Sir Francis Bacon is given credit for the maxim “Knowledge is power.” When I was a younger scholar, that meant being able to answer important questions related to the evaluation of public policies. As I have become less young, it increasingly has meant the ability to define the questions that need to be answered to appropriately evaluate public policies.

This is not a trivial difference. One of my public policy heroes, Professor and later Senator Pat Moynihan, once said that “In public policy debates everyone is entitled to his own opinion, but not his own facts.” But the issue is more complex. Facts are only relevant within some context. Much of what we do as evidence-based policy analysts is use, and in some cases collect, data to determine if a given policy has or will satisfy a set of success criteria. But decisions must be made along the way with respect to what data to select, how it relates to the success criteria, and most importantly what are the success criteria against which the data on outcomes are being measured.

As a 1970s University of Chicago–trained economist who then spent three years as a postdoctoral student with the University of Wisconsin's Institute for Research on Poverty (IRP), the two kinds of questions I ask about any policy are: What are its behavioral implications (efficiency questions), and who gets what because of it (distributional questions)?

At Chicago, I learned to appreciate the ability of entrepreneurs, in competitive markets, in their search for profits, to distribute goods and services efficiently in the product market and to efficiently acquire the available factors of production (land, labor, and capital) via factor markets. I also was trained to use empirical information on changes in the behavior of demanders and suppliers in such markets to determine the size of the negative efficiency effects of government interference in them.

At the IRP, I learned to appreciate the difference between efficient outcomes and outcomes that produce the socially appropriate distribution of income. And it was there that I first saw how public-use data sets like the Current Population Survey (CPS) could be used by researchers to track social success measures and estimate the degree that government policies account for the growth in income and the reduction of poverty and income inequality in our society.

Much of the Wisconsin-style poverty and income measurement research can be traced to Robert Lampman and the early IRP directors (Harold Watts, Robert Haveman, and Irv Garfinkel). But, then and now, I was most influenced by the work of a new generation of poverty and income inequality researchers, Sheldon Danziger, Peter Gottschalk, and Tim Smeeding, who have established many of the
ground rules for this literature—rules that today are used by the Census Bureau in its official measures of poverty, income, and inequality as part of its annual report based on CPS data (U.S. Census Bureau, various years).

But I also came to appreciate how sensitive these measures are to the underlying assumptions either explicitly stated or implicitly implied by their use. Because the public-use CPS best captured the “pre-tax, post-government in-cash transfer income” of households as well as the families within them, most measures of poverty and the levels and trends in income and income inequality use this resource measure, within these sharing units, to capture the household or family size-adjusted resources available to each person in the United States. In doing so, they assume that these resources are equally shared within the sharing unit and there are some returns to scale in their use. (See Besharov & Couch, 2010, for a recent overview of poverty measurement issues. See Salverda, Nolan, & Smeeding, 2009, for a recent overview of inequality measurement issues.)

I am pleased to say that in the three decades since leaving Chicago and Wisconsin, my research, informed by their training, has resulted in my work being equally mistrusted at both. But that training, together with the inspiration I received from two of the best economics-based public policy writers—George Stigler at Chicago and Robert Haveman at Wisconsin—gave me a comparative advantage in academic-based policy analysis over more talented but more narrowly trained labor or public economists. Let me give you two separate but related cases involving the work of two outstanding economists, both of whom are winners of the John Bates Clark Award—David Card and Emmanuel Saez—that point out the importance of getting the question right.

THE MODERN DEBATE ON MINIMUM WAGE POLICY

The minimum wage provisions of the FLSA of 1938 have been repealed by inflation. Many voices are now taking up the cry for a higher minimum. Economists have not been very outspoken on this type of legislation. It is my fundamental thesis that they can and should be outspoken, and singularly agreed. The popular objective of minimum wage legislation—the elimination of extreme poverty—is not seriously debatable. The important questions are rather (1) Does such legislation diminish poverty? and (2) Are there efficient alternatives? The answers are, if I am not mistaken, unusually definite for questions of economic policy. If this is so, these answers should be given. Some readers will probably know my answers already (“no” and “yes,” respectively); it is distressing how often one can guess the answer given to an economic question merely by knowing who asks it. But my personal answers are unimportant; the arguments on which they rest are.


