The Urban-Brookings Tax Policy Center Microsimulation Model: Documentation and Methodology for Version 0304

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A. Introduction

The Urban-Brookings microsimulation tax model is a powerful tool for federal tax policy analysis.[1] The model calculates tax liability for a representative sample of households, both under the rules that currently exist (current law) and under alternative scenarios. Based on these calculations, the model produces estimates of the revenue consequences of different tax policy choices, as well as their effects on the distribution of tax liabilities and marginal effective tax rates (which affect incentives to work, save, and shelter income from tax). The model is also a useful input to research on the effects of taxation on economic behavior.

Overview

The Urban-Brookings Tax Policy Center model is a large-scale microsimulation model of the U.S. federal tax system. The model is similar to those used by the Congressional Budget Office (CBO), the Joint Committee on Taxation (JCT), and the Treasury's Office of Tax Analysis (OTA).

As its name suggests, a microsimulation model uses microdata—or data on individual units—rather than aggregate information.[2] In general, input data are comprised of detailed information at the individual or household level that may be used to calculate tax liability. The sample includes weights that represent how many units are represented by the individual record.[3]

[1] This document details the methodology underlying version 0304 of the model, which was developed in March 2004. The Tax Policy Center will publish revised versions of this paper as it updates the model.

[2] For a detailed explanation of microsimulation models, see http://trim.urban.org

[3] The weights equal the inverse of the sampling probability. Thus, for example, if a record was sampled at a rate of 1 in 1,000 (so the probability equals 0.001), the sample weight would be 1,000. In other words, that record represents 1,000 individuals or households.

Estimates for the entire population may then be derived by multiplying the individual estimates by the sample weights and summing them.

In the case of the tax model, the population is the universe of individuals who file income tax returns as well as those individuals whose incomes are too low to require them to file a return ("nonfilers"). The data are a stratified sample of individual income tax returns augmented by information about nonfilers (see discussion below). The tax-calculator portion of the model then applies applicable tax law to each of the individual records in the microdata file and calculates values for variables such as adjusted gross income (AGI), nonrefundable credits, individual income tax liability, and so on. The values of the variables calculated for each individual record are then multiplied by the weight associated with that record to tabulate aggregate results such as total income tax liability for the entire population.

The tax model is not only able to calculate tax liability under current tax law but is also able to simulate alternative policy proposals. It is therefore straightforward to calculate the change in aggregate tax liability from a tax policy proposal and also to determine which class of individuals would benefit from or bear the burden of the tax change.[4]

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[4] We note two items here: (1) static versus dynamic estimates and (2) statutory versus economic incidence. First, the revenue estimates produced by the model are purely static in nature. A static revenue change ignores the impact of any change in behavior that a policy proposal could cause and also does not take into account any macroeconomic effects of the proposal. For example, an increase in the top statutory marginal tax rate could cause a shift in compensation away from taxable wages and salaries toward untaxed fringe benefits. A purely static analysis would not capture this effect and would likely overestimate the potential revenue gain. Revenue estimates produced by JCT typically include the effect of behavioral changes but not the macroeconomic feedback effects. Behavioral responses can also change the burden of a tax change. For example, the burden of a tax increase on individuals may be smaller than the static change in tax because taxpayers change their behavior to avoid the tax. Thus, static distributional tables tend to overestimate the economic burden of tax increases and underestimate the burden of tax cuts.

Second, burden estimates reflect the *statutory* incidence—that is, the direct effect on individuals who pay the tax. The *economic* incidence of the tax may be different. For example, wage subsidies such as the earned income tax credit (EITC) may partially benefit employers who may be able to pay EITC recipients a lower wage. In that case, the economic incidence of the tax would be shared between the direct recipients (low-wage workers) and the indirect beneficiaries (their employers).

The tax model also has the ability to produce estimates for years beyond the year of the input data file (currently 1999). This is made possible by “aging” the individual records in the microdata file. In the aging process, the information on each record—such as the amount of wages and salaries and other forms of income—as well as the weights associated with each record are adjusted based on forecasts from several sources including CBO and the Bureau of the Census.

History

The TPC produced the first version of its microsimulation tax model in 2002.[5] Some of the early research that used estimates produced by the model included an analysis of the effects of the Economic Growth and Tax Relief Reconciliation Act of 2001 (EGTRRA) on low-income families and children as well as a detailed study on the looming problem of the alternative minimum tax (AMT).[6]

A more comprehensive version of the tax model was put in place in the spring of 2003. This updated version improved the original model and expanded its scope in several ways. First, we updated the input data to incorporate the most recent microdata file available from the IRS. Second, we updated our projections and forecasts using the latest economic data available from CBO. Finally, we added the capability to carry out distributional analysis on the entire population by adding nonfilers for the first time, through a statistical match with the Current Population Survey (CPS).

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[5] John O’Hare and Frank Sammartino were instrumental in developing and programming this first version of the model.

[6] See Burman, Maag, and Rohaly (2002) and Burman et al. (2002).

The most recent version of the model was developed in March 2004 and includes the latest economic forecasts from CBO as well as several model enhancements. First, we added a retirement savings module that, among other things, imputes contributions to tax-deferred savings vehicles such as IRAs (both traditional and Roth) and 401(k) plans. Second, we added an estate tax module to the model that allows us to calculate the expected value of net estate tax liability for each record in the tax model database. We also began distributing the burden of the corporate income tax to individuals. Through these improvements, the distribution tables produced by the TPC now include the following federal taxes that in 2003 accounted for about 93 percent of all federal tax revenues: individual and corporate income; payroll; and estate (CBO 2004). Third, we developed two measures of income for our distribution tables that are broader than adjusted gross income (AGI), the qualifier that we used in tables produced by the first two versions of our model. One measure is similar to the income concepts used by Treasury, JCT, and CBO; the other is a broad measure of economic income similar to the one used at Treasury until 2001.

We are currently producing an education module for the model that will allow us to estimate the revenue and distributional effects of the various education provisions in the tax code. We will also continue to update the model using the latest economic and demographic forecasts and projections, as well as the latest microdata released by the IRS.

B. Source Data

SOI Public Use File

The primary data source for the tax model is the 1999 Public Use File (PUF) produced by the Statistics of Income Division (SOI) of the Internal Revenue Service (IRS).[7] The PUF contains 132,108 individual records, sampled from the 127.1 million individual income tax returns filed for tax year 1999. The records in the PUF are a stratified probability sample; the population of tax returns is divided into subpopulations (strata), from which the samples are then independently selected. The weights associated with each sample are calculated by dividing the total number of returns in a stratum by the number of sample returns for the stratum.

Each record in the PUF has 38 indicator codes and 199 quantitative fields. The indicator codes are descriptive in nature and provide information such as filing status, the number of dependent exemptions, and whether or not certain forms such as those for the alternative minimum tax, the child and dependent care credit, and the general business credit are attached to the return. The quantitative fields include the various sources of income, adjustments to income, itemized deductions, and other quantities reported on lines on the individual income tax form and supporting schedules.[8] Although most fields are taken directly from the lines on the tax forms, some fields are totals or subtotals that do not necessarily appear on the tax forms but which are helpful in programming the calculation of tax liability because they provide information about residual amounts either not reported on the tax return or not included in the PUF.

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[7] For a complete description of the SOI public use file, see Weber (2003). Much of the information in this section draws on that document.

[8] The weight on each individual record is included in the quantitative fields.

The SOI file used by Treasury, JCT, and CBO is more complete than the PUF. In order to protect the identity of individuals, some measures have been taken to ensure that the records on the public version of the file remain unidentifiable. These measures include the following:

- Excluding information such as names, Social Security numbers, and ages.
- Subsampling the high-income group—those with AGI greater than $200,000—at a 33 percent rate and excluding tax returns for 191 individuals with extremely high incomes who might otherwise be easily identified based on publicly available information.[9]
- "Blurring" some fields in the records. Blurring is a process that attempts to obscure individual data without significantly altering aggregate totals for the items that are blurred. Although the specifics are somewhat different for the various blurred fields, in general the records are first sorted in descending order with respect to the given field, such as wages and salaries. Then for every three records, the average of the three values for that field is used as the blurred value for each of the three records. Along with wages and salaries, other fields that are blurred include state and local income tax deductions, real estate tax deductions, net receipts, and alimony paid and received.
- Modifying or removing certain codes and fields for high-income returns. For example, alimony paid and received, all geographic indicators including state of residence, as well as the blindness indicator have been removed; the number of exemptions for children living at home has been top-coded at three.[10]

[9] Other types of returns that are included in the 100-percent sample of the complete tax file are subsampled at that same 33 percent rate for the public-use version. These include those with total income or loss of $5 million or more; those with business plus farm receipts of $50 million or more; and nontaxable returns with AGI or expanded incomes of $200,000 or more.

[10] These modifications are also performed on the other types of returns included in the 100 percent sample of the complete tax file.

In some cases, similar fields have been aggregated or combined and only the total value is provided in the public-use file. For example, capital gains and losses are not provided separately; the PUF gives only a single value for net long-term and net short-term gains (gains less losses). All interest paid deductions, including those for home mortgage interest and investment interest, have been combined into a single field. Similarly, an aggregate value for most AMT tax preference items is provided instead of the individual items themselves. A disadvantage of having access only to these combined fields is that the individual items cannot be aged at different rates, even when separate growth rates would be warranted for each field. In addition, it makes it necessary to use some form of imputation to examine certain policy options. For example, it would be necessary to impute a value for home mortgage interest alone in order to examine the effects of eliminating it as a tax preference while retaining the deduction for investment interest.

In the tax model, some of the missing fields such as age are imputed as described in the section on statistical matching and imputation.

Secondary Data Source: The Current Population Survey

We use the March 2000 Current Population Survey as a secondary source of data for the tax model. We use the CPS data for several purposes: replacing some fields that are missing in the PUF, such as the age of the primary and secondary taxpayer and their dependents; obtaining information on sources of income that are not reported on income tax returns, such as welfare benefits; and creating a database of individuals who do not file federal income tax returns. We use the information on other sources of income to create broader measures of income for use in our distribution tables (see discussion below). Including the nonfilers allows us to carry out distributional analysis for the population as a whole rather than just the subset that files federal individual income tax returns.

The CPS data contain three types of records—household, family, and person level—while the SOI data contain records at the tax return or "tax unit" level, which may be either an individual, family, or household, depending on how many persons are claimed on a tax return. Thus, to make use of the CPS data in the tax model, we first need to create tax units from the information in these CPS records. A tax unit consists of an individual or married couple that would—if their income were above the filing thresholds—file an individual income tax return. The tax filing unit also includes any other persons who would be claimed as dependents on that tax return. For example, a single person who files a tax return for herself is one tax unit, as is a married couple with three children that files one tax return for the whole family. However, a family in which a working daughter files her own tax return and each of her parents files as "married filing separate" would constitute three tax units.

Once they are created, the tax units are then separated into filing and nonfiling records. Finally, the CPS tax unit records are statistically matched to the SOI records; those records in the CPS that are not matched to any SOI records become the database of nonfilers.

Creating Tax Units in the CPS

Creating a tax unit involves joining the records of married individuals, and searching for dependents among other household members and linking them to their parents' records.

We first iterate through all the individuals in a CPS household. If an individual is married, the CPS record has a pointer to his or her spouse's record; this allows us to combine the two records by aggregating their separate income items. The record of the spouse is then flagged so that when we encounter it in the iteration process, we do not treat it as another separate tax unit.

We then search the other household members for dependents of this married couple. Several criteria classify a filer as a dependent. First, the individual must be related to the primary tax unit, be unmarried, and meet the income and support tests. The income test requires all dependents that are not children of the primary taxpayer to earn less than $2,750.[11] If the household member is a child of the primary taxpayer under 18 years of age or attending school but under age 24, this threshold does not apply. The support test stipulates that the primary tax unit must provide more than half the financial support for a household member to qualify that member as a dependent.[12] If there are any dependents, the records of the dependents are linked to the primary tax unit, the count of dependents for this tax unit is incremented, and the record of the dependent is flagged. A separate tax unit is created for each dependent only if his or her income exceeds the tax-filing threshold for dependents.

After all the tax units for a household are created, the tax units within the household are searched for dependencies. If the household is comprised of related subfamilies and if the tax unit with the highest income in the household has more than twice the income of any particular subfamily, we attach the members of that subfamily to the highest-income tax unit as dependents.[13] Furthermore, if these dependent tax units have no income, they are no longer considered to be a separate tax unit. We search for the dependents a second time because during

[11] In practice, we had to relax this threshold to hit the distribution of tax units by filing status.

[12] For example, parents whose family is on welfare most of the year may not be able to claim their children as dependents if the government, and not the parents, has provided more than half the children's support. Similarly, a single parent in this situation may not be able to file as a head of household.

[13] We do not perform this procedure if the tax unit with the highest income in the household is a dependent.

the first pass, we searched for dependents only in the immediate family and not in the subfamilies of the household.

The last step in processing each CPS household is to determine if any tax units within it can qualify for head of household filing status. The status of a nondependent single tax unit is changed to head of household if its income is more than a quarter of the total household income and there is at least one dependent.

After all the households have been processed and the tax units have been created, those tax units that will file an income tax return have to be separated from the nonfilers. We first apply the current-law income thresholds for 1999 to determine whether a CPS tax unit files a tax return.[14] Separating filers and nonfilers in this manner leaves us only with filers who are legally required to file a tax return. Some tax units, although not legally required to do so, file a tax return anyway for various reasons. For example, some file to claim refundable tax credits, or to recover excess withholding of wages and salaries. Other tax units file for no apparent reason. In past versions of the model we have accounted for these filers by simply easing the filing restrictions. That is, in addition to assuming that all wage earners would be tax filers, we lowered the income thresholds for filing until the number of filing tax units in the CPS more closely matched that in the PUF.[15]

In the latest version of the model, however, we employ a different method for determining which of the tax units with income below the filing threshold would actually file a tax return. Cilke (1998) uses probit maximum likelihood to estimate the probability that a tax

[14] The dependent tax units are all classified as filers. Had they not been required to file, they would have been combined with other tax units by this point.

[15] Finally, if required, we would randomly assume records initially designated as nonfilers would instead file tax returns.

unit with income below the tax-filing threshold actually files a tax return.[16] We use the coefficients from Cilke's probit estimates to calculate the probability of filing p for each of the CPS tax units that we initially determined were not required to file. We then draw a random number z between 0 and 1 from the uniform distribution. If $z < p$, then the tax unit is deemed to become a filer. We adjust the constant term in the probits—with separate adjustment factors by filing status and the number of dependents—until we match the number of filing units in the PUF as closely as possible.[17]

The records of the nonfiling units from the CPS are appended to the PUF once the PUF has been matched to the CPS filing units. In the augmented data file, the sum of the filing population and the nonfiling population approximates to the population of the United States in 1999.

Statistical Matching of SOI and CPS data

Statistical matching is a method of combining two or more data sources and constructing a single matched data set that contains joint information that is available only separately on the original data sets.[18] The goal in matching is to merge the data in a manner that preserves the

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[16] Cilke ran probit maximum likelihood on the March 1991 CPS and 1990 SOI Federal Tax Return exact match data file. The population of tax units with income below the filing thresholds was divided into nine unique groups based on dependent status, marital status, presence of children, and whether the age of the primary tax payer was greater than 62. The probits were run separately for each of the groups with the following explanatory variables: AGI divided by filing threshold and dummy variables for gender, education level (less than 10th grade, 11th or 12th grade, 1 to 3 years of college), household status (head of household), race (black, Asian or Indian, Hispanic), living quarters (house or apartment), activity the week before the survey (in the labor force, housekeeping or in school, unable to work, retired), presence of earned income, presence of unearned income, presence of taxable transfers, public housing assistance, presence of food stamps, presence of Social Security benefits, presence of Supplemental Security Income, presence of AFDC, and presence of other benefits.

[17] Although the Cilke estimates are dated, they are the only evidence of which we are aware that details the filing behavior of CPS participants.

[18] For an overview of statistical matching, see Ingram et al. (2000).

relationships between the variables as much as possible. In the tax model, the PUF and CPS records are combined using a specific form of matching called *constrained* statistical matching.

In statistical matching in general, one file is considered the host file and the other the donor file. For our purposes, the PUF serves as the host file and the CPS serves as the donor.[19] Denote the common variables in the two files as *X*, the rest of the variables in the host file as *Y*, and the remaining variables in the donor file as *Z*. The purpose of statistical matching is to create a third file—the matched file—that contains all of the variables *X*, *Y*, and *Z*.

There are two forms of statistical matching: unconstrained and constrained. Unconstrained statistical matching does not require all the records in the donor file to be used in the merging process. Constrained matching uses all records from both the host and the donor file but since the number of records in the two data files is not necessarily the same, some records might be used more than once in the construction of the matched file. A necessary condition for constrained matching to be successful is that the weighted population totals are the same for both data sources.[20] A disadvantage of constrained matching is that the "distance" between the matched *X* variables—the common variables—in the two files might end up being large, as outlined below. The advantage is that the weighted sample means and the variances of the *X*, *Y,* and the *Z* variables are preserved.[21] Although unconstrained matching is simple and intuitive, Paass (1985) and Rodgers (1984) believe that the probability of a "poor" match is higher with

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[19] In what follows, we refer to the CPS as the donor file. To be specific, we mean the file of tax units created from the CPS as described in the previous section.

[20] In practice, this is rarely the case and the weights in the donor file are adjusted to ensure this condition holds. The way in which we do the reweighting in the tax model match is explained in more detail below.

[21] This is only technically true when no weight adjustments are necessary to ensure the population totals are the same for the host and donor files. In practice, with modest weight adjustments such as those that are necessary in the tax model match, the means and variances in the matched file are still close to their original values in the donor file.

unconstrained matching. We use a form of constrained statistical matching to generate the tax model database.

When constructing the matched file, the overarching concern is to match only records that are similar or "close" to each other. The tax model uses *predictive mean matching* to measure the "closeness" of records and perform the match. There are four steps involved in our implementation of a predictive mean match between the PUF and the CPS.

Step One: Partitioning

Partitioning is performed to prevent the merging of records with inherently different characteristics. For example, we do not want to merge records that have different filing statuses. In order to prevent this, data from each file are divided into categories; only records within these categories or "cells" have the possibility of being matched to each other.

In order to conduct the partitioning, we first separate the dependent and nondependent records. The nondependents are then classified by filing status, the number of dependents, the presence of self-employment income, the presence of capital income, and an indicator for whether the primary taxpayer is age 65 or over.[22] The dependents are classified by the presence of self-employment and capital income. After this initial partitioning, certain cells are combined into larger categories to ensure that the cell sizes are not "too small."[23] For example, there are very few single filers with two or three dependents. Thus singles with two or three dependents

[22] The CPS provides age but the PUF does not. Before the match occurs, we impute an "aged" indicator on the PUF using information from the additional standard deduction that those 65 and over are entitled to, as well as the presence of Social Security income. This is discussed in more detail below. In addition, the CPS does not report realized capital gains and so capital income here refers to the presence of interest income (either taxable or tax-exempt) or dividends.

[23] We generally regrouped cells that had fewer than 30 records.

are combined to form one category that includes all singles with more than one dependent. The partitions we use are shown in table 1.

Step Two: Estimation

In predictive mean matching, the procedure is to run a weighted regression with one or more of the *Y* and/or *Z* variables as dependent variables and the common *X* variables as explanatory variables. We implement predictive mean matching by using taxable income as the dependent variable and thus run the following regression using the PUF data:

Taxable Income = β_0 + β_1*(Dummy for the Aged Status) + β_2*(Wages and Salaries) + β_3*(Taxable Interest) + β_4*(Dividend Income) + β_5*(Business income or loss) + β_6*(Farm income or loss) + β_7*(Schedule E Income) + β_8*(Pensions) + β_9*(Social Security Income) + β_{10}*(Unemployment Compensation) + β_{12}*(Alimony) + β_{13}*(Wage Share of Total Income) + β_{14}*(Capital Income Share of Total Income) + β_{15}*(Dummy for Presence of Wage or Salary Income)

The regressions are run separately within each cell; dummy variables are excluded in cells in which all observations have the same value.

Step Three: Obtain Fitted Values

In general, the next step is to calculate the fitted values of the *Y* and/or *Z* variables for both the host and donor files. That is, the coefficients on the *X* variables that were obtained in the regression using the host file, are then used to calculate fitted values for the *Y* and/or *Z* variables in both the host and donor files. Specifically, in the case of the tax model, we use the coefficients from the regression described above, along with the actual values of the explanatory variables in each file, to construct fitted values for taxable income for each record in both the CPS and the PUF.

Step Four: Align Partitions and Perform the Match

A necessary condition for constrained matching is that the weighted population totals must be the same for both files. In order to implement this requirement in our predictive mean match, the weights on each CPS record are multiplied by a factor such that the total of the CPS weights in each partitioned cell adds up to the total SOI weight for that partition (see table 1).

In a general predictive mean match, the records in each cell would then be sorted in descending order by the predicted values of one of the Y and/or Z variables. In the case of our tax model match, the cells are sorted by the predicted values of taxable income. Corresponding records from the PUF and the CPS are then matched within each partitioned cell. Of the two records, the one with the higher weight must be split or duplicated and matched with the next record or next several records in the other file until all of its weight has been "used up." Thus, each record in the host PUF file is matched to that record in the donor CPS file that is "closest" in terms of having the most similar predicted value of taxable income among all records within the partition. Since the weights on the CPS file have been adjusted to equal the total PUF weights, all records are used in the match. One possible disadvantage of using all the records to perform the match is that some records might be matched despite having a large difference between the predicted values of taxable income in each of the files.

