $E(group)$, $E(priv)$, and $C(group)$. This worker currently makes no contribution to employer-provided group coverage (column 1). If the worker accepted the tax credit and switched to private coverage, his or her insurance expenditures would rise to $1,202 (column 2). Whenever $E(priv) > E(group)$, as in this case, $P(accept)$ is negative, which implies that the individual has a 0 probability of switching to private insurance. A glance at Table 1 shows that all cases based on the 20th, 50th, and 80th percentiles have 0 probability of switching from employer-provided to private insurance.

Cases 7 through 11 in Table 1 are five families or single household heads chosen from the CPS because they have a positive probability of switching from employer-provided to private insurance. In Case 7, the employed family member currently contributes $6,000 to employer-provided group coverage (column 1), which is the entire cost of the group health insurance (column 3). Because this worker and his spouse are young and in good health, private coverage is relatively inexpensive, so if the worker accepted the tax credit and switched to private coverage, his insurance expenditures (after the credit) would fall to $2,550 (column 2). The saving of $3,450 in health insurance expenditures (column 4) represents 59 percent of the total cost of the existing group plan (column 5). As a result, the probability of accepting the credit is 0.37 (0.625×0.59—column 6). Cases 8 through 11 in Table 1 can be interpreted similarly.

Cases 7 through 11 in Table 1 make two points clear. First, workers who are likely to accept the credit tend to be paying for a large share of their employer-provided health insurance. (Case 11 is an exception: This female household head is making a modest contribution to an employer-provided plan that is expensive relative to the plan she could buy in the private market.) As substantial employee contributions to employer-provided health insurance become increasingly common, the financial incentives to accept a tax credit—and presumably the likelihood of actually accepting—will increase. Second, the workers who are likely to accept the credit and switch from employer-provided group to private health insurance face low private health insurance premiums. Although it cannot be seen in Table 1, inspection of the data underlying the table shows that Cases 7 through 11 are based on families and single household heads who are young and healthy; as a result, they can reduce their health insurance expenditures by switching.

Overall, the examples in Table 1 suggest that equation (1) generates low probabilities of accepting the tax credit and switching from employer-provided to private insurance, even when workers would substantially reduce their insurance expenses by switching.[2] This is confirmed in Table 2, which displays frequency distributions of the probability of accepting the tax credit and moving to private health insurance that equation (1) generates when we apply it to nationally representative data. (Section 3 discusses these data.) Table 2 shows two alternative simulations of *P*(*accept*) because, as discussed in Section 4, we must impute a value of *E*(*group*) to each observation in the CPS, and we have two alternative imputations of *E*(*group*). For families, the mean *P*(*accept*) is 0.04 under the first simulation and 0.10 under the second. For single household heads, the mean *P*(*accept*) is 0.04 under the first simulation and 0.08 under the second.

Ultimately, take-up probabilities are an empirical issue that can be settled only by

[2] For example, in case 9, equation (1) predicts that a worker who could reduce health insurance expenses from $2,200 to $1,000 by switching to a private plan has only a 13 percent probability of switching.

observing actual behavior. However, for two reasons, we suggest that the probabilities generated by equation (1) represent a lower bound on the take-up behavior that could be expected following adoption of a tax credit. First, employee contributions to group health insurance have increased in recent years. If this trend continues, which seems likely, then $E(group) - E(priv)$—the difference between workers' contributions to group insurance and their after-tax expenditures on private insurance—will increase, which will in turn raise the probability of taking up the credit and switching to private insurance. Second, a review of the take-up behavior associated with other programs (see Section 2.2 below) suggests that the assumptions underlying equation (1) are at the low end of what could be expected if a tax credit were adopted.

In order to obtain an upper bound on the probability of accepting the tax credit, we perform an alternative simulation in which $P(accept) = 1$ whenever a worker with employer-provided health insurance in his or her own name would incur lower expenses by accepting the tax credit and moving to private insurance—that is, whenever $E(priv) < E(group)$. Under this simulation, 20.7 percent of families with employer-provided insurance switch to private insurance, and 28.0 percent of single household heads with employer-provided insurance switch.

2.2. Currently covered by private nonemployer health insurance

Individuals who are currently covered by private health insurance have already shown a preference for nonemployer insurance, and many (or most) could be expected to accept a tax subsidy. Indeed, the tax subsidy would be a windfall to these individuals, and not to accept the subsidy would amount to leaving money on the table. Nevertheless, it is well known that not all individuals who are eligible for a wide variety of benefit programs actually apply for and receive the benefits for which they are eligible. For example, reviews of program take-up by Remler, Rachlin, and Glied (2001) and by Currie (2004) report the following take-up rates (that is, the percentage of eligible individuals who actually enroll) for various means-tested social programs:

- Medicaid—about 73 percent
- State Children's Health Insurance Program (SCHIP)—8 to 14 percent
- Earned Income Tax Credit (EITC)—80 to 87 percent
- Aid to Families with Dependent Children (AFDC)—45 to 90 percent
- Temporary Assistance for Needy Families (TANF)—40 to 55 percent
- Housing subsidies—below 25 percent
- Food Stamp Program—69 percent of eligible households, 86 percent of eligible children
- Special Supplemental Nutritional Program for Women, Infants, and Children (WIC)—about 75 percent
- Child Care Subsidy Program—about 40 percent
- Head Start—about two-thirds of poor 3- to 4-year-old children

Take-up rates for social insurance programs (which are not means-tested) have been more difficult to estimate (Currie 2004). Reliable estimates of take-up rates for Social Security Disability Insurance and Workers' Compensation do not exist. The take-up rate for Medicare is more than 95 percent. The take-up rate for Unemployment Insurance (UI) has ranged over time between 66 and 83 percent. The take-up rate of reemployment bonuses (cash awards to UI recipients who find reemployment quickly) ranged from 15 to 34 percent in three demonstrations conducted in the 1980s (Decker, O'Leary, and Woodbury 2001).

Why eligible individuals choose not to participate in programs that would appear to improve their well-being is a puzzle that has attracted much research. Early work on the issue, such as Moffitt (1983), emphasized the stigma that may attach to participating in a program. Subsequent work shifted the focus away from stigma and toward other kinds of transaction costs associated with participation (Currie 2004). More recently, economists have started to incorporate the insights of behavioral economics in work on program participation. For example, O'Donoghue and Rabin (1999) have emphasized that agents may discount in a way that is "time inconsistent"—that is, they may weigh the present more heavily than a standard model based on rational choice would suggest they should. Madrian and Shea (2001) note that time inconsistency can lead to considerable "stickiness" in behavior; that is, individuals stay with a given choice—a pension plan, a telephone plan, or whatever—even though making a change would appear to improve their well-being. What is particularly interesting about the behavioral economics literature is that it may suggest ways of overcoming such apparently irrational behavior. However, behavioral economics has not yet been used to design programs in a way that would encourage take-up.

