Estimating Personal Consumption Rates for Husbands and Wives:
A Comparison of Income-Strata and Microdata Models

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Abstract

Various studies estimate personal consumption expenditures from Consumer Expenditure (CEX) data. Early analysis relied on CEX data that was aggregated across expenditure categories and income groupings, while later studies used microdata containing disaggregated expenditures across individual items for each surveyed household. These newer studies allocated expenditures for each item to relevant household members, but analyzed results aggregated across income strata. We extend the microdata analysis by examining personal consumption expenditures at the household level. Our results indicate that at all but the lowest incomes, personal consumption rates generated using microdata-level observations differ only slightly from existing models using income-strata data. Forensic experts accounting for personal consumption may, thus, feel comfortable using either method of analysis.

I. Introduction

Now well-entrenched in forensic economics, the practice of estimating personal consumption rates for male and female heads of households began in earnest with the 1991 tables published by Patton and Nelson (1991). Lierman, Patton and Nelson (1998) and Ruble, Patton and Nelson (2000, 2002, 2007, 2011-12, 2019) updated the tables as new data were released, weaving modifications suggested by Bell and Taub (2002) into their subsequent analyses and publications. The Patton-Nelson tables relied on income-stratified summary expenditure data published by the Bureau of Labor Statistics (BLS); the summary expenditures reflect underlying microdata collected as part of the Consumer Expenditure (CEX) Survey. This source persists through later analyses and adaptations of Patton and Nelson's aim to provide relevant personal consumption estimates.

Trout and Foster (1993), Scoggins (2001), and Krueger (2007, 2011, 2015) substituted

CEX microdata for the BLS income-stratified summary expenditure tables, a move Ruble, Patton & Nelson suggested would lend the estimates "additional precision" (Ruble, Patton and Nelson, 2009, pg. 218). Patton and Nelson acknowledged the limits of BLS summary tables and broad categories of expenditures. Durable goods, for example, presented a particular challenge, as including them with expenditures led to overestimated consumption figures, whereas excluding them caused "an understatement of true consumption costs" (Patton and Nelson, 1991, pg. 263).

These microdata-based studies allocated expenditures on individual items to relevant family members. Expenditures on each food item, for example, were allocated across household members.[1] This led to a more refined allocation of expenditures; however, these studies maintained the tradition of aggregating households into income strata. Krueger (2015), for example, aggregated households into five to 12 income groups, depending on the type of household being studied.[2] Across these analyses, either a second-order polynomial or a power function was then fit through the means of the income strata to produce equations predicting expenditures as a function of household income.[3] These equations typically fit the data quite well.

One implication of aggregating households into income strata is that the process masks the variation in spending among households within each stratum. Figure 1 below, for example, shows diary survey expenditures by income for husbands in households with exactly one wage earner.[4] The points are the mean values for each of the ten income strata. A quadratic equation is fit through these ten aggregate observations and the dashed line shows expected expenditures as a function of income. The R^2 for the regression is near 99 percent. Figure 2 shows the underlying

[1] There are some caveats. Baby food, for example, is allocated to children ages two and under.
[2] Examples of household types include husband and wife only households by number of earners and husband and wife households by number of children.
[3] The power function is $Expenditures = \alpha Income^{\beta}$. Taking logs, this is also referred to as a log-linear function with $\log(Expenditures) = \log(\alpha) + \beta * \log(Income)$.
[4] Diary and interview surveys are explained in the data section of this paper.

disaggregated microdata for the households that were aggregated into the income strata in Figure 1. There is much more variation in the disaggregated data.[5]

We extend the consumer expenditure microdata analysis by unmasking the variation in the underlying data. Our analysis follows recent studies in allocating expenditures on individual items to relevant household members. Rather than aggregating households into a limited number of income strata, however, we maintain each household as an individual observation in our analysis of spending patterns. Two models are estimated using the microdata. The first explains personal consumption rates as a quadratic function of income; the second, as a power function of income. Results from both models are compared to results obtained using the standard income-strata approach.