One advantage of a constrained statistical match in which the population totals are the same in the host and donor files is that the means and variances of the variables added to the host file are the same as they were originally in the donor file. As discussed above, however, the population totals for our match are not exactly identical and we adjust the CPS weights to ensure that the weighted totals within each partitioned cell are equal. This can cause the means and variances of the variables added from the donor file to differ from their original values. Table 2 provides an analysis of our match by comparing the means and variances in the original CPS donor file with their values in the matched file. It shows that even with the reweighting to match the PUF, the overall means and variances of the variables brought over from the CPS are, in virtually all cases, very close to their original values.

Imputation of Other Variables

There are several variables important for the calculation of tax liability or for distributional analysis that are not available through the match with the CPS and must therefore be imputed.

"Aged" Indicator: Individuals Age 65 or Over

Beginning with the 1996 PUF, the indicator code for whether the primary and/or secondary taxpayer is age 65 or over is no longer provided. This indicator is useful for at least two reasons. First, to simulate a policy proposal that impacts elderly individuals—such as changing the taxation of Social Security benefits—we want the ability to produce distribution tables showing the impact on just that segment of the population. Second, the indicator is required for us to implement our matching technique. As described above, we separate records in which the individual (or both individuals in the case of a married couple) are under age 65 from those records involving individuals 65 or over. We then match only records within these age categories; this ensures that a 75 year old is not matched to a 25 year old. Thus, before we perform the match, we must impute the aged indicator for each record in the PUF in order to be able to properly assign records into partitioned cells.

To impute the aged indicator, we look first at the size of the standard deduction that the tax unit takes. In 1999, a single taxpayer is eligible for an additional $1,050 if he or she is age 65 or over; a married couple is entitled to an additional $850 for each member of the couple that is age 65 or over. Thus, by examining the amount of the standard deduction actually claimed, it is possible to estimate whether the individual (or members of a couple) are 65 or over.[24] This method cannot be applied if the tax unit itemizes rather than taking the standard deduction. For records that itemize deductions, we make the simplifying assumption that if there is reported Social Security income, then the primary taxpayer is age 65 or over. For married couples, if the Social Security benefits reported exceed the maximum possible amount that can be received by a single person, we assume that both individuals are age 65 or over. This could lead us to overestimate the number of seniors, since individuals can begin receiving Social Security benefits at age 62 and because we have no way of distinguishing between Social Security retirement and disability income. We also miss some taxpayers who are age 65 or over, however, because many state and local government employees participate in retirement programs outside of Social Security and could therefore be age 65 or over yet receive no Social Security income if they did not have sufficient covered earnings from other employment. Similarly, we undercount

[24] This is complicated somewhat by the fact that blind individuals are also entitled to this extra amount. The PUF does not provide the blindness indicator for high-income returns. We assume that all high-income returns that claim an extra standard deduction are age 65 or over. Note that, according to IRS statistics, fewer than 400,000 individuals claim the additional deduction for blindness.

taxpayers age 65 and over who delay claiming Social Security benefits.[25] In addition, our methodology for determining whether both members of a couple are 65 or over could undercount in situations where both spouses receive small amounts of Social Security income that do not total more than the maximum amount for a single individual. To account for all these potential difficulties, we use population projections from the Bureau of the Census to target the number of "aged" tax returns in future years in our aging and extrapolation process (see discussion below).

Other Income in AGI

The PUF provides all of the income items reported on Form 1040 except the various sources that are reported as "other income" on line 21. This includes items such as gambling earnings but also any net operating loss carryforward. Although other income is not large in relation to overall AGI, we impute a value for it as a residual.[26] The residual value for other income is calculated by taking the record's reported total AGI—which *is* provided in the PUF—and subtracting all the other reported income items and adding all adjustments to income for which the public-use file provides values. This procedure is not without complications, however, due to the blurring procedure that is described above. The value for wages and salaries has been blurred and is thus, in almost all cases, not the actual amount reported on the return. It is the actual amount, however, that is used in calculating the total value of AGI that is reported in the PUF. Thus the residual we calculate also captures some of the effect of this blurring. In addition,

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[25] In total, 11 percent of individuals age 65 and over did not receive Social Security benefits in 1998. See Social Security Administration (2000).

[26] According to SOI data for 1999, just under 5 million returns reported positive other income of about $27 billion; another 200,000 returns reported negative other income of about $4 billion. Reported AGI in 1999 was just under $5.9 trillion. About 600,000 returns reported a total net operating loss of $50 billion; 1.4 million returns reported a total of $15 billion in gambling earnings.

there are several adjustments to income that are not provided in the PUF and these will also show up in our residual.

Residual Itemized Deductions

Some itemized deductions, such as those for personal property taxes, are not provided on the PUF, presumably for disclosure reasons. Not including these itemized deductions would lead our model to underestimate the total amount of itemized deductions and the number of itemizers, and overestimate the number of filers taking the standard deduction. In turn, this could inflate revenue estimates for policy options that expand the standard deduction and distort distribution tables that show the impact of changes in the standard deduction.[27]

To avoid these problems, we calculate a residual itemized deduction amount and include it in our calculation of itemized deductions. The residual field is calculated in the same general manner as the residual for other income. We take the record's reported total amount of itemized deductions—which is provided in the PUF—and subtract all itemized deductions for which the public-use file provides values. Again, however, this procedure is affected by the blurring process. The values for state and local income tax deductions, and real estate tax deductions have been blurred and are thus, in almost all cases, not the actual amount reported on the return. It is the actual amount, however, that is used in calculating the total amount of itemized deductions that is reported in the PUF. Thus, as with our calculation of other income, the residual that we calculate also captures some of the effect of the blurring.

[27] SOI data for 1999 show that personal property taxes accounted for about $8 billion and were reported on about 19 million returns. Total itemized deductions for 1999 were just over $741 billion.

Capital Loss Carryover

The PUF provides short-term and long-term capital gains less losses before any capital loss carryover. The PUF also provides a field with the total net gain less loss from the sale of capital assets reported on Schedule D. We use this information to impute a value for the capital loss carryover as follows:

Capital Loss Carryover = Maximum { 0, Short term gains less losses before carryover + long term gains less losses before carryover—total capital gains less losses reported on Schedule D }

Number of Children under 17 and Number of Children under 19

Families may claim the child tax credit if they have the requisite earnings and children under age 17. To calculate this credit, therefore, it is necessary to impute the number of children under 17. There have also been proposals to relax the credit's age requirement to children under 19 and thus having a value for the number of children in each tax unit under that age is also important.[28]

As mentioned above, one of the variables added to the tax model file through the statistical match with the CPS is the age of each dependent; this provides a starting point for calculating the number of children eligible for the child tax credit. If a particular record from the PUF has been matched to a CPS record with the same number of dependents, we use the ages of the dependents that are obtained through the match to determine the number of children under age 17 in the tax model file. If that is not the case, we assume first that the number of children under the age of 17 for that record is the same as the number of exemptions taken for dependent

[28] See, for example, Carasso, Rohaly, and Steuerle (2003).

children living at home.[29] Since, however, dependents can be under age 19 (or under age 24 if in school) this will lead us to overestimate the number of children under 17. Thus we use data obtained from the Urban Institute's TRIM model that provides—by income class—the fraction of dependent exemptions that are for children under age 17. We then use these data, along with a random number draw, to determine the number of children under age 17. For example, suppose that a tax unit with AGI of $35,000 has five dependent children. Suppose that from TRIM, we know that for the $30,000 to $40,000 AGI range, 82 percent of the dependent exemptions that are claimed are for children under the age of 17. Thus each child for whom a dependent exemption has been claimed on the tax model record has a probability of $p = 0.82$ of being under the age of 17. We then iterate through each of the five children in the record, drawing a random number z between 0 and 1 from the uniform distribution each time. As long as $z < p$, then the child is considered under the age of 17. If $z > p$, he or she is considered 17 years of age or older. The same procedure is followed to determine the number of children under the age of 19.

Finally, SOI has published data on the distribution of the number of returns and amount of child tax credit claimed for 1999. We apply adjustment factors by income class to the number of children under age 17 variable in order to ensure that we match this published data as closely as possible.

[29] For example, heads of household with three or more children are one cell in the partitioning process. So it is possible that a head of household with four children in the PUF is matched with a head of household with only three children in the CPS and thus we would not have an age for all of the children on that tax model record.

Aging and Extrapolation

After the match between the PUF and the CPS, and the imputations described above, we have a database of individuals that are representative of the filing and nonfiling population for tax year 1999. To perform revenue and distributional analysis for future years, we “age” the data based on forecasts and projections for the growth in various types of income from the Congressional Budget Office (CBO), the growth in the number of tax returns from the IRS, and the demographic composition of the population from the Bureau of the Census.

We use a two-stage procedure to create a representative sample of the filing and nonfiling population for all years between 2000 and 2014. In the first stage, we inflate the dollar amounts for income, adjustments, deductions, and credits on each record by their appropriate per capita forecasted growth rates. For the major income sources such as wages, capital gains, and various types of nonwage income such as interest, dividends, Social Security income, and others, we have specific forecasts for per capita growth. Most other items are assumed to grow at CBO’s projected per capita personal income growth rate. In stage two, we use a linear programming algorithm to adjust the weights on each record, ensuring that the major income items, adjustments, and deductions match aggregate targets. For future years, we do not target the distribution of any item; wages and salaries on all records, for example, grow at the same per capita rate regardless of income.[30]

[30] We do, however, apply an adjustment factor to account for the drop in wages and salaries at the very top of the income scale that occurred between 1999 (the year of our data file) and 2001.

Stage I

We first need to predict the number of returns by filing status for each year from 2002 through 2014.[31] We begin by growing the number of returns using the annual average growth rate by filing status for the period from 1990 to 2000. We then compare the totals that this process generates to IRS estimates and projections for the aggregate number of individual income tax returns to be filed.[32] In general, this leads us to slightly overestimate the number of returns to be filed. We therefore apply an across-the-board adjustment factor to bring the totals in line with the IRS values.[33] The weight on each record in the tax model file for any given future year is then increased from its original 1999 value by the ratio of the projected number of returns of that filing status for that year to the number of returns in 1999. For example, there were 56.927 million single returns in 1999; our projection is 60.115 million for single returns in 2004. Thus the 2004 weight on each single record in the tax model database is equal to the original 1999 weight in the PUF multiplied by 60.115/56.927 or 1.056.

Next, we need to inflate the dollar amounts of various fields on each record for the years from 2002 through 2014.[34] In its annual Budget and Economic Outlook, CBO publishes estimates and projections for the growth rates of taxable personal income, wage and salary income, net positive long-term capital gains, unemployment compensation, and Social Security

[31] As of the time of our February 2004 extrapolation, SOI had released actual data up through the 2001 calendar year.

[32] These data are available for download at http://www.irs.gov/pub/irs-soi/3d6186t1.xls.

[33] For example, applying the 1990–2000 growth factors by filing status results in a total of 135.383 million returns for calendar year 2004 as compared to the IRS projection of 134.038 million. We then reduce the number of each type of return (single, married filing joint, head of household, and married filing separate) by a factor of 135.383/134.038, or approximately 1 percent, in order to match the IRS projection. Note that nonfiling tax units are grown at the rate appropriate for their "filing status"; that is, nonfiling single tax units are assumed to grow at the same rate as single filers, nonfiling married couples are assumed to grow at the same rate as married filing jointly returns and so on.

[34] Again, at the time of our extrapolation, we had access to actual SOI data for calendar years 2000 and 2001 and could use this actual data to inflate the various fields.

benefits; a single growth rate for all other forms of taxable income can be calculated as a residual (CBO 2004). We use these aggregate growth rates to calculate per capita growth rates for each filing status by dividing the total growth rate by the growth rate of the number of returns for each filing status. These per capita growth rates are then used to inflate the various income, adjustment to income, and deduction fields in the tax model database. For example, the CBO data imply that total wages and salaries in 2004 will be 19.01 percent higher than in 1999. As described above, the total number of single returns will be 5.6 percent higher. We therefore multiply the amount of wages and salaries on each single record by a factor of 1.1901/1.056 = 1.127 to arrive at each record's value for 2004 wages and salaries. Adjustment factors for records with other filing statuses are calculated in a similar fashion. As a default, we grow fields for which we do not have a specific per capita growth rate by the growth rate in per capita taxable personal income.

We make three other adjustments in the first stage of the extrapolation process. First, we adjust the growth rate of records in which the primary and/or secondary taxpayer is 65 years of age or over to reflect projected demographic changes.[35]. We use projections from the Bureau of the Census on the growth rate of the number of individuals age 65 or over compared to the growth rate of the total population. We then adjust the weight on each "aged" record—each record that includes a primary or secondary taxpayer that is 65 or over—by that ratio. For example, in 2014, the total population is projected to be 14.15 percent larger than it was in 1999; the number of individuals age 65 or over is projected to be 29.74 percent higher. We therefore multiply the weight on each "aged" record by a factor of 1.2974/1.1415 = 1.1366 to account for the more rapid growth in the elderly population.

[35] We adjust for other demographic changes including changes in the number of children over time in Stage II.

Second, we apply an adjustment factor to capture the marked drop in the number of people reporting capital gains in 2001 compared to 1999. According to published data from SOI, the number of returns reporting a taxable net gain fell by more than 40 percent between the two years.[36] We therefore randomly eliminate the net gains of approximately 40 percent of the (weighted) records for 2001. For years after 2001, we assume the percentage change in the number of people reporting a net gain equals the percentage change in aggregate net positive long-term gains projected by CBO, adjusted for growth in the population.[37] We then apply an appropriate elimination factor in order to implement this percentage change.

Third, we apply a reduction factor to the wages and salaries of high-income individuals in order to more accurately match the published distribution of wages by AGI class for 2001.[38] We then assume that the wages of those at the top of the income scale will gradually return to their 1999 share over the following years.

Stage II

In the second stage of the aging and extrapolation process, we use a linear programming algorithm to adjust the weights on the individual records in order to meet exogenous, aggregate targets.[39] Although the first-stage adjustments allow us to hit most of our desired targets reasonably well, the second stage eliminates any remaining differences. In addition, there are some targets that cannot be hit using the first-stage methodology. These include the number of

[36] This includes capital gains reported on Schedule D as well as capital gains distributions reported directly on Form 1040. We do not employ separate adjustment factors.

[37] This is roughly what happened between 1999 and 2001. Net positive gains fell by 37 percent; the number of returns reporting gains fell by 44 percent.

[38] Beginning in 2000, SOI began publishing the distribution of income sources and other tax items using a more detailed breakdown of AGI for those returns at the top of the income scale.

[39] We thank John O'Hare for providing us with the linear programming methodology.

children under the age of 17 (qualifying children for the child tax credit), the total population, and the number of dependent exemptions. Table 3 provides a list of the stage-two targets that we use in the latest version of the model.

In many cases, we construct the targets by taking the totals from the last year of published data—generally 2001—and applying the aggregate growth rates calculated during Stage 1 of the extrapolation process.[40] For the number of children under the age of 17, we take the model-generated value for 1999 and grow it at the projected rate of growth for that segment of the population using data from the Bureau of the Census. Similarly, for the number of dependent exemptions, we take the 2001 value and then grow it at the rate projected for individuals under the age of 19. The total population projections also come from the Census.

The linear programming algorithm attempts to hit the targets we provide by changing the weights on the records. It does so by minimizing the sum of the absolute values of the percentage changes in the weights subject to the constraint that the exogenous targets are met. We set a tolerance parameter that limits the maximum percentage change that can be applied to any given weight. Since we have a relatively small number of targets, and since the first stage of the adjustment process brings us very close to many of the targets, we are generally able to impose a small tolerance level. For example, in the latest version of the model, tolerance levels in the various years range from 0.10 to 0.30, implying that none of the weights are changed by more than 30 percent.

[40] The targets for 2000 and 2001 are generally the actual values published by SOI.

C. Tax Calculator

The tax calculator portion of the TPC model contains three elements: (1) a user-provided parameter file that defines the various provisions of the tax law that are to be applied to the microdata records; (2) FORTRAN code that calculates individual income tax liability for each record, as well as payroll taxes, estate taxes, and the imputed corporate tax burden; and (3) FORTRAN code that produces various output files that describe the results of the simulations.

The Parameter File

The parameter file is a text file that contains all the elements of the tax code and other variables that the user is allowed to vary when running simulations. In the current version of the model, the user has the ability to change more than 400 parameters.[41] The user-defined parameters include:

- Statutory marginal tax rates and the associated bracket thresholds;
- Dollar values for items such as personal exemptions, the standard deduction, the AMT exemption, and various credits;
- Phase-in and/or phaseout rates and thresholds for tax programs such as the earned income tax credit (EITC), the child tax credit, the personal exemption phaseout (PEP); the limitation on itemized deductions (Pease); IRAs (both traditional and Roth); and the Hope and Lifetime Learning credits;

[41] This includes parameters governing the individual income tax, payroll taxes for Social Security and Medicare, the estate tax, and the distribution of the burden of the corporation income tax.

- "Switches" that can be used to turn on or off various portions of the tax code such as each individual nonrefundable and refundable credit and the allowance of those credits against the AMT, the AMT itself, indexation of the brackets, standard deduction, exemptions, credit amounts, and various phase-in and phaseout thresholds;
- Average Consumer Price Index levels for the years when various tax programs started so that the inflation factors associated with the brackets and thresholds for these programs can be calculated.

In many cases, switches allow the user to "turn off" provisions that are currently in the tax code to determine the static revenue impact of repeal of such a provision or to determine who benefits from a particular provision. In other cases, these switches allow the user to "turn on" provisions that are not currently in the tax law but which are often mentioned as possible policy changes such as indexing the AMT for inflation.

In addition to the individual income tax parameters, the file also includes:

- Payroll tax rates for Social Security and Medicare, as well as the taxable maximum for the Social Security portion;
- The amount of corporate tax to be distributed to individual records;
- Parameters governing the federal estate tax, including rates and bracket thresholds, the amount of gross estate effectively excluded by the unified credit, and the amount allowed under the Qualified Family-Owned Business Deduction (QFOBI).

Table 4 provides a complete list of all model parameters.

In almost all cases, a tax model "run" consists of a baseline simulation followed by a simulation of an alternative policy proposal. The user therefore provides all of the parameters for the baseline simulation and then changes the required parameters for the alternative simulation in order to implement the specific policy change being considered. A single parameter file can contain the necessary information to run up to twenty simulations; generally, this would consist of a baseline and alternative for each of ten years.

Calculating Individual Income Tax Liability

The tax model contains a detailed tax calculator that captures most features of the federal individual income tax system, including the alternative minimum tax (AMT). The model reflects major income tax legislation enacted through 2004, including the Working Families Tax Relief Act of 2004, the Jobs and Growth Tax Relief Reconciliation Act of 2003 (JGTRRA), the Job Creation and Worker Assistance Act of 2002 (JCWAA), and the Economic Growth and Tax Relief Reconciliation Act of 2001 (EGTRRA). We model most of the major provisions of EGTRRA and JGTRRA, including the changes in marginal tax rates, the new 10 percent tax bracket, credits for children and for dependent care, itemized deduction limitations, personal exemption phaseouts, retirement savings provisions, the AMT, and the marriage penalty relief provisions, which increased the standard deduction, 15 percent bracket, and earned income tax credit for married couples. We also model JGTRRA's changes to the taxation of dividends and capital gains.

The heart of the tax calculator portion of the model is a set of FORTRAN routines that essentially perform the same calculations a tax filer would make in filling out Form 1040 and its accompanying schedules, and usually in the same order. We therefore focus on aspects of the calculations that may not be straightforward or that highlight the tax model's versatility in simulating alternative tax provisions.

After the parameter file is input, the model reads in a single record from the PUF-CPS matched database and ages the record. The first-stage growth factors are applied to all the appropriate fields and the Stage II-adjusted weight is read in from the database. Following this, federal payroll taxes for Social Security and Medicare are calculated. After this, the steps and order of calculations generally follows Form 1040. AGI is determined first and then the standard deduction to which the record is entitled as well as any itemized deductions are calculated. When calculating AGI, the deduction from income for contributions to Individual Retirement Arrangements (IRAs) is determined by the model's retirement savings module. In addition to determining traditional IRA contributions, the retirement savings module determines contributions to Roth IRAs and defined contribution pension plans. Details can be found in appendix A.

The model then performs a loop through which it determines the value of personal exemptions, taxable income, regular income tax liability before credits, alternative minimum tax (AMT), nonrefundable and refundable tax credits, and, finally, income tax liability after credits using first the standard deduction and then the record's itemized deductions. The model then chooses the form of deduction that results in the lowest level of income tax liability after credits.

The tax model has been used extensively to examine issues relating to the AMT and contains a detailed AMT calculator.[42] The PUF provides information on AMT adjustment and preference items for taxpayers who filed Form 6251 in 1999. However, when we simulate tax

[42] See Burman et al. (2004), Burman, Gale, and Rohaly (2003a), and Burman, Gale, and Rohaly (2003b). All three articles are available online at www.taxpolicycenter.org.

law and income levels for future years, individuals who were not subject to the AMT in 1999 could potentially be affected by the tax. This requires calculating AMT adjustments and preferences for all individuals in future years. Using the PUF, we calculate the major items that differ under the AMT system: state and local tax deductions, personal exemptions, miscellaneous deductions above the 2 percent floor, the standard deduction, the additional disallowance of medical deductions, and state and local tax refunds. Together, these provisions account for over 95 percent of the projected reconciliation between alternative minimum taxable income (AMTI) and regular taxable income by 2010 (Tempalski 2001). We also calculate a measure of "lost credits" under the AMT that includes disallowed amounts for the following credits, where appropriate: child, child and dependent care, elderly, HOPE, lifetime learning, general business, and prior year minimum tax.

As well as determining AGI, the model calculates two broader measures of income that we use as qualifiers in our distribution tables: cash income and economic income. Cash income is similar to the measures currently employed by Treasury, the Joint Committee of Taxation, and the Congressional Budget Office. Economic income is a more comprehensive measure still, similar to the measure used by the Treasury Department from the early 1980s until 2001. More details on our income measures can be found in appendix B.