Remler, Rachlin, and Glied (2001) have reviewed the evidence on take-up of social programs with an eye to understanding what that evidence might imply about the take-up of health insurance programs. They examine several factors correlated with take-up—program benefits, inconvenience of applying, cultural attitudes and stigma, and information—and conclude that lack of information about a program and inconvenience are likely to be the main barriers to participation in health-related programs. They suggest that automatic enrollment is the simplest way to ensure a high program take-up rate.

All told, experience with existing programs suggests that participation in a refundable tax credit for health insurance would be less than 100 percent, even among those who are currently privately insured. On the other hand, the transaction costs and stigma associated with welfare and some social insurance programs would likely be less under a refundable tax credit than under many social programs: it would be part of the tax system, in which most individuals already participate, and claiming the credit would be essentially anonymous. As a result, in the long run, participation in the EITC is perhaps a better gauge of the level of participation that might be expected under a tax credit than is participation in other programs mentioned above.

Gruber (2000a) makes upper-bound and lower-bound assumptions about whether someone currently covered by private health insurance would accept the tax credit. The lower-bound assumption is that 50 percent of those covered by private health insurance would accept. The upper-bound assumption is that 90 percent would take up the credit. We follow his practice and simulate acceptance of the tax credit by those who are privately insured with a 50 percent lower bound and a 90 percent upper bound.

2.3. Currently covered by Medicaid

The probability that a family or individual currently covered by Medicaid will accept the credit is simulated as

$$P(accept) = 0.2\left(\frac{C(priv) - E(priv)}{C(priv)}\right)\left(1 - \frac{C(priv)}{income}\right)^2, \qquad (2)$$

where *C*(*priv*) denotes the total private health insurance premium, *E*(*priv*) denotes the expenditure on private insurance after receiving the tax credit [so *C*(*priv*) – *E*(*priv*) is the subsidy or tax credit received for private health insurance], and *income* denotes either family income or income per family member (see below). Accordingly, equation (2) says that the probability of switching from Medicaid to a tax-subsidized private plan increases as the subsidy increases relative to the premium paid for the private plan (the first term in parentheses) and falls as the premium rises relative to income (the second term in parentheses). The constant (0.2) is essentially an elasticity and implies that the probability of accepting the tax credit is (for Medicaid recipients) quite unresponsive to relative changes in the subsidy and income.

Equation (2) can be implemented in either of two ways. First, *C*(*priv*) and *E*(*priv*) can be imputed for an entire family, and *income* is family income. In this case, equation (2) yields a lower-bound estimate of the probability of accepting the credit. Alternatively, *C*(*priv*) and *E*(*priv*) can be imputed separately for each Medicaid-covered individual in the sample, in which case *income* is average income per family member. In this case, equation (2) yields an upper-bound estimate of the probability of accepting the credit.

To see the implications of equation (2), we have calculated the probability of accepting the tax credit for six hypothetical Medicaid recipients (see Table 3). We take the 20th, 50th, and 80th percentiles of *C*(*priv*), *E*(*priv*), and *income* from the nationally representative data used in the simulations—first for families receiving Medicaid, then for singles receiving Medicaid—and apply them to equation (2). For example, Case 2 represents a Medicaid recipient who heads a family at the median *C*(*priv*), *E*(*priv*), and *income* for family Medicaid recipients. This Medicaid recipient faces a private insurance premium of $5,529 and has income of $12,362. For this person, equation (2) generates a probability of 0.022 of accepting the $2,000 family tax credit and buying private insurance. Case 5 represents a *single* Medicaid recipient at the median *C*(*priv*), *E*(*priv*), and *income* for single Medicaid recipients. This person faces a private insurance premium of $5,318 and has income of $6,186. For this person, equation (2) generates a probability of 0.001 of accepting the $1,000 single tax credit and buying private insurance.

Table 4 shows frequency distributions of the probability of Medicaid recipients accepting the tax credit and moving to private health insurance that result from applying equation (2) to the nationally representative sample of Medicaid recipients used in the simulations below. As with equation (1), some imputations are required, this time for *C*(*priv*) and *E*(*priv*). For families, either family or individual measures of *C*(*priv*), *E*(*priv*), and *income* could be applied to equation (2), so we show two alternative distributions of *P*(*accept*). Using family-level data to impute *C*(*priv*) and *E*(*priv*) and using family income in equation (2) yields the distribution of *P*(*accept*) in column 1 of Table 4. (These probabilities are used to give the lower-bound simulations reported in row 4 of Table 9.) Using individual-level data to impute *C*(*priv*) and *E*(*priv*) and using income per family member yields the distribution in column 2 of Table 4. (These probabilities are used to give the upper-bound simulations reported in row 4 of Table 9.) The mean *P*(*accept*) for families is 0.034 using family data and 0.072 using individual data (columns 1 and 2 of Table 4). For singles, only one set of imputations is possible, and the mean *P*(*accept*) is 0.021 (column 3 of Table 4).

2.4. Currently uninsured

For currently uninsured families and individuals, the probability of taking up the credit is simulated as

$$P(accept) = 0.625\left(\frac{C(priv) - E(priv)}{C(priv)}\right)\left(1 - \frac{C(priv)}{income}\right)^2. \tag{3}$$

Note that equation (3) is identical to equation (2) except for the constant elasticity [0.625 in equation (3)]. Accordingly, equation (3) says that the probability of an uninsured family or individual taking up the credit and switching to private health insurance increases as the subsidy increases relative to the premium paid for the private plan, and falls as the premium rises relative to income. The constant elasticity (0.625) in equation (3) is higher than in equation (2) and implies that currently uninsured families and individuals respond more strongly than Medicaid recipients to changes in the subsidy and income. Nevertheless, the elasticity in equation (3) is well below unity, so the simulation assumes that the probability of uninsured individuals accepting the tax credit is rather unresponsive to changes in the subsidy and income. As with equation (2), equation (3) can be implemented either for an entire family or for each individual in the sample separately. As before, the family calculations yield lower-bound estimates of the probability of accepting the credit, whereas individual calculations yield upper-bound estimates.

Table 5 shows the implications of equation (3) by again examining some hypothetical cases. The cases use the 20th, 50th, and 80th percentiles of *C*(*priv*), *E*(*priv*), and *income* from the data used in the simulations—first for uninsured families, then for uninsured individuals—and apply them to equation (3). For example, Case 2 represents the median head of an uninsured family, who faces a private insurance premium of $5,686 and has income of $27,040. For this family head, equation (3) generates a probability of 0.137 of accepting the $2,000 family tax credit and becoming insured. Case 5 represents the median *single* uninsured person, who faces a private insurance premium of $1,419 and has income of $11,440. For this person, equation (2) generates a probability of 0.338 of accepting the $1,000 single tax credit and becoming insured.