David Card is the 1995 winner of the Johns Bates Clark Award given to the best economist under the age of 40. His iconoclastic book with Alan B. Krueger, Myth and Measurement: The New Economics of the Minimum Wage (1995), blasted apart the decades-old consensus view, best articulated by Brown, Gilroy, and Kohen (1982), that job markets for low-skilled adults and teenagers were competitive and that in such markets, minimum-wage legislation will increase wages at the cost of modest but significant reductions in employment (demand elasticities in the range of \(-0.2\) or \(-0.3\)).

Card and Krueger weighed the actual empirical evidence for this consensus view on the behavioral effects of the minimum wage and found it wanting. In its place, using innovative difference-in-differences or natural experimental methods, which Card and a few others were then introducing into the more general applied econometric
literature, they found no evidence of a negative minimum wage effect on employment—but they did find some evidence of a positive effect.

The research at the heart of their book had an important influence on President Clinton, whose party's disastrous mid-term election outcomes of 1994 led him, in his 1995 State of the Union Address, to make an increase in the minimum wage in his major domestic policy proposal for that year. In doing so he stated:

I've studied the arguments and the evidence for and against a minimum wage increase. I believe that the weight of the evidence is that a modest increase does not cost jobs, and may even lure people into the job market. But the most important thing is, you can't make a living on $4.25 an hour. (President Clinton, State of the Union Address, January 1995)

Over the past 15 years, a new generation of applied labor economists, inspired by *Myth and Measurement*, have followed their lead: (a) in considering the labor market conditions in which low-skilled adults and teenagers find themselves; (b) in performing replication studies; and, most especially, (c) in their use of natural experimental methods to look at the behavioral and distributional effects of minimum-wage legislation and many other public policies. Hence, along these dimensions, *Myth and Measurement* continues to have an important bearing on the economics profession.

But what has this new literature discovered with respect to the behavioral and distributional consequences of minimum-wage legislation? David Neumark and William Wascher (2008) report that most of these new minimum wage researchers, while fully embracing the econometric strategies in *Myth and Measurement*, have primarily found that minimum wage increases have small but statistically significant negative employment effects—findings close to the previous consensus values. But, more importantly for policy analysts interested in the distributional consequences of the minimum wage, using difference-in-difference methods, they show that movements onto the poverty rolls by the families of workers whose employment is negatively affected by minimum wage increases more than offset the movement out of poverty by the families of workers whose wage earnings are positively affected by an increase in the minimum wage.

Neumark and Wascher then report on the evidence showing that the Earned Income Tax Credit (EITC) is a far more effective policy mechanism for reducing poverty among working Americans. Unlike the minimum wage, which raises the wages of all affected workers, including the majority who are second or third earners in nonpoor families, the EITC only subsidizes the wages of low-income families and does so via the tax system, avoiding the negative employment effects of minimum wage increases.

These later findings are consistent with my earlier research on the distributional effects of the minimum wage (Burkhauser & Finegan, 1989; Burkhauser, Couch, & Glenn, 1996) and the replications we (Burkhauser, Couch, & Wittenburg, 1996) first report showing that Chapter 9, Table 2 (p. 285) of *Myth and Measurement* does not ask the traditional distribution question with respect to a minimum wage increase: What share of the gains from this policy goes to workers who live in poor or near poor families?

In this table Card and Krueger report on a simulation they perform to determine who will gain from a proposed increase in the minimum wage from $3.35 to $4.25 per hour by income decile, assuming no negative employment effects. To do so, they use data from the public-use CPS to initially focus on a population of individuals age 16 and over and array them into deciles based on their family's pre-tax, post-government in-cash transfer income. In doing so, Card and Krueger do not take into consideration the number of persons in these families over which this income must be shared and hence change the way that resources are usually measured in the
poverty and income inequality literature that they have now entered. Thus the decile brackets they create from this distribution are not well suited for asking the traditional question policy analysts and policymakers have been interested in since Stigler (1946) first laid out the behavioral and distributional case against minimum wage increases as a policy for poverty elimination.

Their change in the question asked becomes clearer in their next step when they assign all workers age 16 and over into one of these brackets and ask the following question: What percentage of workers in each income decile is affected by the policy—that is, what percentage of these workers were earning between $3.35 and $4.24 per hour before the simulated policy change to $4.25 per hour?

In our 1996 paper, we replicate the Card and Krueger analysis and find as they did that workers who live in lower income decile brackets are more likely to be affected by the policy. But then we ask a more appropriate question: What share of the gains from this policy goes to workers who live in poor or near-poor families?