Effective Marginal Tax Rates

The tax model can be used to examine the efficiency of the current tax system and alternative policy proposals since it has the capability of calculating *effective* marginal tax rates. Effective marginal rates often differ from statutory rates because of the phase-in and phaseout of tax provisions such as the Earned Income Tax Credit (EITC) and the child tax credit, as well as certain provisions that were essentially designed to create effective rates different from the statutory rates such as the phaseout of personal exemptions and the limitation on itemized deductions.

The tax model can calculate the effective marginal tax rate on the following types of income: wages and salaries, long-term capital gains, dividend income, taxable interest income, and other income. To calculate the effective marginal tax rate for each record, the tax model first calculates individual income tax liability under the tax law specified by the parameter file. It then increments the amount of income for which the marginal rate is being calculated by an amount that is also specified in the parameter file and recalculates the record's tax liability.[43] The effective marginal rate is then equal to the change in tax liability divided by the change in income. For example, if an additional $1,000 in wage and salary income causes a record's tax liability to rise by $150, then the effective marginal tax rate is reported as 15 percent.

Other Federal Taxes

In addition to determining individual income tax liability for each record in the database, the tax model calculates federal payroll taxes for Medicare and Social Security as well as the expected value of federal estate taxes. The model also distributes the burden of the federal corporate income tax to individual tax units.

[43] There is some flexibility in incrementing the income amounts. The increments can be in absolute dollar amounts, in percentage terms, or a combination of both.

Payroll Taxes

The tax model calculates federal payroll taxes for Social Security and Medicare. These payroll taxes are levied on an individual basis and the Social Security portion is applied only to earnings up to a specified maximum.[44] For married couples, the PUF only provides a joint total for wages and salaries.[45] Thus, in order to calculate payroll taxes for married couples, we need an estimate of the split of wages between each spouse. We use the wage split of the CPS record to which the PUF record was matched. Payroll taxes are actually calculated before individual income tax liability in the model because taxpayers are allowed to deduct one-half of self-employment taxes from their income when determining AGI and thus the calculation of AGI requires that the level of self-employment tax has already been determined. The payroll tax rates and the contribution and benefit base are set by the user in the parameter file.

In our distribution tables, we assume that the employee bears the burden of both the employer and employee portions of payroll taxes. This premise is widely accepted among economists; it is the same assumption made by CBO and JCT in its distribution tables and was the assumption used by Treasury when it produced distribution tables that included all federal taxes.

[44] For 2004, the contribution and benefit base is $87,900. The Social Security Old-Age, Survivors, and Disability Insurance (OASDI) tax rate is 6.2 percent for both employers and employees (12.4 percent on earnings from self-employment) on earnings up to that limit. The limit is adjusted annually for wage growth. There is no taxable maximum for taxes under Medicare's Hospital Insurance (HI) program; rates of 1.45 percent both for employees and employers are applied to all earnings (the rate is 2.9 percent for earnings from self-employment). We use the intermediate cost projections from the OASDI Trustees Report for values of the limit in future years.

[45] The PUF does provide separate values for self-employment earnings. The reported value of self-employment earnings is capped at the taxable maximum, however. We grow the reported amount using our estimate for per capita wage growth.

Corporate Income Tax

The tax model distributes the burden of the corporate income tax across individual records so that it can be included in distribution tables. The incidence of the corporate tax, however, is a controversial issue. Although it only directly taxes corporate income, the corporate tax could be passed on to labor in the form of lower wages, to consumers in the form of higher prices, or to the owners of all types of capital since the after-tax rate of return on corporate equity will affect the after-tax rate of return on other types of capital.[46]

We assume that the burden of the corporate tax falls on all capital income, the same assumption used recently in distributional analyses by CBO and formerly used by Treasury when it provided complete distribution tables; our methodology most closely resembles that of CBO. We first determine each return's share of aggregate capital income, defined as taxable and tax-exempt interest, dividends, realized capital gains, and net income from rents, royalties, and estates or trusts.[47] Each tax filing unit's share of the corporate tax burden is then calculated as total corporate tax liability multiplied by its share of aggregate capital income. Thus a return with 0.05 percent of aggregate capital income is assigned 0.05 percent of aggregate corporate tax liability. We rely on CBO (2004) for our projections of corporate tax liability, although any value for corporate tax liability can be entered in the parameter file. Thus, the tax model can

[46] See Cronin (1999) and JCT (1993) for summaries of the issues involved. Although JCT argued in 1993 for distributing the corporate tax to owners of corporate capital, it has abandoned distributing the corporate tax in its recent analyses of tax proposals.

[47] In order to temper the wide variations in realized capital gains that can occur across years, we apply a smoothing factor to each record's reported realization of long-term and short-term capital gains. The smoothing factor is equal to the ratio of aggregate net positive long-term gains for the given year relative to its average for the five-year period from 1992 through 1996. We rely on CBO (2004) for our forecast of net positive long-term gains.

estimate the distribution of the change in burden from a corporate tax proposal if provided with an estimate of the overall change in corporate tax liability that would result.[48]

Estate Tax

Calculating the burden of the estate tax is complicated. First, the incidence of the tax is unclear. Does it fall on the decedent, or on his or her heirs? In theory, the tax could be borne in part by capital or labor through its effect on saving. We follow Treasury's approach, as outlined in Cronin (1999) and assume the estate tax is borne by decedents, because there is little evidence of incidence on capital or labor, and there is no reasonable basis upon which to measure the effect on heirs.

The second problem is that there is no equivalent of the PUF for estate tax returns. Estate tax data are only publicly available in very aggregate form, and not tied to the income of decedents before they died. As a result, measurements of estate tax liability must be inferred indirectly from data on wealth. We use the Federal Reserve Board's Survey of Consumer Finances (SCF) as the source of our wealth data.[49]

We impute asset items and liabilities to each record in the tax model database based on regressions of those wealth components against variables that exist on both the SCF and PUF-CPS datasets. To mitigate the problem of the small sample size on the SCF (only about 4,400 observations in 2001), we pool data from the 1998 and 2001 surveys. In addition to roughly doubling the sample size, this approach has the added advantage of smoothing out some of the

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[48] There can be, of course, a distinction between the change in burden and the change in tax liability. The general point is that if provided with a dollar value for the aggregate change, the model will distribute that change to the recipients of capital income in proportion to their share of aggregate capital income. The amount of corporate tax to distribute in both the baseline and alternative simulations is set by the user in the parameter file.

[49] The methodology of the SCF is outlined in Kennickell (2000) and other papers available at http://www.federalreserve.gov/pubs/oss/oss2/method.html

temporal variation in asset values. The imputed number of individuals owning each type of asset (and liability) and the aggregate values of each asset (and liability) are calibrated to match the totals on the SCF. The imputed distribution of each asset and liability by income class is also adjusted to more closely resemble the distribution reported in the SCF. In addition to the imputations, the values of most estate tax deductions and credits are estimated based on averages calculated on the SOI estate tax data.

An estate tax calculator then determines estate tax liability for each record based on the record's gross estate, deductions, credits, and the relevant estate tax rates and brackets. Each record's expected value of gross estate and estate tax are then calculated by applying appropriate mortality probabilities. In addition, we employ a linear programming algorithm similar to the one used in Stage II for the aging and extrapolation process to reweight the records and ensure that our estimates of the distribution and aggregate values for gross estate match the most recent published data from SOI. A more detailed description of our estate tax methodology can be found in appendix C.

Model Output

The model produces three outputs: (1) a text file called the output file; (2) a text file called the revenue file; and (3) a binary extract file.

The Output File

The output file is a text file that summarizes and tabulates the results of each simulation in a model run. As a check that the parameter file was correctly specified, it contains the values of each of the parameters for every simulation in the run. It also contains tables that show the tax bracket and rate schedule for each simulation as well as the value of virtually all parameters that have been indexed for inflation. These tables also display most AMT parameters, including the exemption level, exemption phaseout thresholds and tax bracket thresholds. Tables that show the bracket and rate structure for the estate tax, as well as the value of the unified credit and the maximum for the QFOBI deduction are also produced for each simulation.

The next set of tables in the output file tabulate important variables by AGI class including the number of tax units, AGI, taxable income, tax before and after nonrefundable credits, and income tax net of refundable credits. The output file can also produce separate tables for just those returns that claim the EITC or the child tax credit. The user has a great deal of control over which tables to include by changing switches in the parameter file.

In the latest version of the tax model, we have added a set of tables that show the distributional effects of the tax policy change specified in the parameter file. The distribution table in the output file contains all of the information in a standard TPC distribution table including the average tax change in dollars, the share of the total tax change, the percentage change in after-tax income, and average effective federal tax rates before and after the proposal.[50] Through the parameter file, the user can choose the income qualifier to use in the distribution tables: AGI, cash income, or economic income.[51]

The Revenue File

The revenue file currently contains six tables that summarize the effects of the policy simulations on several important variables. The first table shows individual income tax liability

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[50] For a standard TPC distribution table, see http://www.taxpolicycenter.org/TaxModel/tmdb/TMTemplate.cfm?Docid=724&DocTypeID=1

[51] Cash income and economic income are described in appendix B.

net of refundable credits under the baseline and the alternative policy proposal for each year of the model run. It also displays the calendar-year change in liability and fiscal-year change in revenue. In order to calculate the fiscal-year change, the user must set a variable in the parameter file that gives the split of liability between fiscal years. The second table in the revenue file shows the number of AMT taxpayers and AMT revenue under both the baseline and alternative policy proposal. AMT taxpayers are broken out into those with "lost credits" and those with direct AMT liability on Form 6251. A similar breakdown is provided for AMT revenue. The third table displays the number of estate tax returns filed and the amount of estate tax liability under both the baseline and alternative proposal, as well as the change in each due to the proposal.

The fourth table shows several variables related to the child tax credit. For both the baseline and the alternative, the table displays the number of returns claiming the child tax credit (both the nonrefundable and refundable portions) and the number of children in tax units claiming the credit. It also shows the number of returns claiming the full amount of the child credit and the number of children in those tax units.[52] The fifth table shows the number of contributors to traditional and Roth IRAs for each year of the model run, under both the baseline and the alternative proposal. It also gives the total amount contributed to both types of IRAs. The final table in the revenue file tabulates the various education benefits in the tax code under both the baseline and alternative proposal. It shows the number of returns claiming, and the total

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[52] There are two reasons tax units might not receive the full value of the child tax credit. The credit is phased out based on AGI. A tax unit loses $50 of credit for each $1,000 by which its AGI exceeds the threshold value of $110,000 for married couples and $75,000 for others. Thus, a tax unit in the phaseout range will not receive the full value of the credit. Those with low incomes might not receive the full value either. If a tax unit does not have enough tax liability to use the all of the nonrefundable portion of the child credit, they are eligible for a refundable child credit. For 2004, the refundable portion of the credit phases in at a rate of 15 percent on earnings above the threshold value of $10,750 (indexed for inflation). So if a tax unit's earnings do not exceed the threshold by a sufficient amount, it might not qualify for the full value of the credit.

amount claimed, for the Hope and Lifetime Learning credits, the above-the-line deduction for higher education expenses, and the student loan interest deduction.

The FORTRAN code that performs the necessary tabulations and creates the tables in the revenue file is flexible enough for the user to add new tables in a fairly straightforward manner. The tables automatically generated reflect issues that have been studied in the past. The user can modify the code for the revenue file to generate tables that are more related to his or her own project and interests.

The Extract File

Along with the standard tables in the output and revenue files, the user can create custom tabulations and tables by using the third major output of the tax model, the binary extract file. For each record in the tax model database, a record is written to the extract file containing the value of almost 250 input variables and more than 200 model-generated variables.[53] The user can specify which set of simulations in any given model run should generate an extract file by adjusting a switch in the parameter file. With the aid of a statistical software package such as SAS, the user will then be able to manipulate the variables in the extract file and create custom tables.

Case Model

The tax model's calculator can be used to determine the individual income tax liability of hypothetical families. By setting a switch in the parameter file, the model will read in an

[53] The extract file contains the value of the model-generated variables under both the baseline and alternative simulation. Thus the file contains about 650 variables.

alternative input file to the PUF-CPS matched database in which the user can specify the variables of interest for one or more sample families. For example, the user could specify a married couple filing a joint return, with two dependent children under age 17, income from wages and salaries of $75,000, long-term capital gains of $8,000, and the various itemized deductions that the family claims. The tax model will then calculate individual income tax liability for this family and an output file will be produced that shows all the relevant model-generated variables, such as income tax before and after credits, the value of nonrefundable and refundable credits, and so on.

For each hypothetical family, the user can specify values for any of the variables that are found in the PUF, as well as variables that come from the match with the CPS (such as age and amounts of nontaxable forms of income). The user must still provide the standard parameter file that specifies tax law under the baseline and alternative simulations. The case model can also be run for multiple years.

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Appendix A: Retirement Savings Module[54]

This appendix provides details on estimation, imputation, and valuation procedures used to determine the distribution of retirement saving incentives.

<u>Defined Contribution (DC) Plans</u>

<u>Estimation</u>

We use the probit maximum likelihood estimator to estimate the likelihood of being covered by a DC plan. Under the probit model, the coverage is observed if and only if $X_1\beta_1 + \varepsilon_1 > 0$, where ε_1 is assumed to be a standard normal random variable with mean 0 and variance 1, X is a vector of explanatory variables, and β is a vector of parameters to be estimated. Conditional on coverage, we estimate contributions as a function of a similar set of variables.

The procedure is similar to the Heckman two-step estimator, with two differences. First, we estimate the second stage equation using censored regression techniques to account for the fact that contributions are limited by law. Second, we omit a Mills ratio correction in the second stage. This may yield biased coefficient estimates in the second stage, but that is not a relevant concern because we are interested in producing the best fit, conditional on the explanatory variables, rather than the best coefficient estimates.

For employee and employer contributions, we estimate an equation of the form $ln(y^*) = X_2\beta_2 + \varepsilon_2$, where y^* is the desired contribution (before application of statutory limits), and ε_2 is assumed to be normal with mean 0 and variance σ^2. The latent variable, y^*, is not observed. Instead, we observe y, defined as y^* when $y^* < L$, and L if $y^* > L$, where L is the statutory

[54] This appendix is excerpted, with minor modifications, from Burman, Gale, Hall, and Orszag (2004).

contribution limit. The upper limits for the censored regression are based on the law in effect in 2000. The maximum elective contribution to a 401(k) was the lesser of $10,500 or 25 percent of earnings, and the maximum total qualifying contribution (including both employer and employee contributions) was $30,000.[55]

The list of exogenous variables for each probit and censored regression is designed to be an exhaustive set of relevant variables that exist on both the SCF and the PUF. These variables include number of dependents, age (included as 10-year bracket dummies), income (as defined for purposes of the SCF), and the following components of income: income from a farm or business, tax-exempt interest income, taxable interest income, rental income from schedule E, pension income, taxable dividends, and realized capital gains (all defined as the natural logarithm of the income item plus one). We also include dummies for zero values of each income item; dummies for negative overall income, negative income from a business or farm, and negative capital income; as well as interactions between the negative income dummies and the appropriate negative income amount (defined as the natural logarithm of the absolute value of the income item plus one). In addition, we include dummies for whether the individual itemizes deductions on his or her federal tax return, and dummies for whether certain federal tax schedules are filed (C for business income, E for rental income, and F for farm income). The list of explanatory variables is identical for each equation, except for the employer contribution probit and level equations. Those equations include the natural logarithm of employee

[55] In some cases, earnings reported separately for each spouse were inconsistent with total household earnings. In that case, total earnings were apportioned among the spouses in proportion to their reported separate earnings. If positive household earnings were reported, but the individuals did not report earnings separately, we attributed the total amount to the head of household. Some employees reported contributing more than the limit. We assumed that any excess contributions were made to a nonqualifying pension plan.

contributions as an explanatory variable, under the logic that employer contributions are often matching.

Equations are estimated separately for head of household and spouse, but are based on household-level values for the explanatory variables with the exception of age and earnings.[56] It is not appropriate in the SCF to simply run regressions or probits on the entire dataset because of its approach to missing variables. The SCF imputes missing values for a number of fields. To reflect the variance introduced by that process, the SCF database includes five replicates of each observation. Missing values are drawn randomly for each replicate from the estimated probability distribution of the imputed value, whereas nonmissing values are simply repeated. We estimate coefficients by computing each estimate separately for each sample replicate and then averaging the coefficient estimates.[57]

Imputation

Given the estimates of coverage and contributions from the SCF, we impute values to tax filing units in the PUF/CPS database. Imputation is done in three steps. First, we simulate whether the taxpayer has the item. For consistency, pension contributions are attributed only to

[56] The SCF is a household-based survey that records only total income and wealth items for all individuals in the "primary economic unit" (PEU); it does not attribute shares of those amounts to individuals within the PEU. This provides a slight complication for those PEUs that consist of two unmarried individuals living together (with or without other financially interdependent members of the PEU). These individuals will show up in the income tax file as two single tax returns but will show up in the SCF as one unit. We assume that an unmarried couple living together with shared finances behaves like a married couple and thus include them in the married category when running the regressions. The results do not change significantly if these individuals are dropped from the analysis.

[57] We also correct the standard errors using the procedure supplied by the Federal Reserve Board, but it is not a particularly important adjustment given that we are not interested in the parameter estimates. The corrected estimates and standard errors from that procedure, as well as a measure of goodness-of-fit from the first replicate, are available upon request.

tax returns that are not shown ineligible by virtue of their IRA contributions.[58] Using the estimated coefficients from the probit estimation and values of explanatory variables in the tax model database, we calculate Xb_1 (where b_1 refers to the probit estimate for β_1). We then calculate the threshold probability, $z = \Phi^{-1}(X_1 b_1)$, where Φ is the cumulative standard normal probability distribution, and draw a uniform random number, p, between 0 and 1. If $z < p$, we assign a nonzero value for the item.[59]

Second, we estimate employer and employee contribution levels for taxpayers with $z < p$. Using the estimated coefficients from the level equation (b_2) and values for explanatory variables in the PUF, we calculate Xb_2, the desired value for the item, y. In the limit, $E(y^*) = \exp(Xb_2 + s^2/2)$, where s is the estimated standard error for the level regression. However, in finite samples, $\exp(Xb_2 + s^2/2)$ can be a biased estimator, and the biases can be large if the errors are in fact nonnormal. We follow Duan (1983) and instead use a robust empirical “smearing adjustment” to match the sample means of predicted values with the sample mean of the actual SCF data. The adjustment basically amounts to multiplying $\exp(Xb_2)$ by a constant chosen to align the sample means.

Third, we adjust the imputed aggregates to match SCF totals. After the adjustment, the number of participants, employer, and employee contributions match approximately the totals reported in the SCF.

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[58] Tax returns include data on contributions to traditional IRAs. Since taxpayers above certain AGI thresholds may not make contributions to IRAs if their employers offer a pension, any in those categories who report IRA contributions must not participate in an employer plan.

[59] Without adjustment, this process can produce too many or too few individuals with pension contributions on the PUF dataset. We force the numbers to match published totals by shifting the threshold probabilities by a constant (up or down) so the simulated number of contributors matches the estimates on the SCF.

Calculating Gross Wages

After the imputation process is complete, we calculate gross wages by adding employer and employee contributions to DC pension plans to reported taxable wages and salaries. Unlike taxable wages, gross wages are invariant with respect to tax changes, assuming that employer contributions to pension plans and other fringe benefits are paid out of wages. By the same logic, we subtract the employer's portion of additional payroll taxes due on the additional cash compensation from gross wages. We use gross wages as a component of cash income.

IRAs

IRAs raise special issues for three reasons. First, IRA contributions are not reported on the SCF, which we resolve by using the 1996 SIPP. Second, no questions were asked about Roth IRAs in the 1996 SIPP (since the Roth IRA was first enacted in 1997) and there is currently no cross-section information available on Roth IRA contributions. Third, 1997 legislation phased in substantial increases to the income limits for contributions to traditional IRAs—not fully effective until 2007. This last point means that baseline contributions can be significantly greater in later years than the observed values for taxpayers who are at the limit in 1997.

To calculate the IRA participation and contributions, we use a similar method to the one described above, modified to use information on the PUF about contributions to traditional IRAs. We distinguish between individuals who already contribute to a tax-deductible IRA in the PUF and all others.

Individuals who contribute to a tax-deductible IRA as indicated on the PUF in 1999 are assumed to also contribute to such an account in later years. For those who contribute the limit to an IRA in 1999, the desired contribution is at least the limit amount. We calculate the desired contribution based on the estimates from the censored regression equation. Suppose the limit in 1999 was *L*, the actual contribution was *I*, the vector of explanatory variables is *X*, the coefficient vector from the censored regression is denoted as β_3, and the error as ε_3, a random variable with mean 0 and variance σ_3^2. Let $\ln(I^*) = X\beta_3 + \varepsilon_3$ represent the desired contribution. The dependent variable is upward censored at $\ln(L)$, so the observed variable is $\ln(I) = \ln(I^*)$ when $I^* < L$ and $\ln(I) = \ln(L)$ otherwise. For limit contributors, the expectation of I^* is

$$E(I^* \mid I \geq L) = E(e^{X\beta_3+\varepsilon_3} \mid \varepsilon_3 \geq \ln(L) - X\beta_3).$$

It may be shown that

$$E(I^* \mid I \geq L) = e^{X\beta_3+\sigma_3^2/2} \frac{1-\Phi\left(\dfrac{\ln L - X\beta_3 - \sigma_3^2}{\sigma_3}\right)}{1-\Phi\left(\dfrac{\ln L - X\beta_3}{\sigma_3}\right)}.$$

We calculate a consistent estimator for this expected value using the estimates for the coefficient vector and standard error generated by the censored regression equation. This procedure guarantees that predicted contributions are at least as great as the 1999 limit, which means that these people will contribute more when the limit increases.[60]

For all other tax filing units, IRA participation depends on the results of probit equations estimated on the 1997 SIPP data (as described above for 401(k) plans), and the desired level of contribution depends on the predictions of a censored regression equation also estimated on the SIPP. To simplify, we assume that, when eligible for both types of IRA, these households all contribute to Roth IRAs, even if they become eligible for traditional IRAs as the limits increase.