Table 6 shows frequency distributions of *P*(*accept*) that result from applying equation (3) to the nationally representative sample of uninsured families and individuals used in the simulations below. Again, imputations are required for *C*(*priv*) and *E*(*priv*), and for families we calculate two alternative sets of imputations, one using family-level data (and family income), the other using individual-level data (and income per family member). The mean *P*(*accept*) for families is 0.159 using family data and 0.290 using individual data. For singles, the mean *P*(*accept*) is 0.241 (column 3).

3. Data

Like Gruber's (2000a) simulations, the simulations we report here are based on two sets of data—the March 1999 annual demographic file of the Current Population Survey (CPS) (Bureau of Labor Statistics 2000), and the 1999 Survey of Employer-Sponsored Health Benefits, conducted by the Kaiser Family Foundation and the Health Research and Education Trust (Kaiser/HRET Survey). The March 1999 CPS is the basis of the simulations, and we use its data on 132,324 individuals under age 65. (These individuals were part of 57,325 families and 54,147 households.) In general, the individual is the unit of observation, with characteristics of each individual's family used as necessary to execute the simulations. Occasionally, as described below, the family is used as the unit of observation. Although more recent CPS annual demographic files are available, the March 1999 file is useful because it allows direct comparison with Gruber's simulations.

Gruber matched the March 1999 CPS annual demographic file with the February 1999 Contingent Worker Supplement to the CPS. The February Contingent Worker Supplement is attractive because it includes data on whether workers were offered health insurance by their employers, and such data are not included in the March CPS file. The February and March files can in principle be matched to obtain a better profile of the options facing individuals than would occur if either the February or the March file were used alone. However, we have attempted several ways of matching the March and February 1999 CPS files and have found the resulting matches to be unsatisfactory. (See Madrian and Lefgren [1999] for a thorough discussion of the pitfalls in matching CPS respondents across surveys.) Accordingly, in the simulations reported here, we do not use the February data on health offers. It turns out that, for individuals covered by employer-provided insurance, we obtain lower-bound estimates of tax credit take-up that are virtually identical to Gruber's. As a result, we conclude that use of the February data on employer offers of health insurance is not a significant issue.

A key deficiency of the March CPS is that the data do not include the health insurance premiums paid by employers to cover workers who receive employer-provided health insurance. Neither do they include the employee's contribution for those covered by employer-provided insurance. The CPS does report whether a worker is covered by health insurance, and the Bureau of Labor Statistics imputes the *employer's* contribution to the health insurance plan. But the BLS does not attempt to impute the health insurance premium or the employee's contribution. We use the Kaiser/HRET survey to compensate for these deficiencies.

The 1999 Kaiser/HRET survey attempted to collect data on the characteristics of up to four health insurance plans (conventional, HMO, PPO, and POS) in each of 2,694 firms. Because 755 of the companies either did not offer a health insurance plan or did not respond, the survey includes data on 1,939 companies offering 2,837 health insurance plans (many companies offered more than one plan), although data on some plans are incomplete. In addition to detailed characteristics of each plan, the data gathered by the survey include the health insurance premium paid by the firm and the employee contribution for each plan. As described in Sections 4.1 and 4.2, we use these data to impute the health insurance premium [*C*(*group*)] and employee contribution [*E*(*group*)] for each person in the CPS who was covered by employer-provided health insurance. We also use the Kaiser/HRET survey to make regional adjustments to the imputed private insurance premium [*C*(*priv*)]—see Section 4.3.

4. Imputations

Section 2 described the take-up equations that underlie the simulations—equations (1), (2), and (3). Those equations model the probability of accepting the tax credit as a function of four variables:

1) the total health insurance premium for group coverage [*C*(*group*)],

2) the employee's contribution to group health [*E*(*group*)],

3) the premium an individual would pay for private health insurance [*C*(*priv*)], and

4) the post-subsidy expense of private health insurance [*E*(*priv*), which is *C*(*priv*) less the tax subsidy].

None of these is observed in the CPS, so they must be imputed. This section describes the methods of imputation.

4.1. Premiums of those currently covered by group health insurance [*C*(*group*)]

We impute the total health insurance premium (or cost) for a person currently covered by group health insurance in two steps. First, using the Kaiser/HRET Survey data, we estimate two hedonic health insurance premium functions—one for family plans and one for single plans—by regressing the health insurance premium of each health plan coded in the data on company size (6 indicators), industry (9 indicators), an urban/rural indicator, census regional division (9 indicators), and 192 indicators that specify the characteristics of the plan. The resulting estimates are displayed in Table 7.[3] (Coefficients of the plan-characteristic indicators are not reported because there are so many.)

Second, we use the hedonic estimates to predict the group health insurance premium of each worker in the CPS who has employer-provided health coverage in his or her name. We do this by substituting the characteristics of each worker and of his or her employer into the estimated hedonic function. (Firm size, industry, location in an urban or rural area, and census regional division are common to the CPS and the Kaiser/HRET data, making the prediction possible.[4] The mean plan characteristics are assigned to all observations in making the prediction.) For a single worker, the characteristics of the worker's firm are substituted into the hedonic function for a single premium; for workers with dependents, the characteristics of the worker's firm are substituted into the hedonic function for a family premium. The result is an imputed group health insurance premium for each worker in the CPS who has a group health plan in his or

[3] Note that the dependent variable in both regressions is the untransformed monthly premium. Inspection of the premium variables suggested they were approximately normally distributed, making this a natural choice. We also estimated regressions using the natural log of the family and of the single premiums as dependent variables and obtained essentially similar results.

[4] Industry codes differ between the CPS and the Kaiser/HRET survey, so we created a crosswalk between the two classification schemes by matching two-digit industry codes in the CPS to the one-digit codes in the Kaiser/HRET survey. For example, CPS workers in two-digit industries 40 and 41 (hospitals, and health services except hospitals) are assigned to the Kaiser/HRET "health care" industry category; CPS workers in two-digit industries 36 and 44 (business services, and other professional services) are assigned to the Kaiser/HRET "high-tech" industry category.

her name. The mean and other descriptive statistics of the imputed premiums (computed using the CPS observations) are displayed in Table 8 (panel A).

4.2. Employee contributions to group health [*E*(*group*)]

For individuals currently covered by group health insurance, we must also impute the employee contribution to group health insurance. We do this in two ways. The first resembles the method described above for imputing the total health insurance premium of a person covered by group health: We use the Kaiser/HRET Survey data to estimate equations for the shares (or proportions) of the single and family health insurance premiums paid by the employer. (The specifications are similar to those described above for group health insurance premiums, and the estimates are displayed in Table 7.) Then, for each worker in the CPS who has employer-provided health coverage in his or her name, we substitute the characteristics of each worker and his or her employer into the appropriate estimated function (either family or single). For each worker, this yields a predicted share of the group health premium paid by the employer [and a predicted employee's share as well because the employee's share is simply (1 – the employer's share)]. Finally, we multiply the imputed employee's share by the employer-provided health insurance premium that we imputed from the Kaiser/HRET data (Section 4.1) to obtain an imputation of the dollar employee contribution to his or her group health plan.