To do so, we first account for family size in creating our brackets by arraying all persons across the income-to-needs distribution (their pre-tax, post-government in-cash family income divided by the poverty line based on their family's size). Then, like Card and Krueger, we assign all workers into one of these brackets. But in addition we also show the distribution of these workers by their hourly wage rate within each bracket. Doing so, we find as they would have that affected workers (those who earned between $3.35 and $4.24 per hour) who live in poor families (or, in their terms, lower-income deciles) will disproportionally gain from a minimum wage increase.

But we then show that such workers comprise an even smaller disproportionate share of the working population. Hence when we asked the question—what percentage of all workers who gain from a minimum wage increase from $3.35 to $4.24 live in poor families?—we find that only 22 percent do. In contrast, 53 percent live in families whose income is twice the poverty line, and 33 percent live in families with incomes three times the poverty line.

More important for those concerned about ensuring that anyone who works hard and plays by the rules does not live in poverty, only about a quarter of the working poor would have gained from that minimum wage increase, assuming no negative employment effects, because the rest either were not covered by the minimum wage (4.8 percent) or had hourly wage rates above the proposed minimum (68.2 percent). They were poor primarily because they worked too few hours or didn’t have sufficient income from government transfer programs.

In Sabia and Burkhauser (2010), we show that not much has changed since then with respect to the potential effectiveness of minimum wage increases. Using the same methodology, we find that had we increased the current federal minimum wage from $7.25 to $9.50 per hour as proposed by President Obama while running for that office in 2008, the gains to poor workers, assuming no employment effects, would have been even smaller—only about 11.3 percent of affected workers lived in poor households.

Because Card and Krueger do not conceptually link changes in minimum wage policy to the economic resources available to families, their book has proven to be of limited value to policymakers or policy analysts interested in understanding the distributional impact of minimum wage increases on the family size–adjusted income of all individuals, let alone for those interested in ensuring that those who work hard and play by the rules do not live in poverty. More importantly, by not asking the right question about who gets what from the minimum wage, their book distracted those interested in helping the working poor from considering a far more effective policy—the Earned Income Tax Credit.

This fundamental confusion has implications beyond minimum wage policy. For instance, to ensure tax exemptions for their fringe benefit packages, firms are required to provide benefits packages “equitably” across the labor earnings distribution of their
employees. Given the rise of multi-worker families, such firm-based regulations may provide far fewer benefits to low-income families than meets the eye. The same point can be raised with respect to attempts to mandate minimum health or pension benefits for all workers. Supporters of such mandates often assume that low-wage workers live in low-income families.

THE MODERN DEBATE ON TRENDS IN INCOME INEQUALITY SINCE 1993

The public-use CPS is the primary data source used for investigating trends in United States income inequality. The consensus is that household income inequality increased substantially during the 1970s and 1980s. And that this growth continued to outpace that seen in most other Organisation for Economic Co-operation and Development (OECD) countries through the early 1990s (Gottschalk & Smeeding, 1997).¹

However, there are conflicting views about the degree to which United States income equality has grown since 1993. Gottschalk and Danziger (2005), using public-use CPS data and measuring inequality by the ratio of the 90th percentile to the 10th percentile (the P90/P10 ratio), find that the rise in income inequality among their sample of working age adults slowed in the 1990s. However, Thomas Piketty and Emmanuel Saez (the winner of the 2009 Johns Bates Clark Award), using data from Internal Revenue Service (IRS) administrative records, report sustained growth in the income share of the richest 10 percent of tax filers throughout the 1980s to 1998 (Piketty & Saez, 2003, Figure 1).² Their paper used the methods of Piketty (2003), which considered top income shares in France and was one of the first in a growing literature that has used tax return data to examine income inequality trends around the world.³

Because the P90/P10 ratio by definition does not capture changes in the upper tail of an income distribution, the Piketty and Saez results are not necessarily inconsistent with Gottschalk and Danziger's finding if, for instance, growth in inequality slowed in the middle of the distribution but continued to rise in the upper tail. If it is the case that most of the changes in United States incomes have been within the upper tail, then it suggests that public-use CPS data may not be of much value in capturing inequality change in the distribution, especially if inequality is measured using the P90/P10 ratio.