[60] For alternative methods of imputing desired contributions, see Gale and Scholz (1994) and Venti and Wise (1990).

Because the present value of Roth and traditional IRAs is equivalent for an equal after-tax contribution (as discussed below), this assumption does not affect the distribution of tax benefits from IRAs overall. It may, however, lead to an overestimate of the share of IRA contributions in Roth IRAs, especially for those with higher incomes.[61]

We use the estimated probit equation and censored regression estimates to predict whether tax filing units contribute to a Roth IRA and the amount of desired pre-tax contribution (since the traditional IRAs were all made on a pre-tax basis). The procedure is identical to that outlined for 401(k) participation and contributions, except for two modifications. First, the contribution is converted from a pre-tax to an after-tax contribution based on the taxpayer's marginal tax rate (subject to the applicable Roth IRA limit). Second, the estimates for participation and contribution levels are calibrated to match estimates based on IRS data from 2000 (Sailer and Nutter forthcoming.)

Other Policies

The Saver's Credit

The saver's credit is a nonrefundable tax credit equal to a share of employee contributions to DC pensions and contributions to IRAs. We model this credit simply as a reduction in tax based on the credit formula. Following standard distributional analysis conventions, no behavioral response is assumed—that is, we do not assume that saving increases when people have access to the credit. Thus, the credit calculation follows directly from our

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[61] On the other hand, it may be that more higher-income people will shift from traditional IRAs to Roth IRAs over time as awareness of the new (in 1997) program grows. In addition, those who would like to make an after-tax contribution of more than $L\ (1 - \tau)$, where L is the contribution limit and τ is the marginal income tax rate, can only do so through a Roth IRA. So, on balance, this simplifying assumption seems plausible until further data are available.

estimates of IRA and retirement plan contributions. For some scenarios, we assume that the credit is refundable. That means that tax filers get the full benefit of the credit even if it exceeds their income tax liability—even if they do not owe income tax at all.

Changes in Contribution and Income Limits

We simulate the effects of higher contribution limits and changes in income eligibility rules using an analogous procedure. We assume that people who are eligible to contribute in the baseline but do not contribute will not decide to contribute if their contribution limit increases (this assumption could be wrong if there are transaction costs), but those who do contribute in the baseline and are at the limit will increase their contribution, according to their desired contribution equation and adjustments described above. Changes in income limits for IRA contributions could also increase the number of contributors as some newly eligible people would contribute depending on the prediction of the probit participation equation, as discussed above.[62]

The Present Value of Tax Benefits from IRAs and Pensions

Theoretical Determination

We calculate the value of pension and IRA tax benefits by comparing the taxation to a taxable account holding a similar level of after-tax contributions. Consider a contribution of \$1,000 to a traditional (deductible) IRA. The cost of that contribution is \$1,000($1 - \tau$). Call that

[62] This feature would be used to model recent proposals to eliminate income limits entirely for eligibility for contributions to Roth IRAs.

amount V_0. Assuming that, alternatively, that money would be contributed to a taxable account paying a rate of return r and taxed at constant rate, τ, the account would be worth

(1) $$V_t = V_0\ (1+r(1-\tau))^t$$

after t years, where $t = 1,\ldots, N$, and N is the year at which withdrawals start (at the end of the year). Assuming discounting at rate r, the present value of taxes during the N-year accumulation phase is

(2) $$PV_N = \left[1-\left(\frac{1+r(1-\tau)}{1+r}\right)^N\right]V_0$$

If the money is withdrawn in a lump sum at the end of year N, this would be the present value of the tax benefits. We follow Cronin (1999) in assuming that the contribution period is until age 65 and then the money is withdrawn in equal portions starting at age 66 until the end of the life expectancy. Withdrawals are assumed to occur at the end of the year, after interest has accrued.

If life expectancy at age 65 is 65 + T, then the annual withdrawal, A, will solve the following equation

(3) $$V_N = A\left[1-(1+r(1-\tau))^{-T}\right]\frac{1+r(1-\tau)}{r(1-\tau)},$$

where V_N is the value of the taxable account at age 65 (at the end of the year). It may be shown that the value of the taxable account during the retirement period is:

(4) $$V_{N+j} = \gamma^j\left[V_N - A\frac{1-\gamma^{-j}}{1-\gamma^{-1}}\right],$$

where $\gamma \equiv 1+r(1-\tau)$. Tax in period $N+j$ is

(5) $$\theta_{N+j} = \gamma^{j-1}\left[V_N - A\frac{1-\gamma^{-j}}{1-\gamma^{-1}}\right]r\tau .$$

Thus, the present value of the taxes saved is

(6) $$PV = PV_N + \sum_{j=1}^{T}\frac{\theta_{N+j}}{(1+r)^{N+j}}.$$

Parameter Assumptions

For a deductible IRA or 401(k) contribution, V_0 is the after-tax cost of the contribution (i.e., multiplied by $1 - \tau$). For a Roth IRA or 401(k), V_0 is the amount of the contribution. Thus, for someone in the 25 percent tax bracket, a \$2,000 contribution to a traditional IRA would be analogous to a \$1,500 contribution to a taxable account ($V_0 = 1{,}500$). A \$2,000 contribution to a Roth IRA would be analogous to a \$2,000 contribution to the taxable account ($V_0 = 2{,}000$).

For this calculation, τ should be the marginal tax rate on earnings. For simplicity, assume that the tax rate on savings outside of retirement accounts is also τ (as assumed in the calculation above). In fact, the effective rate might be lower if, for example, the account pays returns in the form of capital gains or dividends. This assumption will thus tend to overstate the value of the retirement tax incentives.

We make a conservative assumption about the rate of return on the taxable account. We assume that r is 6 percent—3 percent inflation plus 3 percent real growth—as assumed in the 2003 SSA trustees report. To the extent that the taxable account would be invested in stocks or commercial bonds, there would be a risk premium that would raise the expected return. Thus, this assumption will tend to understate the value of retirement tax incentives, and thus to offset the bias from assuming full taxation of returns. The net effects of these two assumptions on the distribution of benefits are small.

Appendix B: Description of Income Measures

One of the advantages of developing the estate tax module is that we now have a wealth imputation on every record of the tax model, allowing us to create a broader measure of income that better reflects economic status or ability to pay. The new economic income qualifier includes wages and salaries, other returns to labor, returns to capital, and other income. Other returns to labor are measured as a percentage of business income, farm income, rental income, farm rental income, partnership income and income from small business corporation. Returns to capital are assumed to be the nominal risk-free rate on capital, measured as 6 percent of net worth.[63] Other income includes royalty income, Social Security benefits received, unemployment compensation, supplemental security income (SSI), alimony received, Temporary Assistance to Needy Families (TANF), worker's compensation, veteran's benefits, disability benefits, child support, energy assistance, and a cash value for food stamps and school lunches received. Finally, including employer's share of payroll taxes and corporate tax liability puts the income measure on a pretax basis. The comprehensive income measure is divided by the square root of the number of members of the tax unit—the same adjustment employed by the CBO in their distributional analysis.[64] This implies that a married couple filing a joint return with two dependent children and earnings of $100,000 would have the same family-size-adjusted economic income as a single person earning $50,000.

This income measure is preferable to AGI for several reasons. AGI is highly volatile, because capital gains and business income and losses can vary wildly from year to year. The

[63] The net worth measure used in our income classifier differs slightly from that used for estate tax purposes. Here, we include only the cash value of whole life insurance. For estate tax purposes, the relevant measure of life insurance is the face value of both whole life and term life insurance.

[64] For an explanation of the CBO methodology, see CBO (2001).

broader measure reduces this volatility and mitigates the problem that wealthy individuals can have low or even negative AGI because of a big loss in any given year. The broader income measure is also more closely related to permanent income and addresses some of the criticisms of distributional analysis raised by the President's Council of Economic Advisers in its 2003 Economic Report of the President and Penner (2004). It is also similar to Treasury's family economic income measure, which is widely recognized by economists to be a better measure of income than AGI.

We have also developed an income measure that is similar to Treasury's cash income. Our measure of cash income includes wages and salaries, employee contributions to tax-deferred retirement savings plans, business income or loss, farm income or loss, Schedule E income, interest income, taxable dividends, realized net capital gains, Social Security benefits received, unemployment compensation, energy assistance, TANF, worker's compensation, veteran's benefits, SSI, child support, disability benefits, taxable IRA distributions, total pension income, alimony received, and other income including foreign earned income. As with economic income, cash income also includes imputed corporate income tax liability and the employer's share of payroll taxes in order to put it on a pretax basis. Standard TPC distribution tables typically use cash income as a qualifier but we also produce distribution tables using economic income in situations in which we think the difference between the two qualifiers is significant.

Appendix C: Estate Tax Methodology[65]

This Appendix describes the procedures and methodologies used to develop the model's estate tax module.

Determinants of Asset and Liability Ownership Patterns

The first step is to develop equations explaining wealth holdings in the 1998 and 2001 Surveys of Consumer Finances (SCFs). The pooled 1998 and 2001 SCF samples contain wealth and income data for 8,747 households—4,442 from 2001 and 4,305 from 1998.[66] In each subsample, wealth is measured in the current year (e.g., 2001) and income from the prior year. The SCF survey is a stratified random sample that also oversamples high-income families. By design, however, it excludes the extremely wealthy (the Fortune 400). The SCF is widely regarded as the best available data on the details of household wealth accumulation for a nationally representative sample.

We estimate two equations for each asset and liability item. The first determines whether the household owns the item. The second, estimated for those households with nonzero amounts of the item, determines the amount held. We use probit maximum likelihood to estimate the probability of having each item. We assume that the item is observed if and only if $X_1 * \beta_1 + \varepsilon_1 > 0$, where ε_1 is assumed to be a standard normal random variable (mean 0, variance 1).

Conditional on having a particular item, we estimate the amount of the item as a function

[65] This appendix is excerpted, with minor modifications, from Burman, Gale, and Rohaly (forthcoming).

[66] We based our initial estimates on 2001 data alone, but were concerned about the quality of the imputations for at least two reasons. First, because of the stock market bubble, 2001 is likely to reflect anomalous relationships between income and wealth. Second, the number of observations of certain kinds of assets and liabilities was very small. For example, only 44 respondents reported any farm assets in 2001.

of a similar set of variables. Using ordinary least squares, for each item *w*, we estimate an equation of the form $\ln(w) = X_2*\beta_2 + \varepsilon_2$, where ε_2 is assumed to be normal with mean 0 and variance σ^2. This procedure is similar to the Heckman two-step estimator, but without the Mills ratio correction in the second stage. This may yield biased coefficient estimates in the second stage, but that is not relevant here because we have no interest in the point estimates. Our goal is just to produce the best fit, conditional on the explanatory variables.[67]

The specific items that we imputed are listed in appendix table 1. The list of exogenous variables for each probit/regression is designed to be an exhaustive set of relevant variables that exist on both the SCF and the tax model dataset. The explanatory variables we use are shown in appendix table 2. To allow the relation between the wealth components and the explanatory variables to differ by marital status, we run separate probits and OLS regressions for married couples and for unmarried individuals.[68]

It is not appropriate in the SCF to run regressions or probits on the entire dataset because of the survey's approach to missing variables. The SCF imputes missing values for a number of fields. To reflect the variance introduced by that process, the SCF database includes five replicates of each observation. Missing values are drawn randomly for each replicate from the estimated probability distribution of the imputed value, whereas nonmissing values are simply

[67] Also, as a practical matter, there is little basis for excluding any of the right-hand side variables in either the first or second stages. In consequence, identification of a coefficient on the Mills ratio would rely solely on the nonlinearity of the Mills ratio function and the accuracy of the assumption of normally distributed errors terms—an assumption that would be of highly questionable validity for a finite sample.

[68] The SCF is a household-based survey that records only total income and wealth items for all individuals in the "primary economic unit" (PEU); it does not attribute shares of those amounts to individuals within the PEU. This provides a slight complication for those PEUs that consist of two unmarried individuals living together (with or without other financially interdependent members of the PEU). These individuals will show up in the income tax file as two single tax returns but will show up in the SCF as one unit. We assume that an unmarried couple living together with shared finances behaves like a married couple and thus include them in the married category when running the regressions. The results do not change significantly if these individuals are dropped from the analysis.

repeated. We estimate coefficients by computing each estimate separately for each sample replicate and then averaging the coefficient estimates.[69]

Imputations of Wealth Values onto the Tax File

Based on the estimation results from the SCF, we impute values for assets and liabilities onto the individual income tax model. Like the estimation, the imputation proceeds in two steps. The first predicts whether the tax unit holds the item. The second, conditional on holding the items, predicts the quantity held.

To impute whether the tax unit holds the item, we use the following procedure. Using the coefficients from the probit estimation (β_1) and values of explanatory variables in the tax model database, we calculate $X_1*\beta_1$. We then calculate the threshold probability, $z = F^{-1}(X_1*\beta_1)$, where F is the cumulative standard normal probability distribution. The next step is to draw a uniform random number, p, between 0 and 1 and assign a nonzero value for the wealth item if $z < p$.[70] For some assets and liabilities, we also adjust the probabilities so that the number of individuals in the tax model reporting the item more closely matches the figure in the SCF.[71] We employ separate adjustment factors for married and unmarried records.

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[69] We also correct the standard errors using the procedure supplied by the Federal Reserve Board, but it is not a particularly important adjustment given that we are not interested in the parameter estimates. The corrected estimates and standard errors from that procedure, as well as a measure of goodness-of-fit from the first replicate, are available upon request from the authors.

[70] There are two assets for which we do not follow this method. We assume that anyone who reports tax-exempt interest income has tax-exempt bonds. For farm assets, in addition to applying the probit as described above, we ensure that anyone who files a schedule F (farm income) or Form 4835 (farm rental income and expenses) has farm assets.

[71] Again, the tax model groups individuals into tax units; the SCF groups individuals into primary economic units (PEU). As described above, there are more tax units than PEUs. Therefore, we cannot calibrate the number of tax units reporting any particular asset or liability to the absolute number of PEUs claiming that item. Instead, we make an ad hoc adjustment allowing for the higher number of tax units; in most cases, our target for the number of tax units is about five to ten percent higher than the number of primary economic units reporting any particular item.

In the second stage, we impute quantities held for those tax units with $z < p$. To do this, we use the coefficients from the level equation (β_2) and values for explanatory variables in the tax model database, to calculate the fitted values, $X_2*\beta_2$, and then to calculate the expected value for the item, w. In the limit, $E(w) = \exp(X_2*\beta_2+\sigma^2/2)$, where σ is the estimated standard error for the level regression. However, in finite samples, $\exp(X_2*\beta_2+\sigma^2/2)$ can be a biased estimator, and the biases can be large if the errors are in fact nonnormal. We follow Duan (1983) and instead use a robust empirical "smearing adjustment" to match the sample means of predicted values with the sample mean of the actual SCF data. The adjustment basically amounts to multiplying $\exp(X_2*\beta_2)$ by a constant chosen to align the sample means. Again, as with the probability adjustments, we employ separate factors by marital status in order to match the sample means for both married and unmarried individuals.

Appendix figure 1 shows the imputed distribution of net worth by prior-year income compared with the distribution on the 2001 SCF. The correlation is reasonably high—0.93. Net worth is underestimated for those in the bottom 80 percent of the income distribution and in the 95th through 99th percentiles, and overestimated for those in the 80th to 95th percentiles and the top 1 percent. As a direct consequence of the empirical smearing adjustment, aggregate imputed wealth matches the total in the SCF almost exactly. One source of the remaining difference is that we calibrate our totals for the number of farmers and farm assets and debt to match data produced by the Economic Research Service of the USDA based on their Agricultural Resource Management Survey, rather than use the SCF totals.[72] Note also that we include the face value of term and whole life insurance as assets because those would be the relevant values for estate tax purposes if the taxpayer were to die. In its published estimates of net worth using SCF data, the

[72] We used the table generator on the USDA's web site, http://www.ers.usda.gov/data/farmfinancialmgmt/.

Fed only treats the cash value of whole life insurance as an asset.[73]

The figure shows that the share of assets held by the top 1 percent is significantly larger after our imputation procedure than in the SCF, but this is probably not a problem with the tax model database. The SCF lacks the wealthiest 400 households and is pretty thin at the top. As a result, top incomes on the SOI are much higher than top incomes on the SCF and it is appropriate to attribute higher wealth to those taxpayers than may be observed in the SCF.[74]

Next we adjust each of the components of net worth by fixed percentages within all but the top 1 percent and those with negative incomes (not shown) to match the distribution in the SCF.[75] This adjustment is performed separately for married and unmarried individuals in order that our imputed distributions match the SCF for both groups of individuals. Appendix figure 2 shows the "corrected" distribution for all individuals together. The correlation is now 0.95. By construction, the correlation is virtually 1.0 for the subsample excluding the top one percent and those with negative incomes.

Calculate Gross Estate

Once we have imputed values for each asset and liability on all records in the income tax file, we need to calculate each record's gross estate. For single individuals, this simply involves

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[73] We also estimate the presence and amount of the cash value of whole life insurance for the records on the tax model database and use the estimate in our calculation of economic income which is discussed in detail below. The cash value estimates are similarly adjusted to match the aggregate and distribution as reported in the SCF.

[74] Note that we are implicitly assuming that the relation between the net worth components and the variables in our regressions is the same for the excluded Fortune 400 as it is for the rest of the SCF population. That is, we are using the coefficients from our SCF regressions that exclude the Fortune 400 to impute the net worth items to the SOI population that effectively includes some of the Fortune 400 individuals. Note also, however, that the 1999 public-use file from SOI excludes 191 records with "extreme values", presumably primarily those with very high overall incomes or particular sources of income (Weber 2003).

[75] Because of the extremely small number of respondents reporting farm assets in the SCF and the fact that we calibrated the total value of farm assets and debt to USDA data rather than the SCF, we do not adjust the distributions for farm assets or farm debt.

adding up the imputed value of all assets and subtracting the imputed value of all liabilities. For married couples, we assume an equal split for all assets and liabilities between each individual. Thus, in the case in which one of the two spouses dies, only 50 percent of the couple's net worth is included in the decedent's estate.[76]

Thus for each married record, we calculate gross estate twice to account for two possible outcomes: (1) only one spouse dies leaving half of the couple's net worth as an estate; or (2) both spouses die including all imputed wealth in the gross estate.

We then need to predict the distribution and aggregate amounts of the components of gross estate that will show up on estate tax returns. Following Poterba and Weisbenner (2001), and Cronin (1999) we predict the aggregate amounts of the components of gross estate by weighting each record's gross estate in the event of death with the probability of death. Like Poterba and Weisbenner, we assume probability of death follows the annuitant mortality tables, which are appropriate to higher-income and higher-wealth individuals, who also tend to live longer than average.[77] This assumption will result in weights that are too high for lower-wealth individuals, but they would not owe estate tax anyway, so it is immaterial to our estimates. Expected gross estate is then equal to the gross estate held by individuals times the probability of death.

One issue that complicates the calibration of the model is that our estimates are for 2001 decedents, but at the time of our model targeting, the most current estate tax information was for estate tax returns filed in calendar year 2001. Returns filed in 2001 are primarily for 2000 but

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[76] This is the same assumption made by Poterba and Weisbenner (2001).

[77] We use the 1996 U.S. Annuity Basic Tables for males and females available on the web site of the Society of Actuaries (http://www.soa.org). Since we do not have gender identified on the income tax file, we create a mortality table for all individuals by weighting the mortality rates of males and females at each age by the proportion of the population of that age that is male and female as reported by the Bureau of the Census.

also 1999 decedents since estates have 15 months from the date of death to file an estate tax return (Johnson, Mikow, and Eller 2003). In July 2004, the IRS released preliminary data for estate tax returns filed in 2002, which are primarily for decedents in 2001 and also 2000. The IRS has not released figures, however, that are exclusively for individuals who died in 2001 and that would therefore be directly comparable to the numbers generated by our model. We chose to calibrate our model to the aggregate and distribution of gross estate for estate tax returns filed in 2001 but with downward adjustments for the overall number of estate tax returns and amount of gross estate based on assumed lower values for stocks, businesses and retirement assets. As discussed below, our final values—although not specifically calibrated to the 2002 IRS data—turn out to match those data well. The total number of estate tax returns generated by our model for 2001 decedents is within 3.3 percent of the number for returns filed in 2002 and the total gross estate is within 4.6 percent. The total value for net estate tax is virtually identical.

Appendix figures 3 through 6 compare the distribution of estate tax filers and gross estate generated by our model for 2001 decedents with the data from the IRS for returns filed in 2001.[78] Although we match the data for unmarried individuals rather well—particularly on the low and high end of gross estate—there are significant discrepancies with the results for married couples. Overall, we generate more than twice as many estate tax returns filed by married individuals and more than twice the amount of gross estate; this overestimate is spread across all gross estate classes.

There are also some significant discrepancies within asset classes. Our imputations based on the SCF do not match well with the SOI published data for several asset classes including

[78] The distribution by marital status of gross estate, as well as individual assets and liabilities, was provided to us by Barry Johnson at SOI.

personal residences, life insurance, and farms.