The second way of imputing the employee contribution to group health is more straightforward. The CPS includes an imputed annual employer contribution to health insurance. We subtract this imputation from the annualized group health insurance premium that we imputed from the Kaiser/HRET data (Section 4.1) to obtain an alternative imputation of the employee's contribution to group health insurance.

Means and other descriptive statistics of employee contributions imputed using both of the above methods are displayed in Table 8 (panel B).

4.3. Market premium faced by each individual [*C*(*priv*)]

Finally, we must impute the premium (or cost) an individual or family would pay for private nonemployer health insurance. To do this, we use the following function that Gruber (2000a, p. 33) developed using data on the age distribution of private nonemployer health insurance premiums (from Mutual of Omaha) and data on the distribution of medical costs by self-assessed health status (from Actuarial Research Corporation):

$$C(priv) = \$120(health\ factor)(age\ factor) + regional\ factor. \tag{4}$$

In equation (4), \$120 is the monthly premium for a single 40-year-old individual in excellent health. This can be thought of as a "reference premium," which is scaled up or down according to an individual's self-reported health status, his or her age, and his or her region of residence, each of which is reported in the CPS. Consider each of these factors in turn.

The *age factor* for a 40-year-old is 1 (because the 40-year-old is the reference case). For individuals under age 21, *age factor* is 0.456, implying that, other things equal, *C*(*priv*) of a young person is 45.6 percent that of a 40-year-old. For individuals 62–64, *age factor* is 2.8, implying that *C*(*priv*) of a 62- to 64 year-old is 2.8 times that of a 40-year-old. From these three points, it is a straightforward task to interpolate age factors for ages 21–39 and ages 41–61.

The *health factor* for a person who reports himself or herself to be in excellent health is 1 (the reference case, again). For a person in very good health, *health factor* is 1.21; for a person in good health, it is 1.84; for a person in fair health, it is 3.47; and for a person in poor health, it is 5.8.

The regional factors are the estimated coefficients of the regional indicators in the hedonic premium function displayed in Table 7. Our assumption here is that private and group health insurance premiums are highly correlated regionally. For example, the regional factor for a family premium in New England is \$54.63, in east north central states it is –\$14.46, and so on. Note that *regional factor* enters equation (4) additively, whereas *age factor* and *health factor* enter multiplicatively.

For singles (that is, persons living alone or unrelated individuals in a larger household), we obtain *C*(*priv*) by first calculating \$120(*health factor*)(*age factor*), then adding the appropriate regional factor from the single plan hedonic premium function. For a family, we obtain a family *C*(*priv*) by calculating \$120(*health factor*)(*age factor*) for each individual in the family, summing, then adding the appropriate regional factor from the family plan hedonic premium function.

Table 8 (panel C) displays sample descriptive statistics of the monthly *C*(*priv*) for all families, all singles, and several subgroups of each. Not surprisingly, the monthly premium for families is more than twice the average single premium. Also, for workers who have group health coverage, the imputed group premiums are substantially lower on average than the imputed market premiums (compare panels A and C).

Once *C*(*priv*) has been imputed for each observation, it is a straightforward matter to calculate the tax subsidy that each person would receive. Subtracting this tax subsidy from *C*(*priv*) yields *E*(*priv*), the post-subsidy expenditure on private health insurance.

5. Results of the Simulations

Table 9 displays the main results of the simulation model described above. We discuss in turn the results for take-up rates, the number of individuals accepting the credit (including changes in the number of uninsured individuals), and the net government cost of the tax credit.

5.1 Take-up rates, number of individuals switching, and uninsurance

Columns 1 and 2 of Table 9 display the simulated lower- and upper-bound take-up rates of each group, and columns 3 and 4 display the implied number of individuals in each group who accept the tax credit.[5]

For individuals currently covered by employer-provided group health insurance, the lower-bound simulations are based on equation 1, whereas the upper-bound estimates are based on the assumption that any worker with group health insurance who would reduce his or her expenses by accepting the tax credit will do so. The simulations yield a broad range of take-up rates—from 3.3 to 35.4 percent, depending on the underlying assumptions. The simulated range for the number of individuals who would switch from employer-provided to private insurance—from 5 to 53 million—is similarly wide, reflecting the wide range of simulated take-up rates. Simulations using employer contributions to health insurance imputed from the hedonic functions (row 1 of Table 9) give lower take-up rates than those using the BLS's imputed employer contributions (row 2 of Table 9). The lower-bound estimate of 3.3 percent is very close to Gruber's estimate of 3.2 percent, which suggests that we have managed to replicate Gruber's simulation method for workers covered by group health insurance. (Also, as already noted, it suggests that our inability to use the February CPS data on employer offers of health insurance is not a significant issue.)

Most analysts would argue that the upper-bound estimates in column 2 of Table 9 are unrealistically high. Nevertheless, as discussed in Section 2.1, the lower-bound estimates may well be too low, and little basis exists for choosing a most-likely point estimate within the range of simulated take-up rates. We suggest that the range of estimates shown is essentially too wide to be useful to policymakers and that further evidence and research will be needed to narrow the

[5] Except for those already covered by private insurance, the figures reflect the number of individuals who switch from their current health insurance status to private nonemployer insurance.

range.

For individuals covered by private nonemployer insurance, the lower-bound take-up rate is assumed to be 50 percent, and the upper-bound take-up rate is assumed to be 90 percent (row 3 of Table 9). The implied range for the number of privately insured individuals accepting the tax credit (from 10 to 18 million) is quite wide. The lower bound of this range exceeds Gruber's estimate of 8.6 million, which is curious because this is the most straightforward of the simulations performed.

For individuals covered by Medicaid, equation (2) yields a take-up rate of between 3.3 and 6.7 percent, which implies that between 0.6 and 1.3 million current Medicaid recipients would switch to private insurance (row 4 of Table 9). [Recall that the lower-bound estimates result from using family-level data to impute *P*(*accept*) for families, whereas the upper-bound estimates result from using individual-level data to impute *P*(*accept*).] Gruber's take-up rate for Medicaid recipients is 1.8 percent, which suggests that fewer than 0.4 million current Medicaid recipients would switch to private insurance. Although our lower-bound estimates are slightly above Gruber's estimates, they are close enough to suggest that we have replicated Gruber's approach. The point is that the take-up rate for Medicaid recipients would be very low.

The simulations of uninsured individuals (row 5 of Table 9) are central to this exercise because they indicate the extent to which a tax credit would reduce uninsurance. For the uninsured, equation (3) yields a lower-bound take-up rate (and a corresponding reduction in the uninsured population) of 17.5 percent and an upper-bound take-up rate of 28.3 percent.[6] It follows that the tax credit would reduce the number of uninsured by 7.7–12.5 million—from about 44 million (or 18.4 percent of the nonelderly U.S. population) to between 31.5 and 36.3 million (or 13.2–15.2 percent). Gruber's take-up rate (and the corresponding reduction in the

[6] Recall again that the lower-bound estimate results from using family-level data to impute *P*(*accept*) for families, whereas the upper-bound estimate results from using individual-level data to impute *P*(*accept*).

uninsured population) is 11.1 percent, implying that about 4.7 million uninsured would become insured as a result of the tax credit. It appears that we have not replicated Gruber's simulation—our lower-bound estimates remain well above his—and it is unclear what accounts for the difference. In any case, it would be useful to compare the simulations in Table 9 with simulations that were based more convincingly on empirical estimates rather than on conjecture.