One reason Gottschalk and Danziger and other researchers use P90/P10 ratios to measure inequality rather than measures that capture dispersion throughout the entire distribution (like the Gini coefficient) is that topcoding in public-use CPS data has made it difficult to consistently observe changes at the top of the distribution.⁴


² Updated tables from this paper are available on Saez's Web site (2009): http://elsa.berkeley.edu/~saez/, accessed February 24, 2009. The updated data show that with the exception of a decline in inequality from 2000 to 2002, this growth in income inequality has continued through 2006, their last available year of data.


⁴ Burkhauser, Feng, and Jenkins (2009) show that even P90/P10 ratios do not completely overcome the problem of topcoding in the CPS data because CPS topcoding is done for each of its sources of income. We find that a significant minority of persons below the 90th percentile of the household income distribution have some source of their own income or of another household member's income that is topcoded.
In Burkhauser et al. (in press, a), we follow the conventional Wisconsin School style of income distribution analysis by asking the question: How did the distribution of individuals’ household size–adjusted pre-tax, post-government in-cash transfer income change between 1975 and 2004 using the public-use CPS? Unlike other researchers, we also give substantial attention to the problems caused by the top-coding of each income source in the CPS data. Exploiting our access to Census Bureau internal CPS data, which has much smaller income censoring problems than the public-use version of the CPS data, we examine estimates from data incorporating imputations for topcoded incomes derived from cell means as well as estimates from multiply imputed data from parametric distribution models to capture these topcoded values. Doing so, we find the rapid increases in income inequality that began in the mid-1970s and increased in the 1980s slowed markedly after 1993.

Because our findings, using a Gini coefficient as our measure of income inequality, appear to be so different from those found by Piketty and Saez (2003), in Burkhauser et al. (in press, b) we show that these apparently inconsistent estimates are largely reconciled when income distribution and inequality are defined in the same way. Using internal CPS data for 1967 to 2006, we show that estimates of top income shares are quite similar to the IRS data–based estimates reported by Piketty and Saez (2003). That is, when we ask the same question that Piketty and Saez do using CPS data, we find approximately the same answer they find using IRS data.

Rather than using pre-tax, post-transfer government in-cash income and hence including the influence of government transfers on income inequality, Piketty and Saez (2003) focus instead on market or pre-tax, pre-transfer income. In addition, they aggregate income to the level of the tax unit rather than to the level of the household, do not adjust for differences in tax unit size, and examine the distribution among tax units rather than among individuals.

Hence, in their iconoclastic work tracing the market income of Americans from 1913 to 1998, Piketty and Saez (2003) ask a fundamentally different question than has been posed in the past literature on income inequality in the United States. Their question is: How has the share of market income controlled by the top 1, 5, or 10 percent of tax units changed over the 20th century? This is clearly an important question, but it is one that focuses on market income alone, uses the tax unit as its sharing unit, ignores the fact that tax units contain different numbers of people, and most importantly, by excluding the role of government in the measure of resources available to people, implicitly assumes that the level and trends in the distribution of market income they report over time would have been the same in the absence of government.

WHAT IS THE INCOME CHANGE QUESTION POLICY RESEARCHERS SHOULD ANSWER?

In Tables 1 and 2, which come from Burkhauser, Larrimore, and Simon (2010), we show using alternative success parameters—median income (Table 1) and changes in the growth of income by quintile (Table 2)—how importantly the questions asked about income and its growth will affect the answers found. In the first column of

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5 See Scholz and Levine (2002), Corneo and Fong (2008), and Bach, Corneo, and Steiner (2009) for examples of this type of measure.

6 An important issue in this literature is that not all individuals in the United States file a tax return, with non-filers generally having lower incomes. Therefore, estimates of the income share of the top 10 percent of tax filers underestimate the number of tax filers relative to the situation in which non–tax filers are included in the base. That is, when the number of “potential tax filing units” (filers plus non-filers) is the base, a higher share of actual tax filers and hence a larger share of reported pre-tax, pre-transfer income must be included to correctly measure overall income inequality. To address this issue, Piketty and Saez (2003) estimate the total number of potential tax units and calculate the number of returns that make up the top income groups using this number. They define a potential tax unit as a married couple of any age, divorced or widowed individual of any age, or single individuals aged 20 and over.
Table 1. Growth in median incomes using alternative income series.