Personal Residences

Our SCF-based imputations show many more personal residences than appear on estate tax returns. For example, we predict that a value for personal residences will be reported on about 91 percent of single estate tax returns filed in 2001, and 98 percent on married returns. The actual values reported by SOI are 55 percent for singles and 71 percent for married individuals. This could reflect planning—such as selling a home to a child while remaining in it until death. In that case, the home should not be considered owned by the survey respondent, but she may either be confused or unwilling to acknowledge that she no longer owns her home. A more serious issue is that older people near death are more likely to move into a senior community, assisted living facility, or nursing home, but the SCF has no data from nursing homes. Unfortunately, we have no way of identifying directly those especially close to death.

Life Insurance

We also predict too many returns reporting life insurance although the overestimate is not as pronounced as with personal residences. We estimate life insurance should be reported on 58 percent of single returns and 87 percent of married returns; the actual values are 47 and 68 percent. We also overestimate the average amount of life insurance reported on estate tax returns, by almost 50 percent for single individuals and about 25 percent for married persons. Insurance may actually be owned by children or others, with the donor paying the premiums (free from gift tax if the premium is no greater than $10,000 per year). This is one of the most common ways to avoid estate tax and also assist heirs with liquidity problems that might arise at death. See Schmalbeck (2001). Some insurance may also be owned by companies or other entities.

Farms

Our model matches the SOI farm asset data well for married estate tax returns. For single returns, we overstate both the number reporting farm assets and the average amount of farm assets on those returns. Our model predicts 21 percent of single returns to report farm assets; the actual figure is about 13 percent. The model overstates average farm assets for single returns reporting farm assets by about 75 percent; this overestimate is fairly uniform across gross estate classes.

Although we target the total number of farms and the aggregate value of farm assets to published USDA data, it's likely that our imputation for farm assets has a high variance. The regressions that assign the level of farm assets to records in the tax model are based on only about 100 observations reporting farm assets in the pooled 1998 and 2001 SCFs. In addition, the small samples prevented us from being able to target a specific distribution for farm assets, unlike the other components of net worth that were targeted to SCF distributions. Fortunately, our two-stage technique for calibrating the distribution of gross estate (see discussion below) also enabled us to match much more precisely the distribution of farm assets on estate tax returns.

Two-Stage Adjustment Process

To more accurately reflect the actual SOI data for the distribution of gross estate we adjust the data for the considerations noted above. This process is similar to the method we use annually to align the individual income tax component of our model with published values and projections for demographics and income sources.

In the first stage of the adjustment process, we try to correct for overestimates of the percent of returns reporting each type of asset and for over- or underestimates of the average amount reported for each asset type among those returns with a nonzero amount of the asset. By size of gross estate class, by marital status, and for each type of asset, we compare the model's predicted percentage of returns reporting the asset to the actual percentage published by SOI. In cases where we overestimate, we randomly eliminate the asset from records in the tax model database. For example, suppose we overestimate the percentage of married returns with gross estate between $1 million and $2.5 million reporting tax-exempt bonds by 25 percent. We then randomly reassign a value of $0 for the amount of tax-exempt bonds in married records in that gross estate class until we eliminate the 25 percent discrepancy.[79]

After adjusting for the number reporting the various assets, we then turn to adjusting the amounts among those records left reporting a positive value of each asset. The goal in this step is to hit more accurately the average amounts of each item. We again perform the adjustment separately by gross estate class and marital status. For example, if our predicted average amount of retirement assets among single returns with gross estate over $20 million is 30 percent above the value reported by SOI, we reduce the value of retirement assets for all such records by 30 percent. If our predicted values were 30 percent below the SOI values, we would similarly inflate our imputations by 30 percent.

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[79] This is not a purely mechanical process and involves some finesse and several iterations. The main problem is that the classifier depends on the amounts that are changing. In this example, some of the records that are reassigned a value of $0 for tax-exempt bonds would then no longer have between $1 million and $2.5 million in gross estate, which complicates hitting the targets by gross estate class and renders it virtually impossible to hit the targets exactly.

The second stage of the adjustment process involves using a linear programming algorithm to adjust the weights on the records in the model in order to hit a targeted distribution of the number of returns and amount of gross estate reported by size of gross estate class. Our targeted distribution begins with the SOI data for estate tax returns filed in 2001 and then ratchets downward the number of returns and the amount of gross estate in an attempt to capture the fall in the value of assets—primarily stock—between 2000 and 2001.[80] We have separate distributional targets for single and married filers.[81] Appendix figures 7 through 10 show the distribution of gross estate and tax filers by size of gross estate for both singles and married individuals after the two-stage adjustment process has been carried out. Again, the total for our predicted estates is smaller than the SOI published data since our predictions are technically for individuals who die in 2001—after the decline in the stock market—whereas the SOI data are mostly for 2000 decedents. Regardless, the model now clearly matches the actual distributions of estate tax filers and amount of gross estate extremely well. Appendix figures 11 and 12 compare the model's predicted distributions against the recently-released SOI data for estate tax returns filed in 2002 (primarily 2001, but also 2000, decedents). Although the model still matches very well, we do not capture the large increase in the amount of gross estate in the $20 million and over gross estate class, nor the drop in the number of returns and amount of gross estate in the lowest gross estate category. Overall, however, we are within about 5 percent for aggregate gross

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[80] We assume, based roughly on historical patterns, that the number of estate tax filers would drop by about 7.5 percent across all gross estate classes. We also impose reductions of between 10 and 20 percent for the amount of stocks, retirement assets, and business assets as well as a reduction of 5 percent in the number of returns claiming these assets.

[81] In addition, Barry Johnson of SOI was kind enough to provide us with a more detailed breakdown of the distribution of gross estate than is published on a regular basis. For disclosure reasons, he was unable to provide a finer breakdown at the top of the gross estate scale (estates valued at $20 million and up), but we were provided with a finer breakdown for other gross estate classes (for example, ranges of $500,000 up through $5 million of gross estate).

estate and about 3 percent for the total number of estate tax returns, noting again that the SOI data for returns filed in 2002 does not represent precisely the same population as the 2001 decedents that our model captures.

Calculate Taxable Estate and Net Estate Tax

To calculate taxable estate, we must impute the value of deductions from gross estate in order to estimate the taxable estate. To estimate most deductions, including charitable contributions, funeral expenses, executor's commissions, attorney's fees, and other expenses and losses, we randomly assign the deduction to returns to match the published distribution by gross estate class and marital status.[82] Those randomly selected were then assigned the average amount for all returns in their gross estate class. This is similar to the method used by Poterba and Weisbenner (2001), although they do not vary their imputations by marital status. We also added in adjusted taxable gifts and subtracted out gift tax paid in the same manner.

Married decedents are allowed an unlimited deduction for bequests to a spouse, and most such returns take full advantage of the deduction and thus have no estate tax liability. About 20 percent, however, pay at least some estate tax. We model the marital deduction by first determining the percentage of nontaxable married returns within each gross estate class. We then randomly select returns and assign them a 100 percent marital deduction (i.e., eliminate their estate tax liability) to match the percentage of nontaxable married returns within their gross estate class. For the other returns, we assume that the deduction equals the average marital deduction as a percentage of gross estate for each class.

There are alternative methods for allocating the marital deduction. For example, it might

[82] We are grateful to Barry Johnson and his staff of the SOI division of the IRS for supplying these estimates.

be reasonable to assume that: (1) households with taxable estate (before the marital deduction) of less than $20 million will split the estate—that is, give half to the surviving spouse and the other half to other heirs; and (2) households with taxable estate greater than $20 million will make bequests of $10 million and pass the remainder on to the surviving spouse. Assuming that the estate does not grow or shrink after the first spouse's death and assuming a discount rate of zero, this is the optimal strategy because it takes maximum advantage of the progressive rates (it minimizes undiscounted estate tax liability for the two spouses).

However, since married taxpayers are such a small fraction of all taxable estates, the overall distribution of net estate tax liability is likely not very sensitive to which of these assumptions is used so we apply the simpler model.

We estimate that about 4,100 estates were potentially eligible for the QFOBI deduction in 2001, because farm or business assets accounted for at least half of the value of the gross estate. SOI estimates show that only about 1,000 estate tax returns filed in 2001 actually claimed the QFOBI deduction.[83] To implement QFOBI in our model in the base case, we randomly assign the deduction to qualifying returns within each gross estate class in order to match the actual distribution of the deduction as reported by SOI. The participation rates we use range from 15 percent for returns in the lowest gross estate class (under $1 million) to 40 percent for those with gross estates valued between $2.5 and $5 million.

To simulate policy changes, we assume 100 percent take-up for substantial increases in the QFOBI deduction. This clearly overstates utilization, but the number of potentially qualifying farms and businesses and the value of the qualifying assets are so small that variations in the assumed take-up rate result in proportionately minor changes in revenue costs. It is, of course,

[83] These data were again provided to us by Barry Johnson.

possible that a very large expansion in QFOBI could result in much more than 100 percent utilization as wealthy people rearranged their asset holdings to shelter nonfarm and business wealth from taxation, but such responses would have to be estimated off the model.

Calculate Credits against the Estate Tax and Other Adjustments

Once we have calculated the taxable estate for each record, we apply the estate tax rate and bracket structure in order to calculate tentative estate tax liability. Two credits can substantially reduce estate tax liability—the unified credit and the state death tax credit. First, the unified credit implements the current $1.5 million exemption level. Note that the exemption is implemented as a credit rather than a deduction, because a credit is worth the same for those with relatively small estates as for those with quite large ones. The value of a deduction, however, depends on the estate's marginal tax rate and would be worth most to estates in the highest estate tax brackets. For the same reason, a credit that exempts $1.5 million from the estate tax costs significantly less in lost revenues than a $1.5 million deduction. Implementing the unified credit is a simple matter of subtracting the fixed credit from tentative estate tax liability and calculating the positive balance, if any, as the estate tax.

The state death tax credit is larger than the unified credit for very large estates. As noted, almost all states in 2001 assessed an estate tax at least as large as the state death tax credit, because the tax is fully credited against the federal estate tax. We assume that every decedent claims the maximum state death tax credit. EGTRRA gradually phases out the state death tax credit between 2002 and 2004 and replaces it in 2005 with a deduction for state estate taxes actually paid.[84] We assume that this continues to be true as the credit phases out. After the credit is eliminated in 2005, we assume that the deduction would be equal to one-half of the state death tax credit for which the estate would qualify under 2001 law.[85]

We do not model other small credits and adjustments such as the credit for foreign death taxes, credits for tax on prior transfers and pre-1977 gift taxes, and generation-skipping transfer taxes. Those other credits only amounted to $220 million in 2002 and very few estate tax returns claimed them.

Appendix figure 13 summarizes how, after all the adjustments and imputations, our estate tax calculation compares with published estimates. The total estate tax that we calculate is very close to the published total for 2002. It is about 8 percent less than the published total for 2001. Most of the estate tax model's estimates are within 5 percent of the published data in at least one of the two years. The exception is the estimate for estates between $1 and $2.5 million. Our estimate is bracketed by the two very different totals published by the IRS, but the average error is about 9 percent. Overall, the fit is close enough to suggest that the model predictions provide a reasonable basis for distributional analysis and revenue estimation.

<u>Extrapolation of Estimates to Later Years</u>

Our imputation technique produces values for assets and liabilities held by individuals in the 2001 calendar year. In order to estimate the revenue and distributional implications of

[84] For 2002, the state death tax credit that an estate can claim equals 75-percent of its pre-EGTRRA value; for 2003, it's 50 percent; and for 2004, it's 25 percent.

[85] This is an arbitrary assumption that accounts for the fact that many states are reducing or eliminating their estate and inheritance taxes. Since we cannot identify the state of residence for high-income tax returns, we have no way of imputing actual state "death taxes" eligible for credit.

various estate tax reform options, it is necessary to project values for the components of net worth for future years through the end of the budget window (currently 2014).

We assume that the relation between our explanatory variables and the components of net worth is stable across time and so we use the same coefficients from our probit and regression analysis for each future year. The fact that our estimates are based on a pooled dataset of the 1998 and 2001 SCFs helps to smooth out variation over time in the relationship between the wealth items and the explanatory variables.

Our methodology implies that the predicted amounts for the assets and liabilities on each individual record in the tax model database will change over time as the underlying explanatory variables—such as the various components of income—change for that record. The way in which we adjust the income variables on our tax file is described in detail below. The aggregate number of returns reporting each component of net worth and the aggregate amount for each item will change over time for two reasons: (1) the amounts on the individual records will change; and (2) the weights on the individual records will change over time reflecting projected growth in the number of tax returns for that particular demographic group.

For the purposes of projecting assets and liabilities, we rely on the two-state aging and extrapolation process described in the text to predict our explanatory variables—and thus the values for the components of net worth—for future years. Without any further adjustment this process leads to growth in net worth that is less than projected growth in nominal GDP.[86] Historically, at least before the mid-1990s, the ratio of household net worth to GDP has been fairly constant. We therefore apply an adjustment factor to all assets and liabilities to ensure that

[86] Our projections for nominal GDP growth come from CBO (2004).

our predicted value for aggregate net worth grows at approximately the same rate as nominal GDP in future years.

Table 1
Statistical Matching: Partitioning of Records into Cells

Partition Number	Dependent Return	Filing Status	Aged	Number of Dependents	Presence of Self-Employment Income	Presence of Capital Income	Number of PUF Records	Number of CPS Records	Weighted PUF Count	Weighted CPS Count	Scale Factor
1	No	Single	No	No Dependents	No	No	6,345	9,806	19,061,833	20,248,214	0.9414
2	No	Single	No	No Dependents	No	Yes	10,666	8,077	13,833,747	17,280,609	0.8005
3	No	Single	No	No Dependents	Yes	No	1,400	466	1,699,055	940,075	1.8074
4	No	Single	No	No Dependents	Yes	Yes	3,787	640	2,071,195	1,308,487	1.5829
5	No	Single	No	1 Dependent	No		805	945	1,677,977	1,872,622	0.8961
6	No	Single	No	1 Dependent	Yes		293	22	209,530	39,517	5.3023
7	No	Single	Yes		No		5,383	3,672	6,359,442	7,610,796	0.8356
8	No	Single	Yes		Yes		823	126	427,616	263,211	1.6246
9	No	MFJ	No	No Dependents	No	No	1,315	2,300	3,263,581	4,623,823	0.7058
10	No	MFJ	No	No Dependents	No	Yes	17,685	5,766	8,886,947	12,041,350	0.7380
11	No	MFJ	No	No Dependents	Yes	No	782	330	828,227	633,833	1.3067
12	No	MFJ	No	No Dependents	Yes	Yes	11,291	1,111	3,337,356	2,219,199	1.5039
13	No	MFJ	No	1 Dependent	No	No	933	1,511	2,565,181	2,926,832	0.8764
14	No	MFJ	No	1 Dependent	No	Yes	7,118	2,809	4,796,418	5,862,279	0.8182
15	No	MFJ	No	1 Dependent	Yes	No	579	189	642,341	365,211	1.7588
16	No	MFJ	No	1 Dependent	Yes	Yes	4,431	489	1,775,312	1,032,758	1.7190
17	No	MFJ	No	2 Dependents	No	No	989	1,615	2,672,607	3,100,800	0.8619
18	No	MFJ	No	2 Dependents	No	Yes	10,642	2,996	5,652,275	6,196,116	0.9122
19	No	MFJ	No	2 Dependents	Yes	No	652	213	742,004	421,372	1.7609
20	No	MFJ	No	2 Dependents	Yes	Yes	6,104	608	2,114,548	1,209,441	1.7484
21	No	MFJ	No	3 Dependents	No	No	486	891	1,263,567	1,621,821	0.7791
22	No	MFJ	No	3 Dependents	No	Yes	6,570	1,102	2,120,272	2,197,595	0.9648
23	No	MFJ	No	3 Dependents	Yes	No	337	129	327,287	231,749	1.4122
24	No	MFJ	No	3 Dependents	Yes	Yes	3,600	252	889,677	523,647	1.6990
25	No	MFJ	No	4 Dependents	No		487	625	847,839	1,152,823	0.7355
26	No	MFJ	No	4 Dependents	Yes		413	113	274,999	228,492	1.2035
27	No	MFJ	No	5+ Dependents	No		208	253	373,462	454,141	0.8224
28	No	MFJ	No	5+ Dependents	Yes		173	46	143,119	85,390	1.6761
29	No	MFJ	Yes		No	No	362	441	612,395	884,313	0.6925
30	No	MFJ	Yes		No	Yes	10,118	2,069	6,514,989	4,315,042	1.5098
31	No	MFJ	Yes		Yes	No	110	63	115,046	120,085	0.9580
32	No	MFJ	Yes		Yes	Yes	4,444	301	1,431,392	599,324	2.3883
33	No	HOH	No	No Dependents	No	No	148	184	401,634	407,938	0.9846
34	No	HOH	No	No Dependents	No	Yes	350	167	433,814	377,375	1.1496
35	No	HOH	No	No Dependents	Yes		159	31	94,460	64,885	1.4558
36	No	HOH	No	1 Dependent	No	No	2,054	1,713	6,175,085	3,530,009	1.7493
37	No	HOH	No	1 Dependent	No	Yes	1,293	1,129	2,174,454	2,382,596	0.9126
38	No	HOH	No	1 Dependent	Yes		808	185	844,844	359,738	2.3485
39	No	HOH	No	2 Dependents		No	1,622	1,121	4,558,564	2,296,600	1.9849
40	No	HOH	No	2 Dependents		Yes	759	558	1,010,881	1,139,966	0.8868
41	No	HOH	No	3+ Dependents	No	No	452	734	1,367,305	1,458,435	0.9375
42	No	HOH	No	3+ Dependents	No	Yes	181	221	280,528	411,905	0.6811
43	No	HOH	No	3+ Dependents	Yes		157	49	140,527	99,100	1.4180
44	No	HOH	Yes		No	No	50	173	94,120	356,002	0.2644
45	No	HOH	Yes		No	Yes	213	106	287,184	202,967	1.4149
46	No	HOH	Yes		Yes		37	13	26,869	24,322	1.1047
47	Yes				No	No	1,935	2,813	6,209,887	5,588,072	1.1113
48	Yes				No	Yes	2,403	1,088	5,217,435	2,137,479	2.4409
49	Yes				Yes		156	87	226,361	174,237	1.2992
Total									#########	#########	1.0279

Source: Urban-Brookings Tax Policy Center.

Table 2
Non-Zero Observations: Summary Statistics for the Matched Data File (Nonfilers Included)

Variable	Matched File (PUF is the host)					CPS (Donor File)				
	Number of Records	Weighted Number (Millions)	Mean	Amount (Billions)	Variance	Number of Records	Weighted Number (Millions)	Mean	Amount (Billions)	Variance
Age of Tax Unit Head	201,052	144.49	44.16	6.38	19.28	68,994	141.03	44.14	6.22	18.56
Age of Tax Unit Spouse	104,897	54.48	47.47	2.59	16.41	28,910	58.30	46.02	2.68	15.90
Age of Dependent #1	83,100	58.78	13.99	0.82	9.92	27,546	54.75	13.91	0.76	9.93
Age of Dependent #2	47,268	30.23	10.15	0.31	7.50	14,729	28.84	9.96	0.29	7.42
Age of Dependent #3	17,419	10.13	9.10	0.09	8.61	5,444	10.34	8.99	0.09	8.84
Age of Dependent #4	3,603	2.88	8.51	0.02	9.66	1,671	3.09	8.69	0.03	10.59
Age of Dependent #5	1,193	0.85	7.88	0.01	9.54	502	0.89	8.15	0.01	10.21
Age of Youngest Child	61,157	39.18	10.41	0.41	10.16	18,356	36.83	10.28	0.38	10.01
Age of Oldest Child	66,588	42.47	13.20	0.56	10.87	19,956	40.01	13.29	0.53	10.79
HI: Covered (HEAD)	201,037	144.46	1.28	0.19	0.45	68,980	141.01	1.29	0.18	0.45
HI: Employer-Provided (HEAD)	114,651	79.16	1.15	0.09	0.35	37,231	77.61	1.14	0.09	0.35
HI: Employer Pays (HEAD)	95,065	67.59	1.77	0.12	0.55	31,633	66.39	1.77	0.12	0.55
HI: Covered (SPOUSE)	103,087	53.52	1.17	0.06	0.38	28,337	57.22	1.20	0.07	0.40
HI: Employer-Provided (SPOUSE)	51,726	25.66	1.15	0.03	0.35	12,871	26.32	1.14	0.03	0.35
HI: Employer Pays (SPOUSE)	43,644	21.87	1.78	0.04	0.55	10,954	22.53	1.80	0.04	0.55
Pension: Offered (HEAD)	160,222	107.30	1.43	0.15	0.50	52,861	107.90	1.45	0.16	0.50
Pension: Included (HEAD)	87,087	60.98	1.23	0.08	0.42	28,095	58.85	1.23	0.07	0.42
Pension: Offered (SPOUSE)	79,442	35.72	1.33	0.05	0.47	19,843	40.08	1.40	0.06	0.49
Pension: Included (SPOUSE)	47,961	24.08	1.16	0.03	0.36	11,744	24.23	1.17	0.03	0.37
Health Status (HEAD)	201,053	144.49	2.28	0.33	1.13	68,995	141.04	2.29	0.32	1.12
Health Status (SPOUSE)	105,302	54.58	2.23	0.12	1.08	28,961	58.39	2.24	0.13	1.08
Supplemental Security Income	3,140	3.75	4547.84	17.06	3188.58	1,750	3.60	4610.11	16.61	3266.53
Public Assistance (TANF)	2,684	2.61	2960.31	7.72	2821.36	1,105	2.18	3054.57	6.67	2833.03
Worker's Compensation	2,070	1.65	5520.63	9.08	8457.78	841	1.70	5499.43	9.33	7773.85
Veterans Benefits	3,320	2.65	8234.01	21.86	8965.40	1,212	2.44	8075.99	19.72	8924.28
Child Support	6,522	5.91	4071.09	24.07	4464.78	2,425	4.99	4118.73	20.56	4439.49
Disability Income	1,674	1.45	11365.66	16.45	13852.38	698	1.42	10471.76	14.87	12844.45
Social Security Income	40,558	33.24	11498.38	382.24	6602.52	14,567	29.81	11191.94	333.59	6219.79
Home Ownership (TENURE)	118,760	71.35	1.00	0.07	0.00	34,016	70.02	1.00	0.07	0.00
Wage Share (Lesser Earner)	51,875	29.97	0.31	0.01	0.14	14,941	30.27	0.31	0.01	0.14
Energy Assistance	3,023	2.80	221.49	0.62	428.39	1,267	2.44	224.35	0.55	444.64
Food Stamps	7,781	7.34	1432.12	10.51	1283.83	3,325	6.46	1400.43	9.05	1313.19
School Lunches	39,083	25.83	228.22	5.90	303.60	12,839	24.96	236.96	5.92	318.92

Source: Urban-Brookings Tax Policy Center.