Finally, row 6 of Table 9 aggregates the implications of the simulations and shows that, all told, between 23.6 and 85.6 million individuals would accept the tax credit. Most of the breadth of this range comes from the wide take-up range we obtained for workers covered by employer-provided insurance.

5.2. Program costs

The net government cost of a refundable tax credit can be calculated in a straightforward manner from the simulations. First, consider individuals covered by employer-provided health insurance. For each of these individuals, the net cost of the tax credit (G) is the product of (a) the probability of accepting the tax credit and (b) the difference between the tax credit going to that individual and the tax expenditure on that individual if he or she continued to receive employer-provided insurance:

$$G = P(accept)\ \{[C(priv) - E(priv)] - mtr[C(group) - E(group)]\}. \qquad (5)$$

In equation (5), mtr denotes the individual's marginal tax rate. The term in brackets is the difference between the tax credit going to the individual $[C(priv) - E(priv)]$ and the tax expenditure on that individual, which is the marginal tax rate (mtr) times the employer's contribution to health insurance $[C(group) - E(group)]$. Taking the sample-weighted sum of G calculated for each individual gives the government's net cost of the tax credit for all individuals covered by employer-provided insurance.

For each person covered by private nonemployer insurance and for each uninsured individual, the net cost of the tax credit is the product of (a) the probability of accepting the tax credit and (b) the tax credit going to that individual:

$$G = P(accept)\,[C(priv) - E(priv)], \tag{6}$$

where the notation is as above.

For each Medicaid recipient, the net cost of the tax credit is the product of (a) the probability of accepting the tax credit and (b) the difference between the tax credit going to the individual $[C(priv) - E(priv)]$ and the Medicaid expenditure on that individual:

$$G = P(accept)\,\{[C(priv) - E(priv)] - E(medicaid)\}, \tag{7}$$

where $E(medicaid)$ denotes the government's Medicaid expenditure on the individual (U.S. Census Bureau 2003).

Columns 5 and 6 of Table 9 display the resulting simulated net government cost for each group. For individuals covered by employer-provided insurance, the wide simulated range of net cost ($1.9–$22 billion) reflects the wide simulated range of take-up rates. The simulated range for those covered by private nonemployer insurance ($9.5–$17 billion) is also wide. Net government cost for those initially covered by Medicaid actually falls by $2.2–$4.9 billion because it is less expensive to subsidize private nonemployer insurance for these individuals than to provide them with Medicaid.

The simulations suggest that tax credit expenditures on those who were previously uninsured would be between $7.4 and $9.7 billion—or between $776 and $961 per newly insured person. However, the net government cost of the tax credit ranges from $16.6 to nearly $44 billion because the credit can be applied by groups other than the previously uninsured. If the low end of the range ($16.6 billion) pertains, then the average cost to insure a previously uninsured person under the tax credit would be just over $2,100. However, if the high end ($43.9

billion) pertains, then the average cost per previously uninsured person would be about $3,500. (Note that these estimated costs take account of the fact that individuals who switch from employer-provided to private nonemployer insurance would give up a tax subsidy in the form of untaxed employer expenditures for health insurance.)

The simulation model we use makes performing sensitivity analysis straightforward. As more is learned about actual behavioral responses to health insurance tax credits, different behavioral parameters can be substituted into the model. Accordingly it should be straightforward to simulate the implications of new research using the model.

6. Summary and Conclusions

In this paper, we have replicated simulations of refundable tax credits for health insurance reported by Gruber (2000a,b) and Gruber and Levitt (2000). We have focused on clarifying the behavior Gruber and Levitt assume in their simulations, writing down the equations that specify the behavior of different groups of families and individuals, and describing the imputations needed to implement the simulations. The lower-bound estimates that result from our replication of Gruber's simulations accord closely with Gruber's estimates in two cases—workers covered by employer-provided health insurance and Medicaid recipients. They differ somewhat from his estimates in two other cases—individuals covered by private nonemployer insurance and the uninsured—although the differences are not large enough to raise concerns.

Overall, our simulations suggest that a relatively modest tax credit—$1,000 for a single individual and $2,000 for a family—would reduce the number of uninsured individuals by between 17.5 and 28 percent while requiring new government spending of between $16.6 and $44 billion, of which about $7.4–$9.7 billion would go toward covering previously uninsured individuals. Clearly, these ranges are quite wide and draw attention to the difficulty and uncertainty associated with modeling the impacts of tax credits for health insurance.

Pauly and Herring (2001, 2002) and Pauly, Song, and Herring (2001) are even more emphatic in warning about the uncertainty inherent in simulating the effects of health insurance tax credits. They point to model specification and assumptions about the premiums faced by the uninsured as the main sources of uncertainty. These add up to great uncertainty about the extent to which families and individuals would take up a tax credit. As they write, "this uncertainty ... should be front and center in the evaluation of tax credit schemes since we as analysts have minimal experience with large subsidies directed at low-income individuals" (Pauly, Song, and Herring 2001, p. 17). In addition, some tax credit proposals could lead to broader changes in health insurance markets, such as greater price competition among insurers. This is yet another source of uncertainty in modeling tax credit proposals.

The next question is whether direct empirical evidence could reduce uncertainty about tax credit take-up rates. As discussed in Section 2, Remler, Rachlin, and Glied (2001) and Currie (2004) have reviewed evidence on take-up of a wide range of social programs and show that take-up rates vary greatly from program to program. Their reviews suggest that little basis exists for choosing a most likely point estimate from the range of simulated take-up rates displayed in Table 9: the lower-bound estimates in column 1 of Table 9 may well be too low, and the upper-bound estimates in column 2 may be optimistically high, but little more can be said.

Obtaining convincing empirical evidence on take-up of a health insurance tax credit will not be cheap: it may require a demonstration project or social experiment. But progress on the issue of tax credits for health insurance will require improved evidence on the likely take-up rate of a credit, and the time and expense of such a demonstration may well be justified if it leads to convincing estimates of how tax credits would expand coverage and what they would cost.

References

Bureau of Labor Statistics. 2000. *Current Population Survey Design and Methodology* (Technical Paper 63). Washington, DC: U.S. Department of Labor. http://www.bls.census.gov/cps/tp/tp63.htm (accessed June 28, 2005).

Burman, Leonard E., Cori E. Uccello, Laura L. Wheaton, and Deborah Kobes. 2003. "Tax Incentives for Health Insurance." Discussion Paper No. 12, Urban-Brookings Tax Policy Center. Washington, DC: Urban Institute.