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<tbody>
<tr>
<td>1979–1989</td>
<td>0.2%</td>
<td>4.5%</td>
<td>6.6%</td>
<td>9.2%</td>
<td>12.0%</td>
</tr>
<tr>
<td>1989–2000</td>
<td>9.1%</td>
<td>10.0%</td>
<td>9.3%</td>
<td>13.4%</td>
<td>14.4%</td>
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<tr>
<td>2000–2007</td>
<td>--5.5%</td>
<td>--2.2%</td>
<td>--1.2%</td>
<td>--0.1%</td>
<td>1.0%</td>
</tr>
<tr>
<td>1979–2007</td>
<td>3.2%</td>
<td>12.5%</td>
<td>15.2%</td>
<td>23.6%</td>
<td>29.3%</td>
</tr>
</tbody>
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Note: From Burkhauser, Larrimore, and Simon (2010) using public-use March CPS data. Changes in income between 1992 and 1993 are suppressed and assumed to be zero given the trend break resulting from the CPS redesign in those years.

*a* Health insurance information not available prior to 1988. The rate of growth in the value of health insurance from 1979 to 1989 is assumed to match that of post-tax, post-transfer income.

Table 2. Quintile income growth using alternative income series, 1979 to 2007.

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<tbody>
<tr>
<td>Bottom quintile</td>
<td>--33.0%</td>
<td>25.8%</td>
<td>9.9%</td>
<td>15.0%</td>
<td>26.4%</td>
</tr>
<tr>
<td>2nd quintile</td>
<td>--8.9%</td>
<td>0.5%</td>
<td>3.7%</td>
<td>9.7%</td>
<td>29.1%</td>
</tr>
<tr>
<td>Middle quintile</td>
<td>2.2%</td>
<td>13.9%</td>
<td>22.8%</td>
<td>29.5%</td>
<td>36.9%</td>
</tr>
<tr>
<td>4th quintile</td>
<td>12.3%</td>
<td>21.1%</td>
<td>29.2%</td>
<td>34.6%</td>
<td>40.4%</td>
</tr>
<tr>
<td>Top quintile</td>
<td>32.7%</td>
<td>33.6%</td>
<td>42.0%</td>
<td>49.4%</td>
<td>52.6%</td>
</tr>
</tbody>
</table>

Note: See Table 1.

*a* Health insurance information not available prior to 1988. The rate of growth in the value of health insurance from 1979 to 1989 is assumed to match that of post-tax, post-transfer income.

Table 1, we ask the Piketty and Saez question: How much did the market income (pre-tax, pre-transfer income) of the median tax unit in the United States change across the last three business cycles of (1979 to 1989, 1989 to 2000, and 2000 to 2007) and overall between 1979 and 2007?

The answer is quite startling. Real median income measured in this way shows little change over this almost 30-year period measured from peak to peak to peak of these three business cycles. The gains experienced in the first two business cycles are almost completely erased by the losses over the last business cycle. If we updated these numbers to 2009, the latest CPS income year and one that includes the current recession, the overall change is negative. However, this measure of income growth does not recognize that tax units are a subset of households and that income sharing can occur across tax units within households. (For example, two unmarried persons who live together must file their income tax forms separately. Doing so makes them two separate sharing units in the Piketty and Saez world of column 1, but they are nevertheless likely to share their market income between them in their single household.)

When this standard assumption of equal sharing within a household is used in column 2 (noting that effectively Piketty and Saez, by not accounting for number of people in their sharing unit, are assuming perfect returns to scale) and we look at how much the market income of the median household changed over the entire period, we find that median income has risen from 3.2 percent in column 1 to 12.5 percent in column 2. This is still a relatively small increase over almost 30 years, but is almost four times greater than the growth found in column 1.
In column 3, we include in-cash government transfers going to those households as a household resource. When we do so, we find that the overall increase in the pre-tax, post-government in-cash transfers of the median household rises to 15.2 percent, almost five times the growth found in column 1.

When we then acknowledge that households are of different sizes and that the income available to a given individual will be affected by the number of persons in his or her household (returns to scale are not perfect) and adjust our measure of income in column 4 accordingly, we find that the increase of the median person's household size–adjusted pre-tax, post-government in-cash income increased by 23.6 percent, more than seven times the growth in column 1. The definition of income used in column 4 is the one most often used in the United States poverty, income, and income inequality literatures.