Table 3
Stage-Two Targets

Total Single Returns
Total Married Filing Joint Returns
Total Head of Household Returns
Total Married Filing Separate Returns
Total Aged Returns
Wages and Salaries
Taxable Interest Income
Dividend Income
Business Income
Business Loss
Net Capital Gains in AGI
Schedule E Income
Schedule E Loss
Social Security Income
Number of Dependent Exemptions
Number of Children under Age 17
Total Population

Table 4
Description of Tax Model Parameters

Parameter Name	Description
STAGE 1 FILE	Location and filename of Stage I Aging Factors file
TOTSIM	Total number of simulations (two per year)
AGEDATA	Switch to perform aging
OUTFIL	Number of Binary Extract files to be output
CASE	Switch for turning on Case Model
MAXBRACK	Maximum number of Income Tax Brackets (6 under current law)
BASEYEAR	Year of the Statistics of Income (SOI) Public-Use Datafile
AUXYN	Switch for producing Auxiliary Tables
INCTAX_SWITCH	Switch for turning on Income Tax Calculator
ESTATE_SWITCH	Switch for turning on Estate Tax Calculator
BROADINC_SWITCH	Switch for calculating Economic Income for each Tax Unit
ESMAXBRK	Maximum number of Estate Tax Brackets (17 under pre-EGTRRA law)
OUTPUT FILE	Location and filename of Binary Extract file(s)
LASTFY	Last fiscal year for this run
SPLIT	Fiscal year split (value specified is between 0 and 1)
REVTABLE	Switch for producing revenue table
TITLE	Title for this simulation
TAXLAW	Year or name of the hard-coded tax law that will be simulated (if user inputs USERDEF, rates and brackets are specified below as parameters)
YEARSIM	Year of the simulation for aging purposes (for example, 2004 means that the variables for each record will be aged to 2004)
CLASSIFIER	Specifies the income quintiles to use for tabulation purposes. Quintiles differ because cash and economic income differ with tax law. (1 = Pre-EGTRRA income quintiles, 2 = Pre-JGTRRA quintiles, 3 = Current law)
INFO1-5	Five Information Parameters that provide a one-word description of the tax law or provisions in the simulation (can also be used as switches)
EXTRACT	Switch specifies whether Binary Extract file is to be output for this year or not
ESEXTRACT	Switch specifies whether the model generated variables from the Estate Tax calculation are to be output in the Binary Extract file
AGITAB_ALL	Switch for tabulating various variables by AGI in the output file
AGITAB_ITAB	Switch for tabulating various variables by AGI and filing status in the output file
EICTAB_ALL	Switch for tabulating EITC statistics for all filers
EICTAB_DEP	Switch for tabulating EITC statistics by filing status
DISTAB	Switch for producing TPC standard distribution tables by AGI
CITAB	Switch for producing TPC standard distribution tables by Cash Income
BITAB	Switch for producing TPC standard distribution tables by Economic Income
MRATES	Switch for calculating effective marginal tax rate for each record
MRINC	Amount for marginal increase in income when calculating effective marginal tax rates
CPI_CY	CPI for the tax year of the simulation
CPIBRK_10PCT_BY	Base year CPI if indexing the 10 percent bracket
CPISKNKADD_BY	Base year CPI if indexing the increase in the EITC threshold for married couples
CPIBRK_BY	Base year CPI if indexing tax brackets
CPISTD_BY	Base year CPI if indexing the standard deduction
CPIPSE_BY	Base year CPI if indexing the threshold for the phaseout of itemized deductions and personal exemptions
CPIEIC_BY	Base year CPI if indexing the Earned Income Tax Credit thresholds
CPIEXM_BY	Base year CPI if indexing the personal exemption
CPICTC_BY	Base year CPI if indexing the threshold and amount of the Child Tax Credit
CPICTC_ADDON_BY	Base year CPI if indexing a user-specified add-on amount for the Child Tax Credit
CPIED_BY	Base year CPI if indexing the education credits (Hope and Lifetime Learning)
CPIAMT_BY	Base year CPI if indexing the AMT exemption, brackets, and phaseout thresholds

Table 4 (continued)
Description of Tax Model Parameters

Parameter Name	Description
CPI_SAVCRD_BY	Base year CPI if indexing the saver's credit
INDEX_10PCT	Switch for indexing the 10 percent bracket
INTERESTDIVEXCL1-2	Allows a dollar amount of dividends and interest income to be excluded from AGI (currently not in use)
EDCREDIT_SWITCH	Switch for turning on the Hope and Lifetime Learning Credit
EDINDEX_SWITCH	Switch for turning on indexation of the education credits
EDCREDIT_AMT	Treatment of the education credits against the AMT*
EDCREDIT_THRESH1-4	Threshold for the beginning of the phaseout range of the education credits
EDCREDIT_LENGTH1-4	Length of the phaseout range of the education credits
HOPEKINK	Kink for the Hope Credit
LIFEMAX	Maximum Lifetime Learning Credit
RNDFCTR	Multiple to which inflated brackets, deductions, etc. are rounded (ex. 50)
RNDFCTR_EIC	Multiple to which the inflated EITC parameters are rounded
PEASE	Threshold for the phaseout of itemized deductions (Pease)
STANDARD_SWITCH	Switch for turning on the standard deduction
STANDARD1-3	Standard deduction amount for the various filing statuses
ADDITIONAL1-3	Additional deduction amount for those over 65 or blind
DEPSTD	Standard deduction amount for dependent filers
ITEMDED_SWITCH	Switch for turning on itemized deductions
EICERN_ADD	Add-on for earnings for dependent standard deduction
EITC_SWITCH	Switch for turning on the EITC
EITC_AMT	Switch for limiting the EITC based on AMT liability
EITC_MODAGI	Switch for using modified AGI for EITC purposes
FKINK1-3	End of the phase-in region of the EITC
SKINK1-3	Start of the phaseout region of the EITC
EICPU1-3	Phase-in rate for the EITC
EICPD1-3	Phaseout rate for the EITC
INDEX_SKINKADD	Switch for indexing the addition to the EITC plateau for married couples
SKINK_ADDITION	Amount by which the EITC phaseout threshold is raised for marriage-penalty relief provision of EGTRRA
POPE1-4	Threshold for the phaseout of personal exemption by filing status
POPEINT1-4	Phaseout interval for personal exemption by filing status
EXAMT	Personal exemption amount
ALTEX_SWITCH	Switch for using an alternative system for the calculation of exemptions
ALTEX1-4	Alternative exemption amounts by filing status
DEPEX_SWITCH	Switch for turning on dependent exemptions
SECMAX	Social Security wage base
CGMAX	Maximum capital loss that can be used to offset ordinary income
FILARY1-6	Variable for converting filing status
RNTMAX	Maximum allowable passive loss from real estate
RNTTHRSH	AGI phaseout threshold for rental income
IRAMAX1-4	Maximum allowable contribution to traditional and Roth IRAs
IRAPHS(1)1-4	Start of phaseout range for traditional IRAs
IRAPHS(2)1-4	End of phaseout range for traditional IRAs
ROTHPHS(1)1-4	Start of phaseout range for Roth IRAs

Table 4 (continued)
Description of Tax Model Parameters

Parameter Name	Description
ROTHPHS(2)1-4	End of phaseout range for Roth IRAs
SAVECRD_SWITCH	Switch for turning on the saver's credit
SAVEREFUND_SWITCH	Switch for making the saver's credit refundable
INDEX_SAVCRD	Switch for indexing the saver's credit
SAVECREDIT_AMT	Treatment of the saver's credit against the AMT
SAVELIM	Maximum amount for the saver's credit
SAVEBRACK1-3	Bracket thresholds for the saver's credit
SAVERATE1-3	Credit rates for the saver's credit
RETPLAN	Switch for law governing pension plans (0 = pre-EGTRRA, 1 = EGTRRA)
PCONMAX	Maximum elective deferral contribution for employee
DCMAX	Maximum employer and employee contributions to defined contribution plans
DC_PCT	Maximum percentage of salary eligible for elective deferral contribution
CATCHUP	Maximum additional elective deferral contribution amount allowed for those age 50 or over
IRACATCHUP	Maximum additional IRA contribution allowed for those age 50 or over
INT_RATE	Interest rate used in present-value calculations
EHIRAT	Medicare tax rate for employers
EMPRAT	Social Security tax rate for employers
INCRAT	Inclusion rate for Social Security benefits in modified AGI
SSBPHS1-2	Inclusion rates for Social Security benefits in AGI
SSMAXR1-2	Inclusion rates for Social Security benefits in AGI
SSBTHRSH(1)1-4	Thresholds for including Social Security benefits in AGI at lower rate
SSBTHRSH(2)1-4	Thresholds for including Social Security benefits in AGI at higher rate
SEHRAT	Inclusion rate for self-employed health insurance
MOVEADJ	Switch to treat moving expenses as an adjustment to income
MSCRAT	Floor rate for miscellaneous itemized deductions
MEDRAT	Floor rate for medical expenses
PINTRAT	Inclusion rate for personal interest in itemized deductions (currently not in use)
AMT_SWITCH	Switch for turning on the alternative minimum tax (AMT)
AMTIND_SWITCH	Switch for indexing the AMT
AMTMEDRAT	Additional floor rate for itemizing medical expenses for AMT purposes
AMTX1-4	AMT exemption by filing status
AMTHRSH1-4	AMT exemption phaseout thresholds by filing status
AMTPHS	Phaseout rate for AMT exemption
AMTBRK1-4	AMT brackets by filing status
AMTRAT1-2	AMT rates
AMTDEPEX	Switch for allowing dependent exemptions for AMT purposes
AMTMEDEX	Switch for allowing medical expenses for AMT purposes
AMTMSCFLR	Switch for allowing miscellaneous business expenses for AMT purposes
AMTSTLTAX	Switch for allowing deduction for state and local taxes for AMT purposes
AMTSTDED	Switch for allowing the standard deduction for AMT purposes
DISTHRSH	Threshold of investment income over which EITC is disallowed
DEPCARECREDIT_SWITCH	Switch for turning on the Child and Dependent Care Tax Credit (CDCTC)
DEPCARECREDIT_AMT	Treatment of the CDCTC against the AMT*
CHCAR1	Percent of expenses allowed for CDCTC
CHCAR2	Percent by which CDCTC is reduced when AGI exceeds the threshold
CHDLIM	Dependent care expense limit per child

Table 4 (continued)
Description of Tax Model Parameters

Parameter Name	Description
DEPCARECREDIT_THRESH	Threshold over which CDCTC rates are gradually reduced
CHCARSTEP	Number of phaseout steps for CDCTC
ELDCREDIT_SWITCH	Switch for turning on the Elderly Credit
ELDCREDIT_AMT	Treatment of the Elderly Credit against the AMT*
ELDCAP1-4	Maximum Elderly Credit by filing status
ELDAGI1-4	Phaseout threshold for Elderly Credit
ELDRAT	Elderly Credit rate
EXMPCT	Rate at which personal exemptions are phased out under PEP
PHSEXM	Switch for turning on the phaseout of personal exemptions (PEP)
PHASEOUT_FRACTION	Variable that implements EGTRRA's elimination of PEP and Pease
SSRAT	Social Security tax rate (employee share)
HIRAT	Medicare tax rate (employee share)
CHILDCREDIT_SWITCH	Switch for turning on the Child Tax Credit (CTC)
CHILDINDEX_SWITCH	Switch for indexing the CTC amount
CHILDADDIND_SWITCH	Switch for indexing the user-specified add-on amount for the CTC
CHLD_THRSHIND_SWITCH	Switch for indexing the CTC phaseout thresholds
CHILD_ADDON	Add-on amount for the CTC
CHILDCREDIT_AMT	Treatment of the nonrefundable portion of the CTC against the AMT*
CTC_AGE	Eligibility age for the CTC
CHILDCREDIT_AMOUNT	CTC amount
CHILDCREDIT_THRESH1-4	Phaseout threshold for the CTC by filing status
CHILDREFUND_SWITCH	Switch for allowing the additional CTC (i.e., the refundable portion)
CHILDREFUND_THRESH	Phase-in threshold for the refundable portion of the CTC
CHILDREFUND_RATE	Refund rate for the refundable portion of the CTC
ALTGN_SWITCH	Switch for taxing long-term capital gains at lower rates than ordinary income
ALTGNAMT	Switch for allowing same treatment for capital gains under AMT as under regular tax
DIVCG_SWITCH	Switch for allowing dividends to be taxed at the same rate as long-term capital gains
ALTRAT1-4	Alternative rates for the taxation of capital gains
GNBCRD_SWITCH	Switch for turning on the General Business Credit
AMTCRD_SWITCH	Switch for turning on the credit for prior-year AMT
FORCRD_SWITCH	Switch for turning on the Foreign Tax Credit
REGTAX_SWITCH	Switch for turning on the regular individual income tax
CORPTAX_SWITCH	Switch for distributing the corporate income tax burden
CORP_METHOD	Method of allocating the corporate tax burden
CORPREV	Total corporate tax burden ($ billions) to be distributed
CONSTAX_SWITCH	Switch for turning on the consumption tax (not currently in use)
CONSRATE	Consumption tax rate (not currently in use)
CONSSTUB1-9	Income stubs for consumption tax assignment (not currently in use)
DIVPLAN	Dividend exclusion plan (not currently in use)
MROPT	Method for determining incremental amount in the effective marginal tax rate calculation
MRPCT	Percent of AGI to be used as the increment amount in the effective marginal tax rate calculation
NBRACK	Number of tax brackets (if user specifies TAXLAW as USERDEF)
SBRACK1-6	Tax brackets for single filers
MBRACK1-6	Tax brackets for married couples filing jointly
HBRACK1-6	Tax brackets for head of household filers
RATES1-6	Statutory marginal individual income tax rates

Table 4 (continued)
Description of Tax Model Parameters

Parameter Name	Description
CTABREAL_SWITCH	Switch to convert classifier for distribution tables into real dollars
TABREAL_SWITCH	Switch to convert variables in distribution tables into real dollars
TABLE_BASEYEAR	Base year for the conversion of the variables in distribution tables into real dollars
BASE_DEFLATOR	Deflation factor for base year
CY_DEFLATOR	Deflation factor for current year
DEP_SWITCH	Switch for including dependent filers in the distribution tables
ESINFO1-5	Estate tax information parameters which provide a one-word description of the estate tax law or provisions in the simulation (can also be used as switches)
ESCPIBRK_BY	Base year CPI if indexing the estate tax brackets
ESCPIUC_BY	Base year CPI if indexing the estate tax unified credit
ESCPIQF_BY	Base year CPI if indexing the QFOBI amount
ESBRKIND	Switch for indexing the estate tax brackets
ESUCIND	Switch for indexing the Unified Credit
ESQFIND	Switch for indexing QFOBI amount
ESRNDFCT	Multiple to which the inflated estate tax parameters are rounded
ESBRK1-17	Estate tax bracket thresholds
ESRATE1-17	Statutory estate tax rates
ESNBRK	Number of estate tax brackets
ESSURTAX_SWITCH	Switch for turning on estate tax surtax (or bubble)
ESSURTAX_BRACK1-2	Estate tax surtax brackets ($ thousands)
ESSURTAX_RATE	Estate tax surtax rate
ESEXC	Amount of gross estate effectively excluded by the Unified Credit
ESQFOBI	Maximum QFOBI amount
ESQFPCT	Percent of gross estate that needs to consist of farm and small business assets in order to qualify for QFOBI
ESQFMAX	Maximum amount that can be excluded by the combination of the unified credit and QFOBI. Note that when the effective exclusion is greater than this amount, there is no QFOBI.
ESSTATEADJ	Adjustment to gross estate to arrive at estate for state death tax credit purposes
ESSTFACTOR	Percent of pre-EGTRRA law state death tax credit allowed
ESSTDED_SWITCH	Switch for allowing deduction for state estate taxes actually paid
ESSTDED_PCT	Percent of pre-EGTRRA law state death tax credit to apply as a deduction

Note: All dollar values are specified in real terms.
* 0 = credit fully allowed against the sum of the tax before credits and the AMT liability, 1 = credit not limited by the AMT but not allowed against the AMT, 2 = credit limited by the AMT and not allowed against the AMT liability

Appendix Table 1
Assets and Liabilities Imputed Using SCF Data

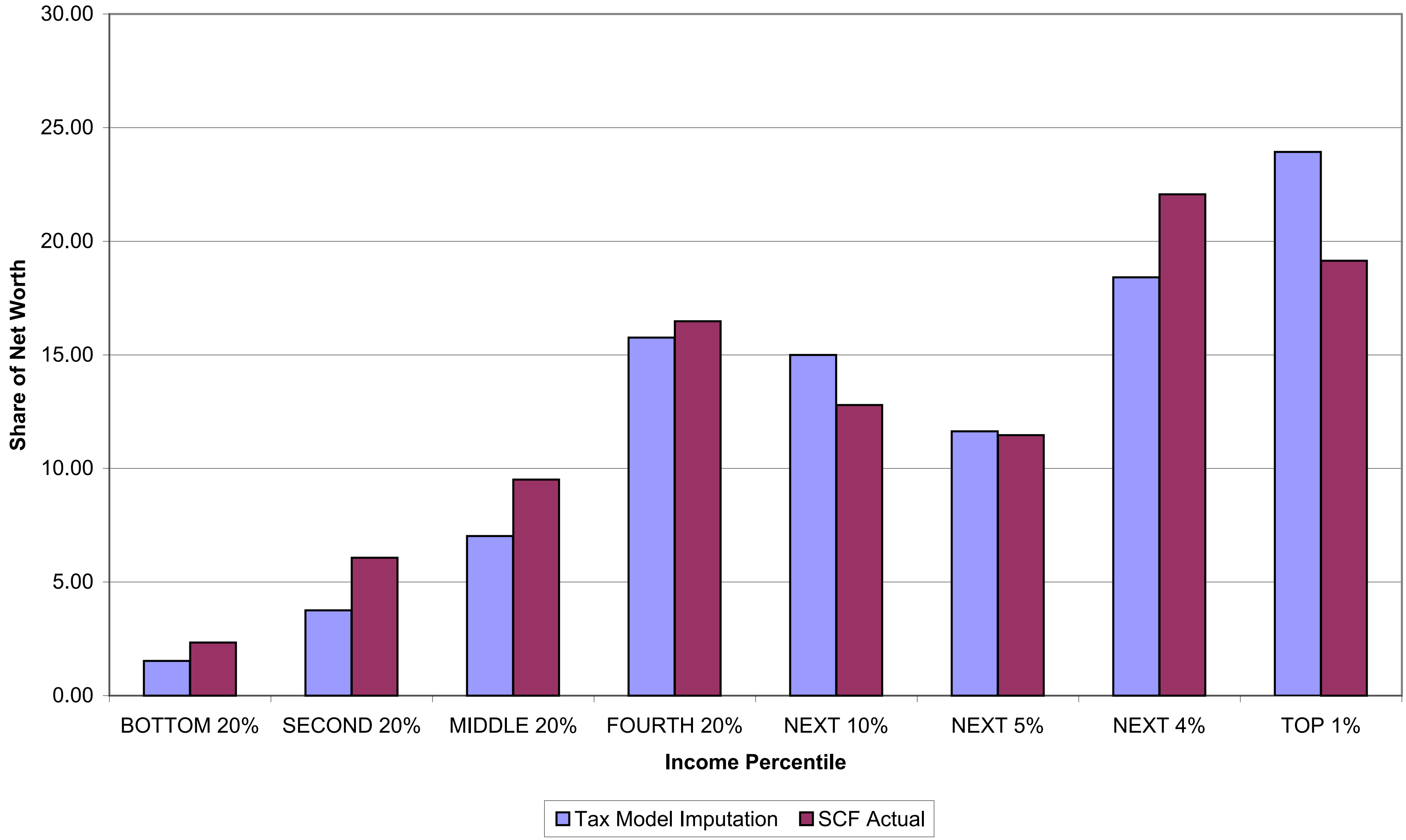
Assets	
	Cash
	Tax-exempt bonds
	Taxable bonds
	Stock
	Retirement assets
	Face value of life insurance
	Other financial assets
	Vehicles
	Personal residences
	Other real estate
	Farm assets including land
	Actively managed business assets (e.g., a family-owned business)
	Passively owned business assets (e.g., partnership shares)
	Other nonfinancial assets
Liabilities	
	Mortgage and home equity line of credit
	Real estate debt
	Farm debt
	Credit card balances
	All other debt