Currie, Janet. 2004. "The Take Up of Social Benefits." NBER Working Paper No. W10488. Cambridge, MA: National Bureau of Economic Research.

Decker, Paul T., Christopher J. O'Leary, and Stephen A. Woodbury. 2001. "Participation in the Reemployment Bonus Experiments." In *Reemployment Bonuses in the Unemployment Insurance System*, Philip K. Robins and Robert G. Spiegelman, eds. Kalamazoo, MI: W.E. Upjohn Institute for Employment Research, pp. 77–103.

Glied, Sherry, Dahlia Remler, and Joshua Zivin. 2001. "Approaches to Modeling Health Insurance Expansions." Manuscript, Mailman School of Public Health, Columbia University.

Gruber, Jonathan. 2000a. "Tax Subsidies for Health Insurance: Evaluating the Costs and Benefits." Report prepared for the Kaiser Family Foundation. NBER Working Paper No. W7553. Cambridge, MA: National Bureau of Economic Research.

Gruber, Jonathan. 2000b. "Microsimulation Estimates of the Effects of Tax Subsidies for Health Insurance." *National Tax Journal* 53 (September, Part 1): 329–342.

Gruber, Jonathan, and Larry Levitt. 2000. "Tax Subsidies for Health Insurance: Costs and Benefits." *Health Affairs* 19 (January/February): 72–85.

Helms, Robert B. 2001. "Positive Economics and Dismal Politics: The Role of Tax Policy in the Current Health Policy Debate." In *The Political Economy of Health Care Reforms*, Huizhong Zhou, ed. Kalamazoo, MI: W.E. Upjohn Institute for Employment Research, pp. 125–146.

Hubbard, R. Glenn, John F. Cogan, and Daniel P. Kessler. 2004. "Healthy, Wealthy, and Wise." *Wall Street Journal*, May 4, A:20.

Madrian, Brigitte C., and Lars John Lefgren. 1999. "A Note on Longitudinally Matching Current Population Survey (CPS) Respondents." NBER Technical Working Paper No. T0247. Cambridge, MA: National Bureau of Economic Research.

Madrian, Brigitte C., and Dennis F. Shea. 2001. "The Power of Suggestion: Inertia in 401(k) Participation and Savings Behavior." *Quarterly Journal of Economics* 114 (November): 1149–1187.

Moffitt, Robert. 1983. "An Economic Model of Welfare Stigma." *American Economic Review* 73 (December): 1023–1035.

O'Donoghue, Ted, and Matthew Rabin. 1999. "Doing It Now or Later." *American Economic Review* 89 (March): 103–124.

Pauly, Mark V. 1999. "Extending Health Insurance through Tax Credits." Kaiser Project on Incremental Health Reform. Menlo Park, CA: Henry J. Kaiser Family Foundation.

Pauly, Mark V., and Bradley Herring. 2001. "Expanding Coverage Via Tax Credits: Trade-Offs and Outcomes." *Health Affairs* 20 (January/February): 8–26.

Pauly, Mark V. and Bradley Herring. 2002. *Cutting Taxes for Insuring: Options and Effects of Tax Credits for Health Insurance*. Washington, DC: American Enterprise Institute for Public Policy Research.

Pauly, Mark V., David Song, and Bradley Herring. 2001. "Tax Credits, the Distribution of Subsidized Health Insurance, and the Uninsured." NBER Working Paper No. W8457. Cambridge, MA: National Bureau of Economic Research.

Remler, Dahlia, Jason E. Rachlin, and Sherry Glied. 2001. "What Can the Take-Up of Other Programs Teach Us about How to Improve Take-Up of Health Insurance Programs?" NBER Working Paper No. W8185. Cambridge, MA: National Bureau of Economic Research.

U.S. Census Bureau. 2003. *Statistical Abstract of the United States: 2002*. Washington, DC: U.S. Census Bureau. Table 516, p. 344.

Wozniak, Gregory D., and David W. Emmons. 2000. "Tax Credit Simulation Project Technical Report." Discussion Paper 00–1. Chicago: American Medical Association, Center for Health Policy Research.

Table 1
Implications of Equation (1) for Accepting the Tax Credit and Switching from Employer-provided Group Insurance to Private Health Insurance, Selected Cases

Cases	*E*(*group*) (1)	*E*(*priv*) (2)	*C*(*group*) (3)	(1)–(2) (4)	(4)/(3) (5)	*P*(*accept*) (6)
1. Family—20th percentile	0	1202	5397	–1202	–0.223	0.00
2. Family—median	1362	3607	5617	–2245	–0.400	0.00
3. Family—80th percentile	2101	7758	5846	–5657	–0.968	0.00
4. Single—20th percentile	0	88	2054	–88	–0.043	0.00
5. Single—median	295	792	2168	–498	–0.229	0.00
6. Single—80th percentile	411	2761	2280	–2350	–1.031	0.00
7. Family case 1	6000	2550	6000	3450	0.58	0.37
8. Family case 2	2900	660	5500	2240	0.41	0.26
9. Family case 3	2200	1000	5800	1200	0.21	0.13
10. Single case 1	2100	200	2100	1900	0.90	0.56
11. Single case 2	400	100	2100	300	0.14	0.09

NOTES: Variable definitions are as follows: *E*(*group*) = worker's contribution (or expenditures) for employer-provided group health insurance; *E*(*priv*) = worker's expenditure on private insurance after tax credit; *C*(*group*) = total cost (employer's and worker's shares combined) of group health plan.

Figures in columns 1, 2, and 3 are derived from the 1999 Current Population Survey and 1999 Survey of Employer-Sponsored Health Benefits. See Section 3 for a description of the data and Section 4 for a discussion of the required imputations.

Simulations assume that the employer-provided plan and the private plan offer identical coverage, deductibles, and co-payments. Accordingly, column (4)—the difference between the worker's contribution to the employer-provided plan and the worker's post-subsidy private insurance premium—represents the full difference in expenditures incurred by the worker from accepting the tax credit.

Table 2
Frequency Distributions of the Probability of Accepting the Tax Credit [*P*(*accept*)] Generated by Equation (1)

	Based on hedonic imputations of *E*(*group*)		Based on BLS imputations of *E*(*group*)	
P(*accept*)	families (1)	singles (2)	families (3)	singles (4)
P = 0.0	0.768	0.747	0.589	0.677
0.0 < *P* ≤ 0.1	0.083	0.146	0.102	0.087
0.1 < *P* ≤ 0.2	0.077	0.072	0.099	0.074
0.2 < *P* ≤ 0.3	0.042	0.012	0.082	0.060
0.3 < *P* ≤ 0.4	0.011	0.003	0.061	0.043
0.4 < *P* ≤ 0.5	0.007	0.005	0.040	0.029
0.5 < *P* ≤ 0.625	0.012	0.016	0.028	0.031
Mean *P*(*accept*)	0.039	0.032	0.095	0.075

NOTES: Distributions shown are based on a nationally representative sample of individuals covered by employer-provided group health insurance. See Section 3 for a description of the data and Section 4 for a discussion of the required imputations.