In addition to the role government plays in supplementing the income of households via in-cash government transfers, it also does so via its tax policy. In column 5 we use the National Bureau of Economic Research (NBER) tax simulation package to subtract income and payroll taxes and add the income from the Earned Income Tax Credit to estimate the increase in disposable income (household size–adjusted post-tax, post-transfer income) of the median person. We find that the disposable income of the median person increased by 29.3 percent or nearly ten times the growth found in column 1.

Although this measure is not normally reported in United States comparisons of poverty, income, or income inequality, it is standard practice in EU countries and in OECD cross-national comparisons of income and income inequality (Besharov & Couch, 2010). The new supplementary poverty numbers that are scheduled to be released by the Census Bureau in 2011 will also account for taxes in this manner. (See Garner, 2010; Short & Renwick, 2010, for examples of the use of the new supplemental poverty measure.)

Finally, in column 6 we take into account a resource that has grown substantially in value for the median American but is ignored in estimates of how the resources available to American households have changed over the last 30 years. Workers are compensated by employers both in cash wages and in fringe benefits. We include the ex ante or insurance value of the most important of these fringe benefits, employer-provided health insurance, as well as the insurance value of government-provided Medicare and Medicaid going to these households. When this value is included, we find that the overall increase of the median person's household size–adjusted post-tax, post-government in-cash plus the value of health insurance income increased by 36.7 percent, almost 12 times the value reported in column 1.

Table 1 does not provide evidence as to which of the questions answered in these six columns are the most important for public policy. It does show that the answers to the questions reported here are quite different. Piketty and Saez offer a perfectly reasonable measure of how much the owners of the land, labor, and capital used in the production of goods and services in the United States report on their personal income tax statements (pre-tax, pre-transfer income—a value that nevertheless misses the market value of employer-provided health insurance and other fringe benefits because they are tax exempt) and how it has changed over time. But this is a far cry from accounting for the post-tax, post-transfer resources available to the median American and how that has changed over time.

Table 2 goes even further in showing how the question asked will affect the answer found. Here we show how much mean income by income quintile has changed between 1979 and 2007 using the alternative income series discussed in Table 1. The change in the middle quintile, not surprisingly, is roughly equal to that found for the median across the income definitions—a 2.2 percent increase in market income of tax units that grows to a 36.9 percent increase for household size–adjusted post-tax, post-government in-cash plus health insurance income of persons.
It is instructive to look at what is happening in the bottom quintile. There has been a dramatic decline in the market income of these low-income tax units—33 percent. But this decline turns into an increase using any of the other measures. Hence, it is the case that the market income of low-income tax units has declined substantially since 1979, but it is not the case that the post-tax, post-transfer household size-adjusted resources available to the bottom quintile of the population have declined. They are up almost 15 percent over that period and 26 percent when the insurance value of health insurance is included. This value would be even higher if other in-kind transfers targeted on low-income people were included in our measure (e.g., food stamps, WIC).

What these tables suggest is that just as the hourly wage rate is a poor indicator of the household size-adjusted resources available to workers, so is the market income of a tax unit a poor indicator of the household size-adjusted resources available to people. Researchers or policy analysts using answers to questions about the levels or the changes in the wage or the market income inequality of tax units to answer questions about the levels or the changes in inequality with respect to the total resources available to people will surely get it wrong.

CONCLUSIONS

The iconoclastic research of Card and Krueger at the heart of their book *Myth and Measurement*, published in 1995, resulted in a rejuvenation of interest by a new generation of researchers in better determining the behavioral and distributional consequences of minimum wage increases. After 15 years, this new generation of research provides more plausible evidence that such increases are a poor way of helping the working poor, especially when compared with increases in the Earned Income Tax Credit.

The iconoclastic research of Piketty and Saez has had a similar impact on the income inequality literature. It too has resulted in a rejuvenation of interest by a new generation of researchers in better measuring levels and trends in income inequality. What Burkhauser et al. (in press, b) and Tables 1 and 2 demonstrate is that it is not primarily differences between the CPS and IRS data that are responsible for the dramatically different levels and trends in income and income inequality found by researchers using these data sets, but in the questions they have used these data to answer. It remains to be seen which of these questions will be more salient in informing future public policies meant to affect trends in the level and distribution of income. What is certain is that you can’t answer questions about how the household size-adjusted resources available to people have changed using answers to a different question.

RICHARD V. BURKHAUSER, who is at Cornell University, presented this Presidential Address on November 5, 2010, at the Annual Meeting of the Association for Public Policy Analysis and Management, Boston, MA.

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