Appendix Table 2
Explanatory Variables for Probits and Regressions

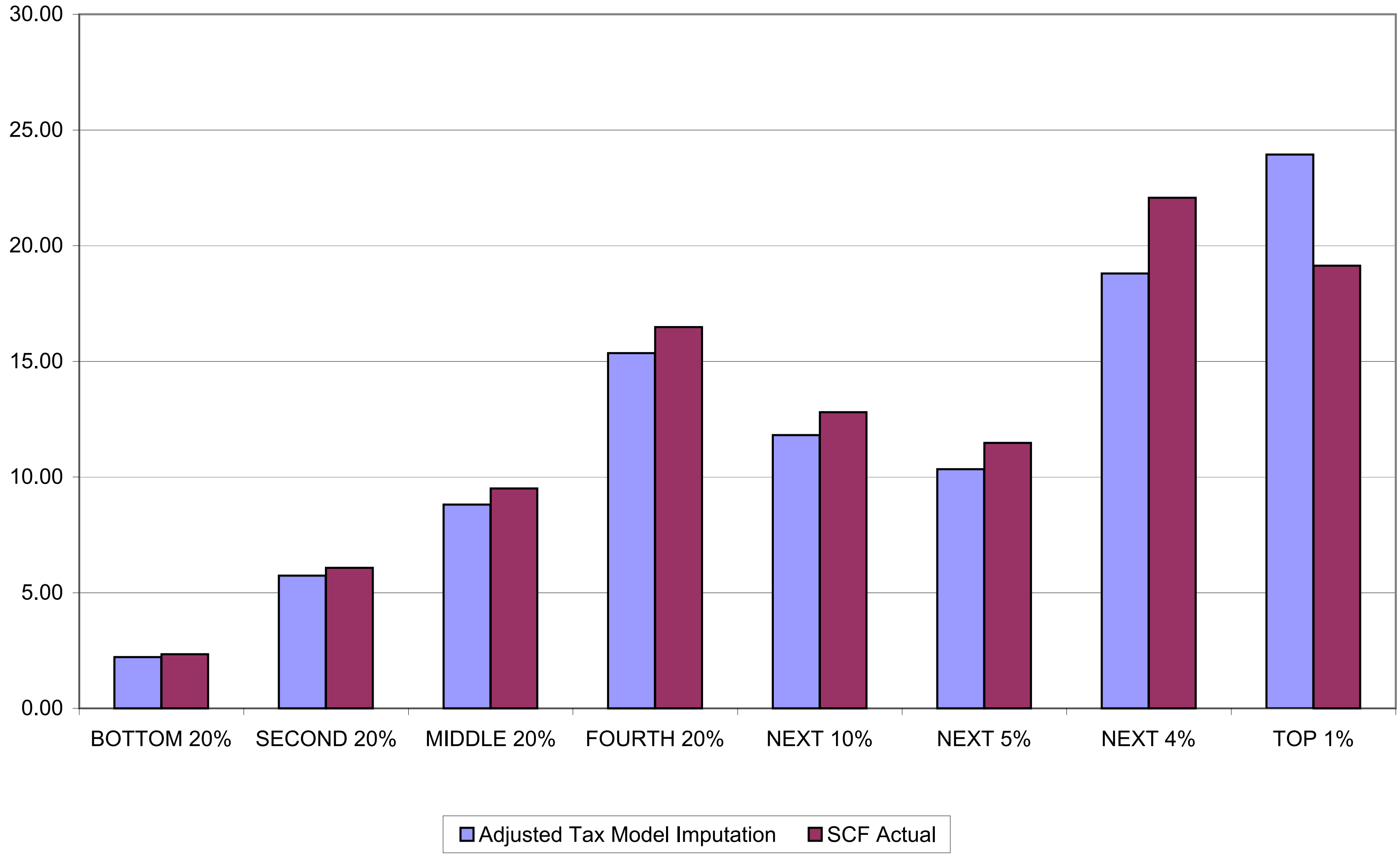
1	Number of dependents
2	Age of head (10-year bracket dummies)
3	Total household income (as defined for purposes of the SCF)
4	Income from a farm or business
5	Tax-exempt interest income
6	Taxable interest income
7	Rental income from Schedule E
8	Pension income
9	Taxable dividends
10	Realized capital gains
11	Separate dummies for zero values of (3) - (10)
12	Separate dummies for negative values of (3), (4), and (10)
13	Interaction terms for (12) and appropriate income item
14	Dummy for whether or not individual itemizes deductions
15	Separate dummies for filing Schedule C, E, or F

Note: Income items are defined as the natural logarithm of the item plus 1.

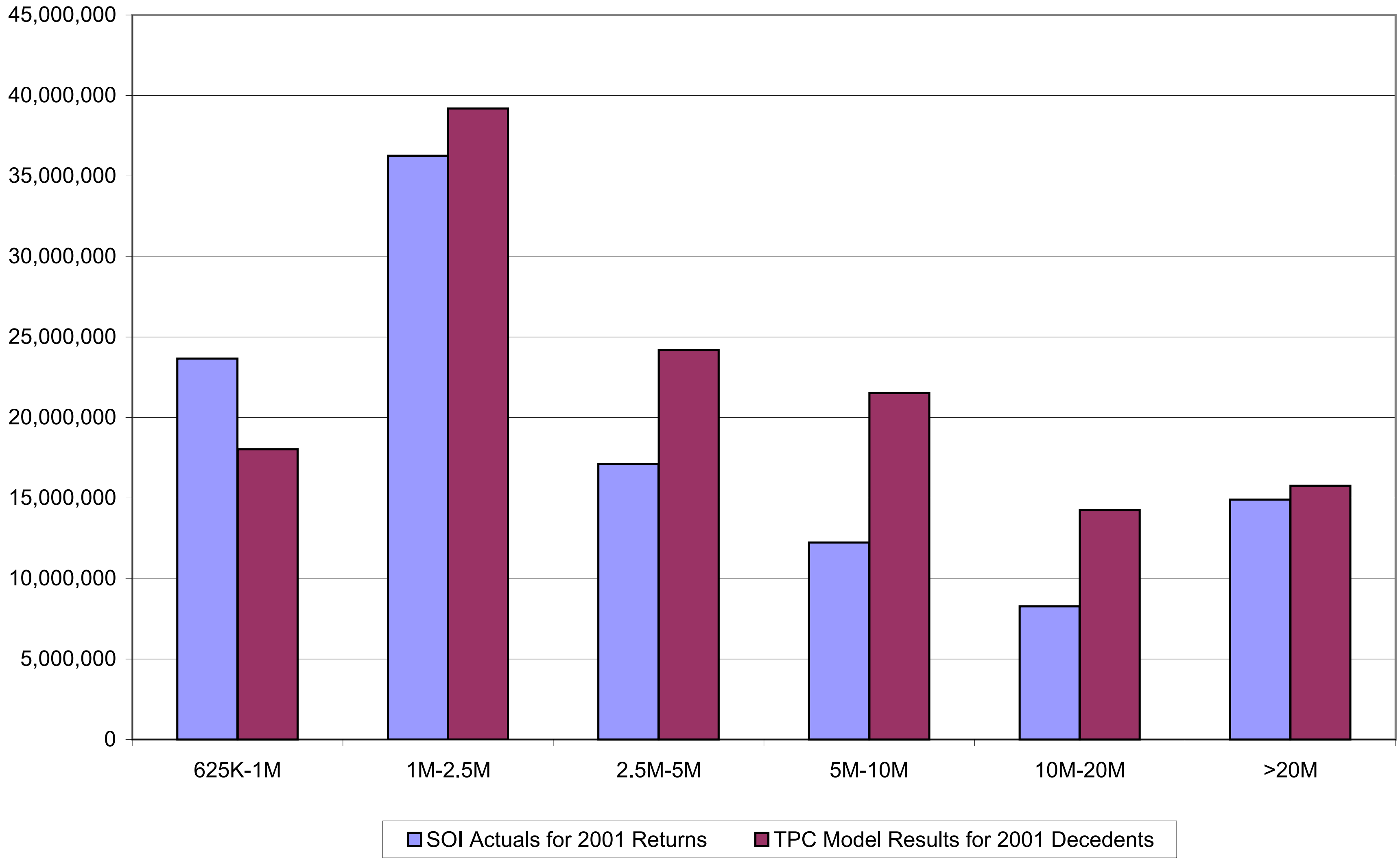
Appendix Figure 1
Distribution of Net Worth by Income, SCF Versus Unadjusted Tax Model Imputations, 2001



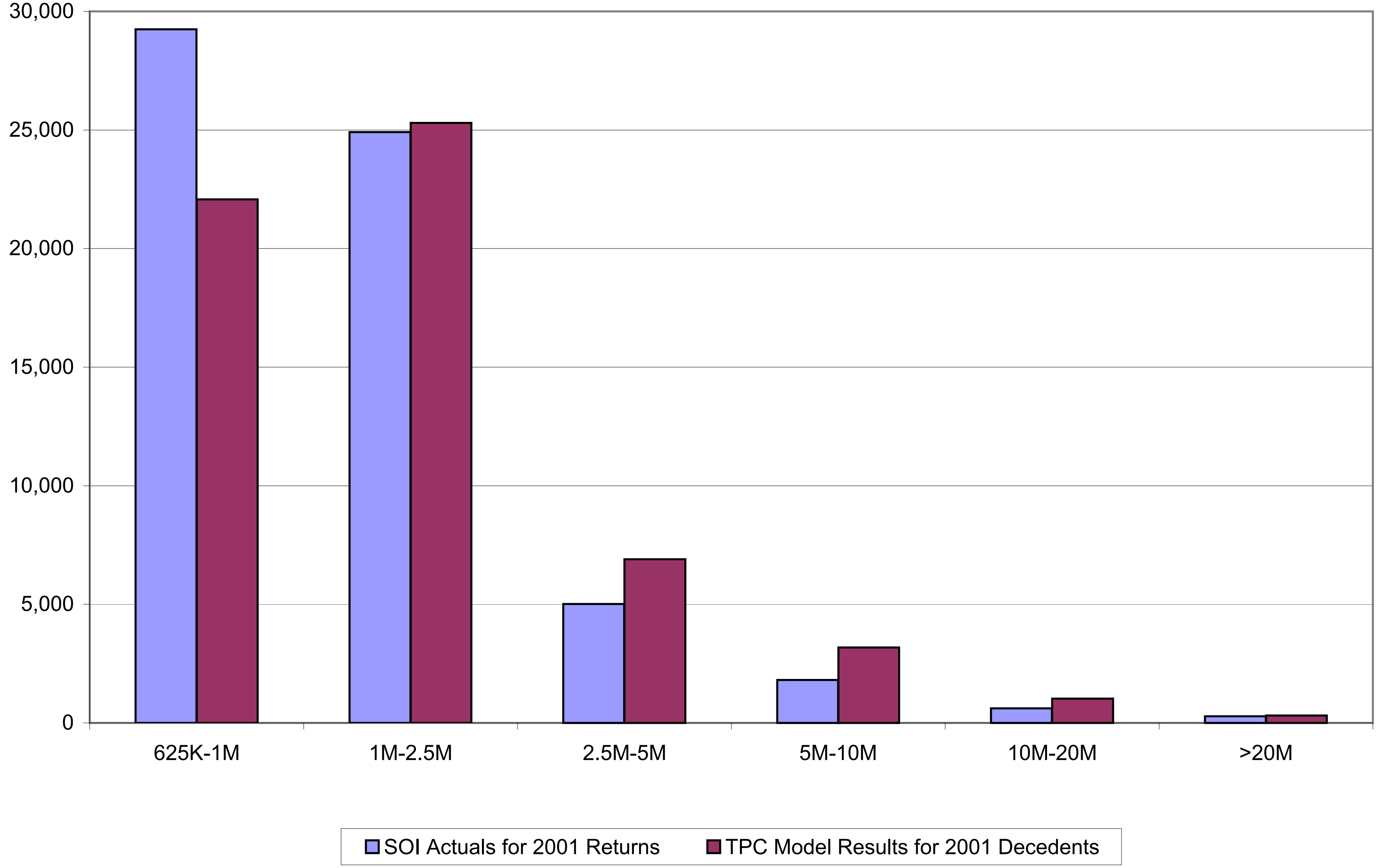
Appendix Figure 2
Distribution of Net Worth by Income, SCF Versus Adjusted Tax Model Imputations, 2001



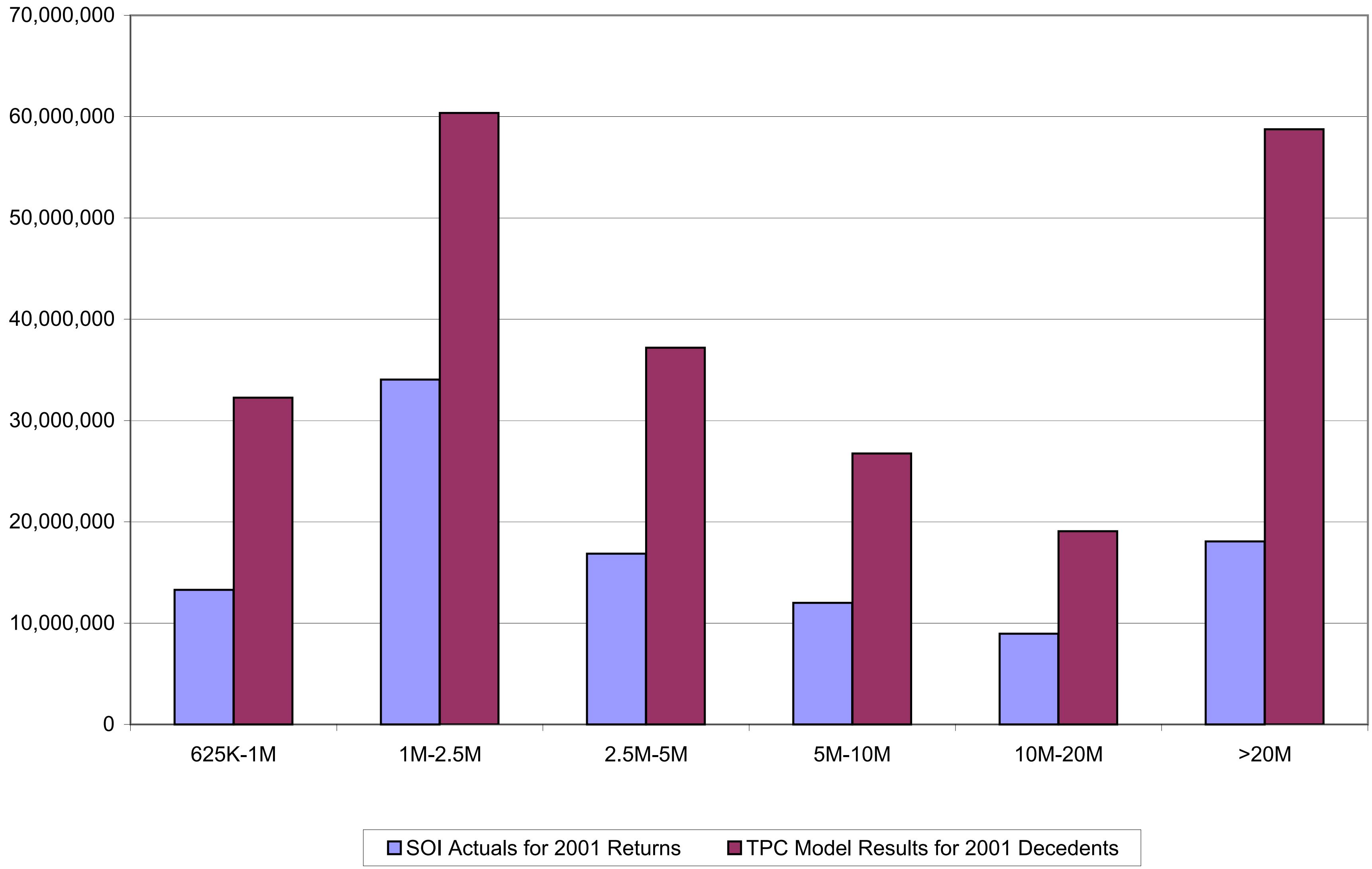
Appendix Figure 3
Distribution of Gross Estate before Retargeting, Single Individuals, 2001



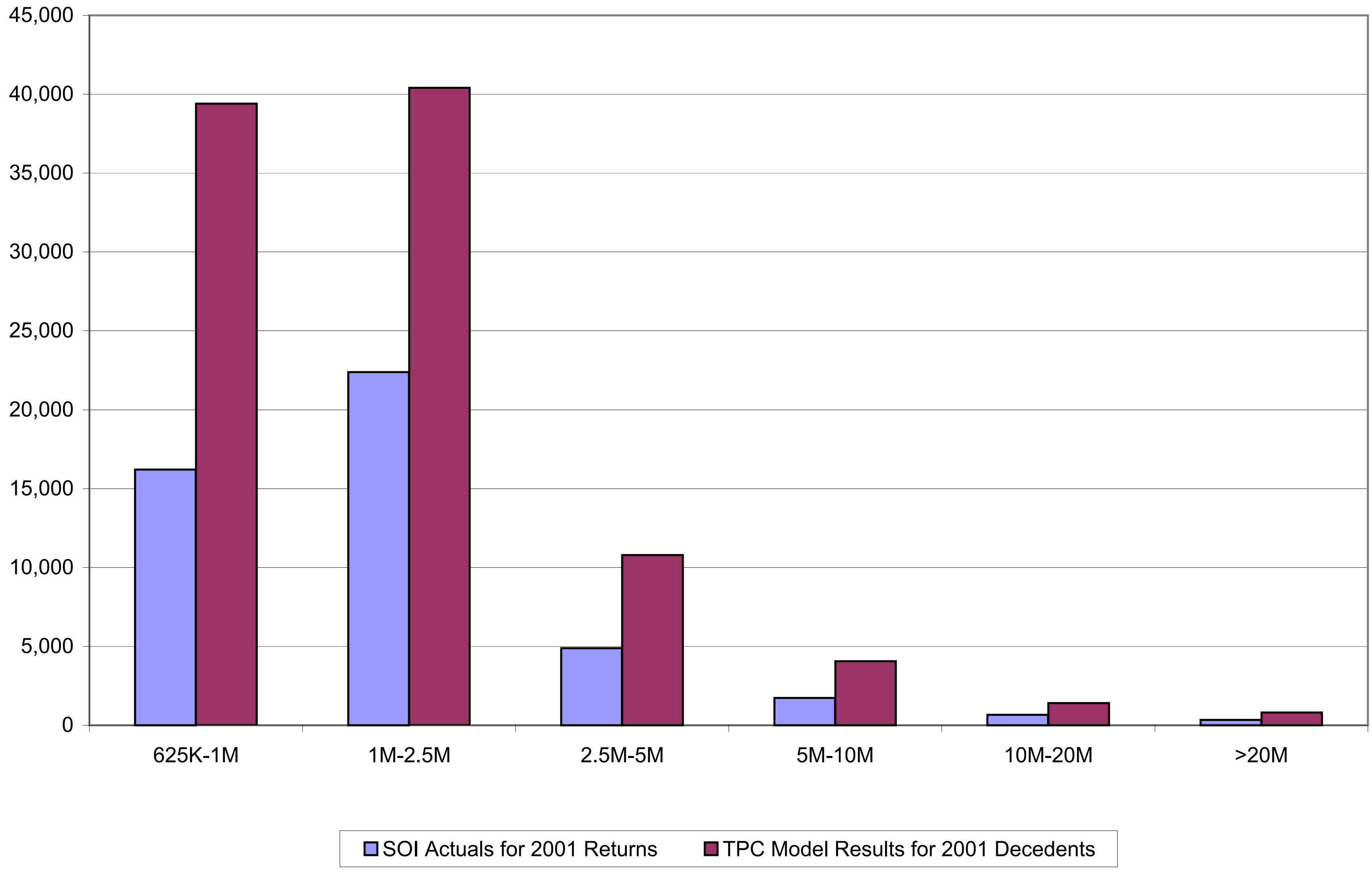
Appendix Figure 4
Distribution of Estate Tax Filers before Retargeting, Single Individuals, 2001



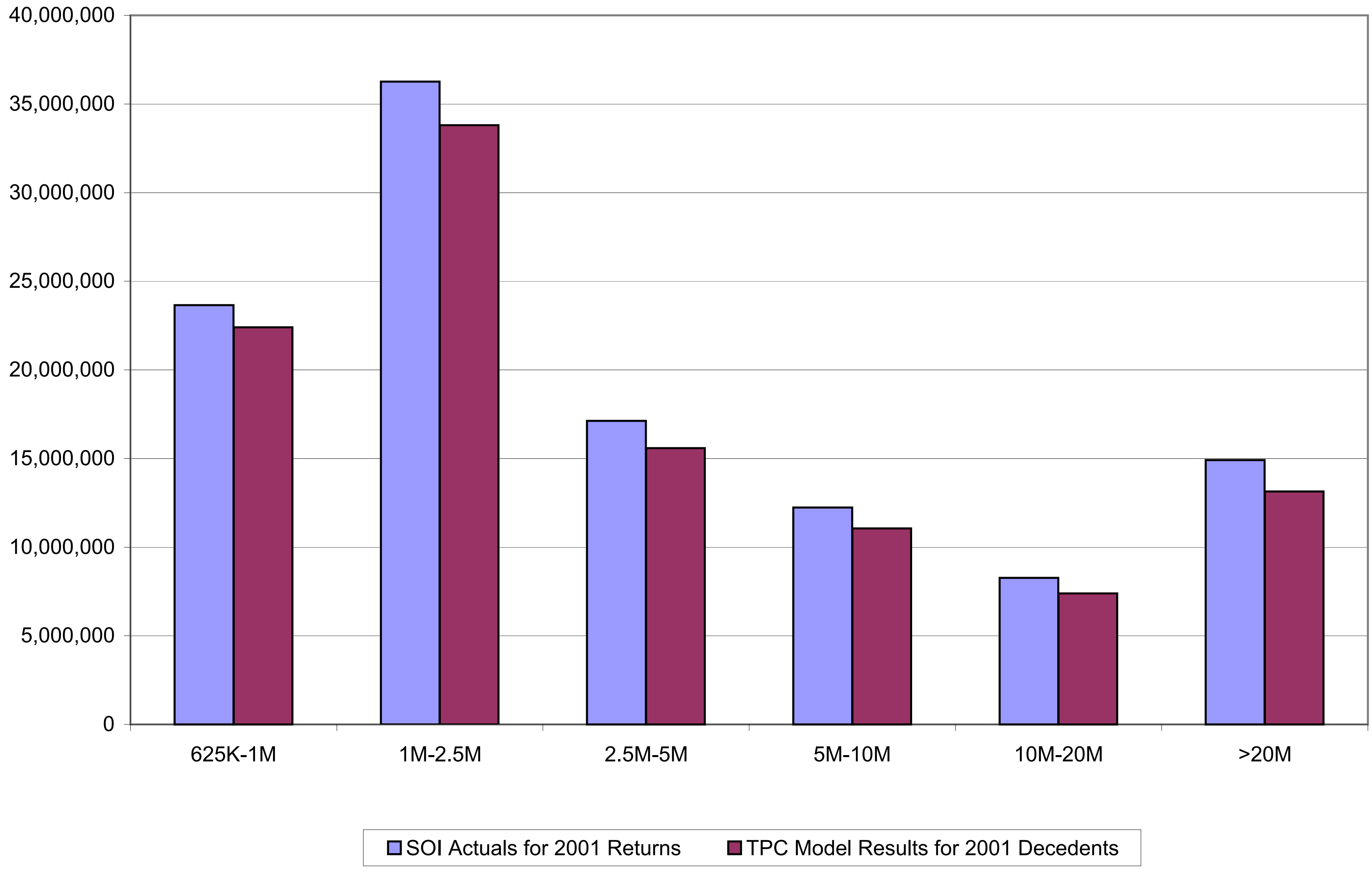
Appendix Figure 5
Distribution of Gross Estate before Retargeting, Married Individuals, 2001