Simulations 1 and 2 derive from two alternative imputations of *E*(*group*) in equation (1). See Section 4.2 for discussion. Briefly, the distributions in Simulation 1 (columns 1 and 2) are calculated when *E*(*group*) is imputed from the hedonic health insurance and premium functions displayed in Table 7 (see also Table 8, line B.1). The distributions in Simulation 2 (columns 3 and 4) are calculated when *E*(*group*) is imputed from the hedonic health insurance premium function in Table 7 and the BLS-imputed employer contribution reported in the CPS (see also Table 8, line B.2).

Table 3
Implications of Equation (2) for Accepting the Tax Credit and Switching from Medicaid to Private Health Insurance, Selected Cases

Cases	*C*(*priv*) (1)	*C*(*priv*) – *E*(*priv*) (2)	*income* (3)	*C*(*priv*) / *income* (4)	Income factor (5)	*P*(*accept*) (6)
1. Family—20th percentile	2,980	2,000	5,855	0.509	0.241	0.032
2. Family—median	5,529	2,000	12,362	0.447	0.306	0.022
3. Family—80th percentile	11,672	2,000	24,084	0.485	0.266	0.009
4. Single—20th percentile	1,223	1,000	1,768	0.692	0.095	0.016
5. Single—median	5,318	1,000	6,186	0.860	0.020	0.001
6. Single—80th percentile	13,182	1,000	9,984	1.320	0.103	0.000

NOTES: Variable definitions are as follows: *C*(*priv*) = premium for private nonemployer health insurance; *E*(*priv*) = expenditure on private insurance after tax credit; *income* = family income; "Income factor" in column (5) refers to the squared term in equation (2).

Data in columns 1, 2, and 3 are derived from the 1999 Current Population Survey and the 1999 Survey of Employer-Sponsored Health Benefits. See Section 3 for a description of the data and Section 4 for a discussion of the required imputations. The simulations assume that Medicaid and the private plan offer identical coverage.

Table 4
Frequency Distributions of the Probability of Accepting a Tax Credit and Switching from Medicaid to Private Health Insurance [*P*(*accept*)] Generated by Equation (2)

	Families		Singles
P(*accept*)	imputations based on family data (1)	imputations based on individual data (2)	imputations based on individual data (3)
$P = 0.0$	0.253	0.225	0.567
$0.0 < P \le 0.1$	0.643	0.394	0.344
$0.1 < P \le 0.2$	0.104	0.381	0.090
Mean *P*(*accept*)	0.034	0.072	0.021

NOTE: Distributions shown are based on a nationally representative sample of Medicaid recipients. For the family distribution in column 1, *P*(*accept*) is calculated with *C*(*priv*) and *E*(*priv*) imputed using family-level data and *income* equal to family income. For the family distribution in column 2, *P*(*accept*) is calculated with *C*(*priv*) and *E*(*priv*) imputed using individual-level data and *income* equal to income per family member. See Section 3 for a description of the data and Sections 2.3 and 4 for a discussion of the required imputations.

Table 5
Implications of Equation (3) for Accepting the Tax Credit and Switching from Uninsured Status to Private Health Insurance

Cases	*C*(*priv*) (1)	*C*(*priv*) – *E*(*priv*) (2)	*income* (3)	*C*(*priv*) / *income* (4)	Income factor (5)	*P*(*accept*) (6)
1. Family—20th percentile	3,108	2,000	12,393	0.251	0.561	0.226
2. Family—median	5,686	2,000	27,040	0.210	0.624	0.137
3. Family—80th percentile	11,211	2,000	53,170	0.211	0.623	0.069
4. Single—20th percentile	861	861	1,000	0.861	0.019	0.012
5. Single—median	1,419	1,000	11,440	0.124	0.767	0.338
6. Single—80th percentile	3,630	1,000	24,258	0.150	0.723	0.124

NOTES: Variable definitions are as follows: *C*(*priv*) = premium for private nonemployer health insurance; *E*(*priv*) = expenditure on private insurance after tax credit; *income* = family income; "Income factor" in column (5) refers to the squared term in equation (3).

Data in columns 1, 2, and 3 are derived from the 1999 Current Population Survey and the 1999 Survey of Employer-Sponsored Health Benefits. See Section 3 for a description of the data and Section 4 for a discussion of the required imputations.

Table 6
Frequency Distributions of the Probability of Accepting a Tax Credit and Switching from Uninsured Status to Private Health Insurance [*P*(*accept*)] Generated by Equation (3)

	Families		Singles
P(*accept*)	imputations based on family data (1)	imputations based on individual data (2)	imputations based on individual data (3)
$P = 0.0$	0.125	0.122	0.251
$0.0 < P \leq 0.1$	0.316	0.161	0.130
$0.1 < P \leq 0.2$	0.249	0.119	0.111
$0.2 < P \leq 0.3$	0.139	0.095	0.101
$0.3 < P \leq 0.4$	0.074	0.114	0.105
$0.4 < P \leq 0.5$	0.048	0.145	0.114
$0.5 < P \leq 0.625$	0.049	0.245	0.189
Mean *P*(*accept*)	0.159	0.290	0.241

NOTE: Distributions shown are based on a nationally representative sample of Medicaid recipients. For the family distribution in column 1, *P*(*accept*) is calculated with *C*(*priv*) and *E*(*priv*) imputed using family-level data and *income* equal to family income. For the family distribution in column 2, *P*(*accept*) is calculated with *C*(*priv*) and *E*(*priv*) imputed using individual-level data and *income* equal to income per family member. See Section 3 for a description of the data and Sections 2.4 and 4 for a discussion of the required imputations.

Table 7
Estimated Hedonic Functions for Group Health Insurance Premium and Employer's Share of Health Insurance
(OLS coefficients with absolute value of t-statistics in parentheses, except where noted)