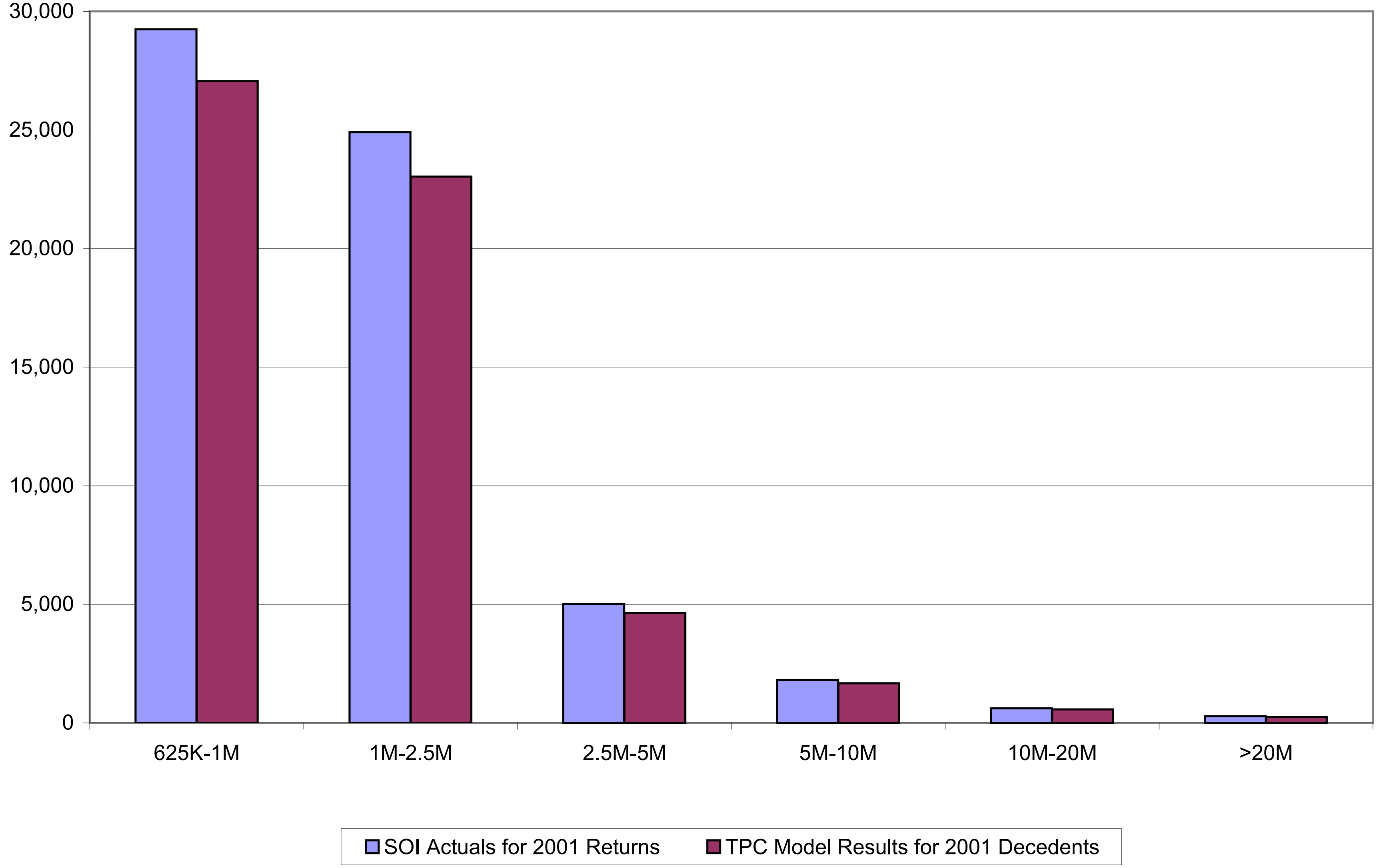
Appendix Figure 6
Distribution of Estate Tax Filers before Retargeting, Married Individuals, 2001



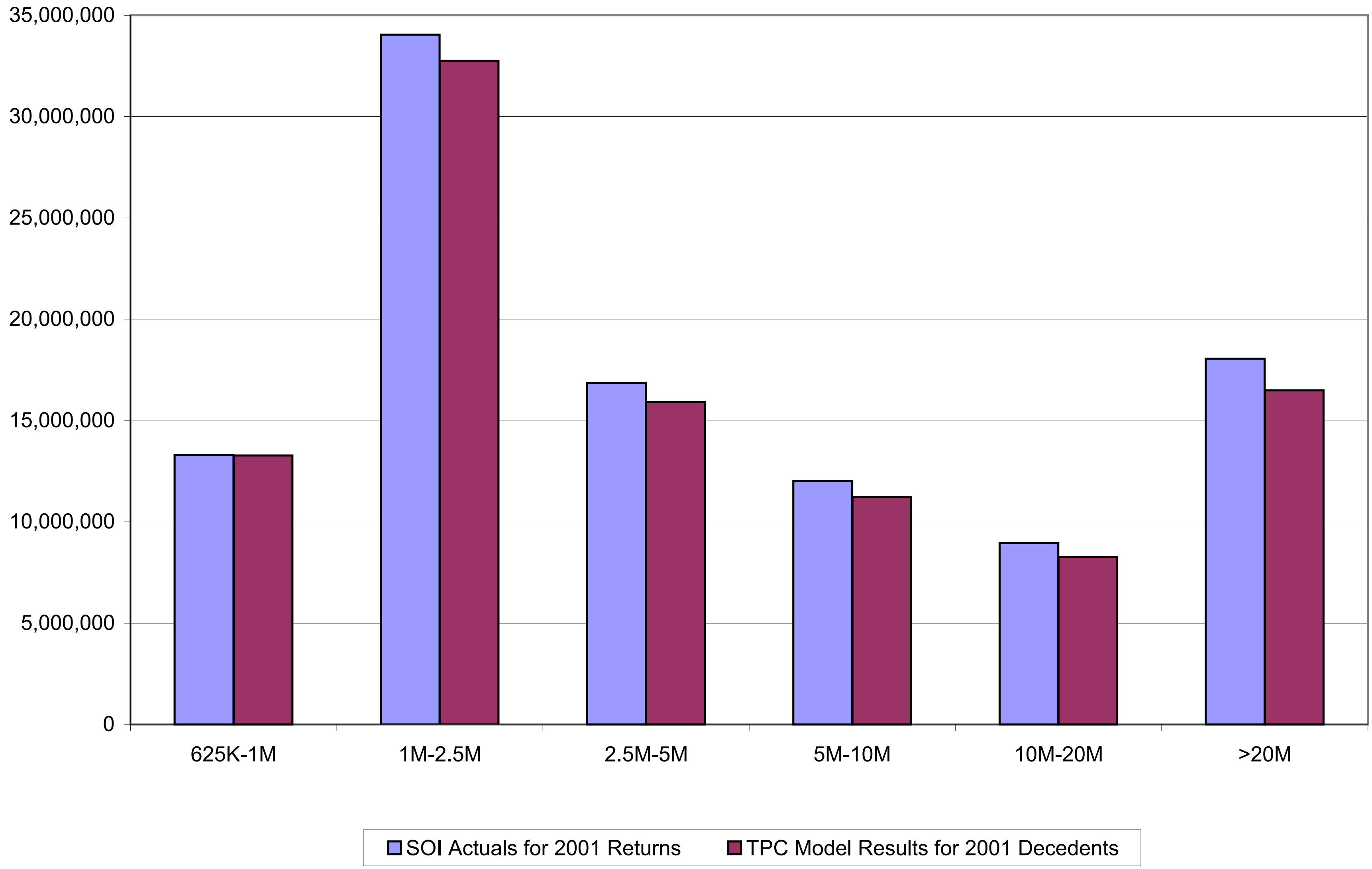
Appendix Figure 7
Distribution of Gross Estate after Two-Stage Adjustment, Single Individuals, 2001



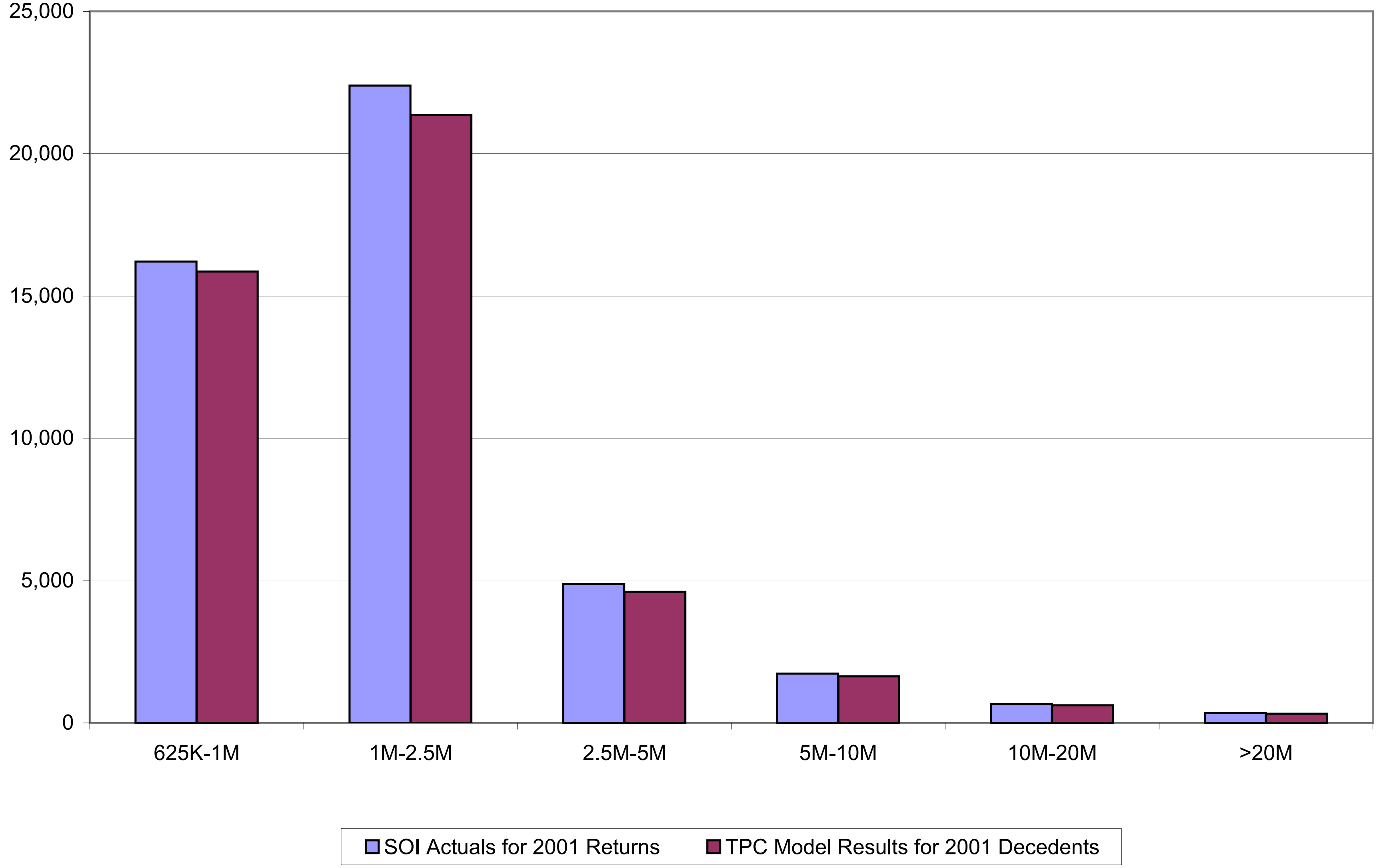
Appendix Figure 8
Distribution of Estate Tax Filers after Two-Stage Adjustment, Single Individuals, 2001



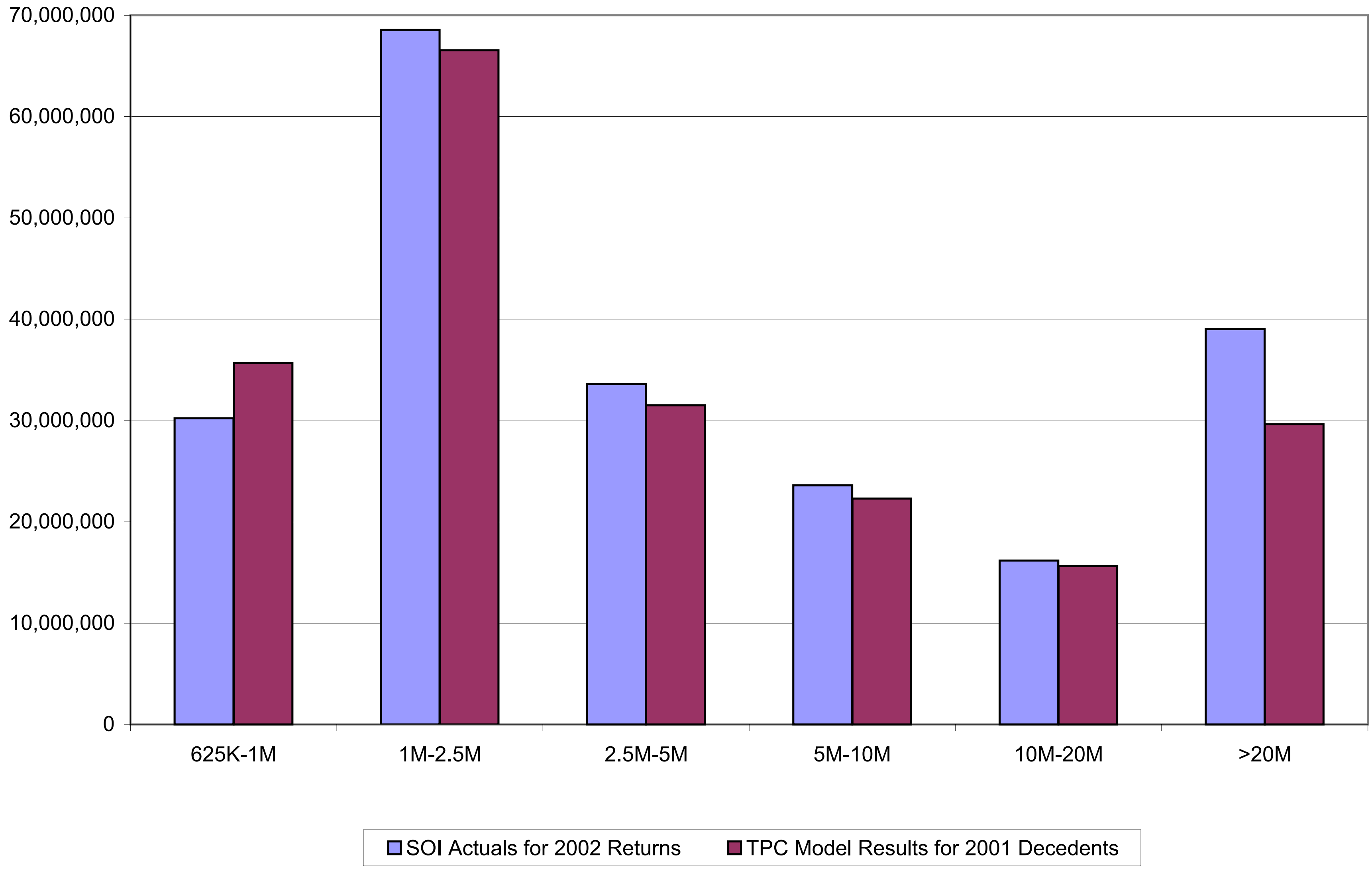
Appendix Figure 9
Distribution of Gross Estate after Two-Stage Adjustment, Married Individuals, 2001



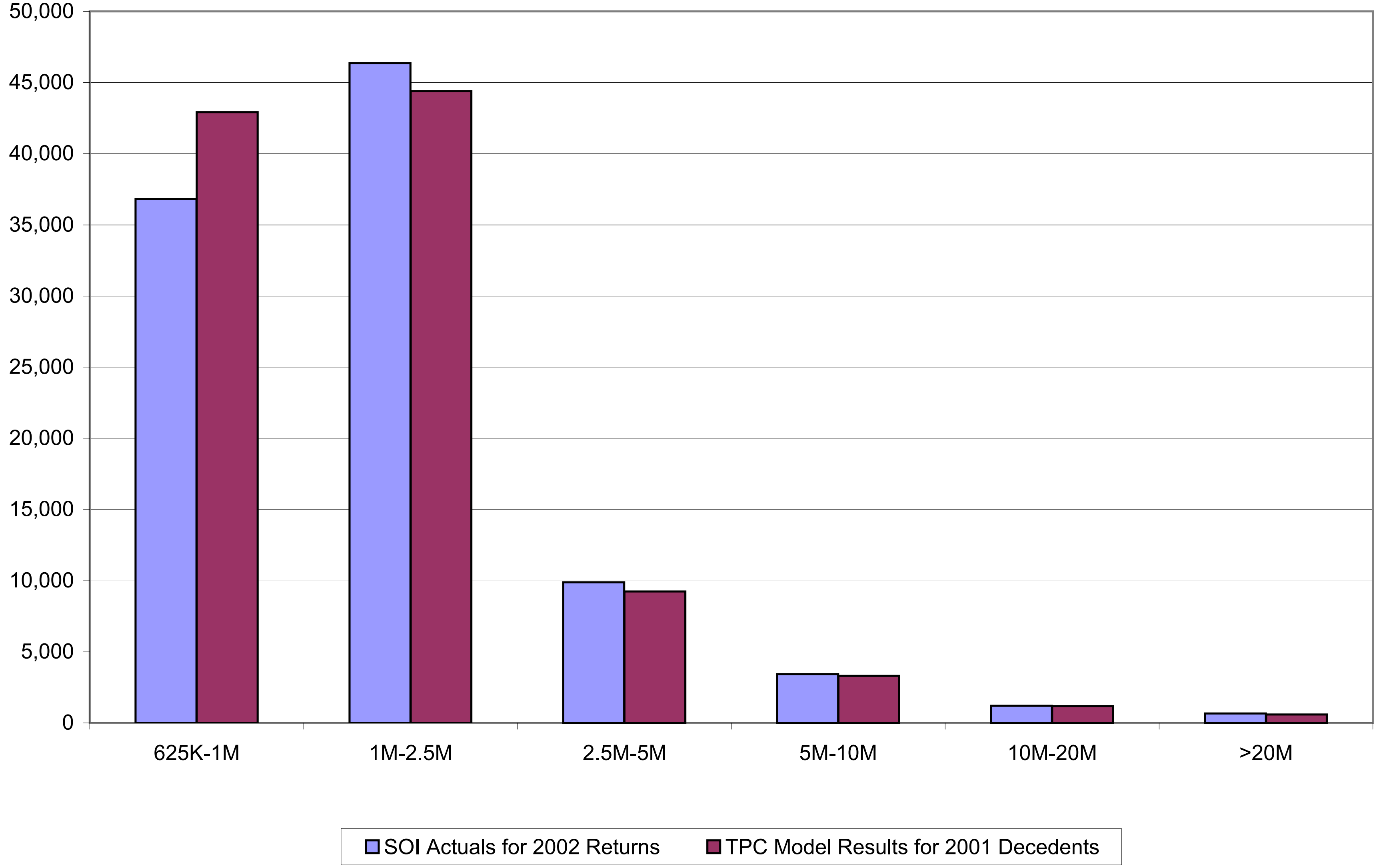
Appendix Figure 10
Distribution of Estate Tax Filers after Two-Stage Adjustment, Married Individuals, 2001



Appendix Figure 11
Distribution of Gross Estate after Two-Stage Adjustment, All Estate Tax Returns, Predicted 2001 Decedents vs. Actual 2002 Returns Filed



Appendix Figure 12
Distribution of Estate Tax Filers after Two-Stage Adjustment, All Estate Tax Returns, Predicted 2001 Decedents vs. Actual 2002 Returns Filed



Appendix Figure 13
Net Estate Tax