	Group health insurance premium		Proportion paid by employer	
	family plan	single plan	family plan	single plan
Company employment				
<10	–23.73	4.03	0.070*	0.035
	(1.81)	(0.64)	(2.53)	(1.69)
10–24	16.17	6.60	0.040	0.034
	(1.34)	(1.14)	(1.54)	(1.72)
25–99	19.03*	–0.96	–0.063**	–0.01
	(2.10)	(0.22)	(3.39)	(0.66)
100–499	25.85*	0.58	0.028	0.000
	(2.54)	(0.12)	(1.39)	(0.01)
500–999	1.59	–8.89*	0.065**	–0.006
	(0.20)	(2.30)	(4.55)	(0.53)
>999	ref	ref	ref	ref
Industry				
mining, construction, wholesale trade	0.06	–13.02*	0.032	–0.085**
	(0.00)	(2.09)	(1.23)	(4.21)
manufacturing	–26.52*	-9.43	0.008	–0.092**
	(2.28)	(1.69)	(0.34)	(5.10)
transportation	–17.20	–18.86**	0.081**	–0.069**
	(1.20)	(2.73)	(2.85)	(3.03)
retail trade	20.53	–18.36**	–0.162**	–0.232**
	(1.56)	(2.85)	(6.34)	(11.48)
finance	–11.076	–4.89	–0.047	–0.074**
	(0.88)	(0.80)	(1.84)	(3.74)
service	-1.43	–0.28	–0.060**	–0.058**
	(0.14)	(0.06)	(2.80)	(3.50)
health care	20.69	7.87	–0.092**	–0.099**
	(1.72)	(1.35)	(3.96)	(5.45)
high tech	1.11	–14.34*	–0.010	–0.084**
	(0.09)	(2.31)	(0.41)	(4.26)
state/local government	ref	ref	ref	ref
Urban	1.36	–3.79	0.012	–0.012
	(0.22)	(1.27)	(0.95)	(1.23)
Region				
New England	54.63**	6.86	–0.033	–0.059**
	(3.87)	(1.01)	(1.17)	(2.61)
Middle Atlantic	ref	ref	ref	ref
East North Central	–14.46	0.74	0.006	–0.035*
	(1.38)	(0.15)	(0.29)	(2.20)
West North Central	–27.30*	–11.30*	–0.122**	–0.056**
	(2.29)	(1.98)	(5.23)	(3.07)

South Atlantic	–3.84	–4.98	–0.167**	–0.057**
	(0.36)	(0.98)	(8.06)	(3.49)
East South Central	–18.30	–19.25**	–0.116**	–0.048*
	(1.27)	(2.77)	(3.99)	(2.14)
West South Central	–0.48	1.33	–0.201**	–0.05**
	(0.04)	(0.23)	(8.59)	(2.72)
Mountain	–22.77	–8.60	–0.178**	–0.041
	(1.59)	(1.26)	(6.22)	(1.83)
Pacific	–16.73	0.62	–0.087**	0.011
	(1.39)	(0.11)	(3.75)	(0.63)
Constant	479.32**	225.69**	0.791**	0.969**
	(9.75)	(11.51)	(31.09)	(48.54)
Dependent variable mean	476.0	184.6	0.696	0.842
(standard deviation)	(115.8)	(156.3)	(0.249)	(0.191)
Observations	1823	1823	1612	1669
R-squared	0.20	0.21	0.18	0.10

NOTES: OLS regressions estimated using Kaiser/HRET Survey of company health insurance plans. All plans with complete information are included in the sample. Many companies report multiple plans. In addition to the independent variables displayed, the regressions include 192 indicator variables for characteristics of the plan.

"ref" denotes the reference category in a set of dummy variables.

* Significantly different from 0 at the 5% level (two-tailed- test).

** Significantly different from 0 at the 1% level (two-tailed test).

Table 8
Imputed Premiums and Employee Contributions for Employer-provided Health Insurance and Imputed Premiums for Market-based Health Insurance

	Mean monthly premium or contribution ($) (std. dev.) (1)	Min./max. ($) (2)	Annualized mean ($) (3)	N (4)
A: Imputed premiums for employer-provided group health insurance [*C*(*group*)]				
Family	472 (27.4)	396/585	5,664	28,349
Single	180 (12.7)	128/217	2,160	7,766
B: Imputed employee contributions for group health insurance [*E*(*group*)]				
B.1. Imputed employee share times imputed premium (from panel A)				
family	117 (111)	0/578	1,399	28,349
single	28 (38)	0/206	333	7,766
B.2. Imputed premium (from panel A) minus CPS-imputed employer contribution				
family	240 (131)	0/578	2,883	28,349
single	56 (61)	0/207	668	7,766
C: Imputed premiums for market-based health insurance, various groups [*C*(*priv*)]				
All families	585 (505)	27/7540	7,020	31,305
All singles	263 (311)	35/1956	3,156	15,139
Families with group health insurance	564 (450)	27/4962	6,768	20,896
Singles with group health insurance	228 (231)	35/1956	2,736	7,938
Uninsured families	565 (525)	32/6945	6,780	5,454
Uninsured singles	224 (278)	35/1950	2,688	4,012
Privately insured families	613 (538)	27/5895	7,356	2,316
Privately insured singles	224 (261)	39/1950	2,688	1,858
Families on Medicaid	666 (684)	55/7540	7,992	1,918
Singles on Medicaid	615 (542)	43/1956	7,380	948

NOTES: Imputations summarized in panel A were obtained by applying characteristics of CPS workers and their employers to the hedonic health insurance premium functions displayed in Table 7.

See Section 4.1.

Imputations summarized in panel B.1 were obtained by applying characteristics of CPS workers and their employers to the share functions displayed in Table 7, then applying the imputed shares to the imputed health insurance premiums (panel A). Imputations summarized in panel B.2 were obtained by subtracting the employer contribution reported in the CPS (imputed by BLS) from the imputed premium (panel A). See Section 4.2.

Imputations summarized in panel C were obtained from equation (4). See Section 4.3.

Table 9
Results of Simulation: Group Take-up Rates, Number of Individuals Accepting Tax Credit, and Net Government Cost of Tax Credit

	Take-up rate (%)		Number of individuals accepting (millions)		Net government cost ($ billions)	
Group	lower bound (1)	upper bound (2)	lower bound (3)	upper bound (4)	lower bound (5)	upper bound (6)
1. Covered by employer-provided group insurance						
a. hedonic imputation of employer contribution	3.3	21.6	4.9	32.4	1.9	9.8
b. BLS imputation of employer contribution	7.4	35.4	11.1	53.2	5.5	22.0
2. Covered by private nonemployer insurance	50.0	90.0	10.4	18.6	9.5	17.1
3. Covered by Medicaid	3.3	6.7	0.6	1.3	–2.2	–4.9
4. Uninsured	17.5	28.3	7.7	12.5	7.4	9.7
Total	na	na	23.6–29.8	64.8–85.6	16.6–20.2	31.7–43.9

NOTES: For individuals covered by employer-provided group health insurance, lower-bound simulations are based on equation (1); upper-bound simulations are based on the assumption that all workers who would reduce their expenses by switching to private insurance do so. See Section 2.1. The alternative simulations for individuals covered by employer-provided insurance are based on two alternative imputations of *E*(*group*). See Section 4.2 and Table 2.

For individuals covered by private nonemployer insurance, lower-bound simulations are based on the assumption that 50 percent of covered individuals accept the tax credit; upper-bound simulations are based on the assumption that 90 percent accept the tax credit. See Section 2.2.

For individuals covered by Medicaid and for uninsured individuals, lower-bound simulations are based on the assumption that decisions to accept the tax credit are made for entire families; upper-bound simulations are based on the assumption that decisions to accept the tax credit are made individually. See Sections 2.3 and 2.4.