The two microdata models and the income-strata model produce qualitatively similar results. At all studied income levels, both husbands and wives in households with no children consume more of their income than their counterparts in households with children. Again, at any income level, as the number of children in the household increases, husband and wife personal consumption rates fall.

Looking across models, at very low incomes, the income-strata model and the two microdata models produce somewhat divergent results. This divergence is most pronounced in households without children. At an income of $15,000, for example, in a childless household with

[5] The CEX is comprised of two surveys, the diary and interview surveys. There is no one-to-one correspondence between diary and interview observations. The existing income-strata studies get around this issue by aggregating all of the microdata observations into 10 (or fewer) income-strata grouping. They weight the observations in each strata, aggregate, and then combine interview and diary data to get a strata average combined diary and interview expenditure. Table 1 shows the coefficients generated when estimating this average combined expenditure across income strata. Since this analysis uses each microdata observation, there is no way to combine a diary observation with an interview observation. Hence, diary and interview equations are estimated separately and then aggregates the coefficients. Figure 1 is included as a contrast to Figure 2. Figure 1 shows the nice pattern of just diary survey income-strata midpoint estimates and a fitted line. It is not the equation generated by the coefficients in Table 1. Figure 2 uses the same microdata diary observations as in the income-strata model but leaves them as individual microdata observations. Hence the much larger and more dispersed number of point observations.

both spouses working, the divergence in personal consumption rates between the income-strata and microdata models ranges between 32.2 percent and 45.9 percent. These divergences, however, attenuate fairly quickly; for incomes beyond $30,000, the differences are in the range of one to three percentage points. In households with children, the divergences between model estimates are even smaller. Collectively, the analysis suggests that, with the exception of low-income households, the tradition of using income-strata data produces results very similar to the personal consumption rates estimates using microdata models. Forensic experts accounting for personal consumption may, thus, feel comfortable using either method of analysis.

To allow for statistical testing, 95 percent confidence intervals are calculated for the income-strata estimates. The microdata estimates are then compared to see whether they lie within those intervals. Beyond very low incomes, the microdata logarithmic results track within or just above the income-strata confidence interval. The microdata quadratic results deviate a bit more, tending to begin below the confidence interval, rise above it at middle income levels and then fall back below it at higher incomes. The gaps between the microdata estimates and the income-strata confidence intervals, however, become smaller as family size increases. Collectively, our analysis suggests that, with the exception of low-income households, disaggregated microdata does not significantly alter estimated personal consumption rates when compared to income-stratified consumption data.

II. Data

The Bureau of Labor Statistics (BLS) assimilates the findings of two independent samples, known as the Quarterly Interview Survey and the Diary Survey, and extrapolates the results to represent all relevant US consumer behavior[6] (U.S. Bureau of Labor Statistics, n.d.). The Diary Survey provides tremendous detail on frequent purchases such as food, alcohol, and tobacco products. This survey resembles a catalog order form, in which participants are asked to denote a specific subcategory for each purchase over a two-week period. Items listed in the Diary Survey Form for 2013 include wheat bread, nonprescription sunglasses, and postage stamps; by contrast, the Interview Survey's extended time frame and design allow the BLS to observe larger, less frequent expenses, such as home and vehicle purchases. The Diary and Interview Surveys combine to form a more complete description of household expenditures for the CEX.

Using code originated by Krueger, we develop data from the 2011- 2013 BLS CEX Surveys.[7] For the Interview Survey, we draw raw expenditure data from the quarterly files published by the BLS. After excluding irrelevant expenses—those not relatable to personal consumption by the husband or wife—we categorize the remaining Universal Classification Coded items (UCCs) by intuitive attribution among members of the household (U.S. Bureau of Labor Statistics, 2017). Methods for allocating expenditures for each UCC among family members are drawn directly from Krueger (2007).[8] For example, outlays for alcohol and college tuition are considered "Adult divisible" expenditures; women's suit and sport coat expenses are assigned to "Age 16 and older females," and so forth. This arrangement enables a straightforward and consistent allocation of expenditures within each household. Demographic data regarding household composition are also included for each consumer unit. These rich microdata files allow for determination of personal consumption expenditures (PCEs) for the male and female heads of

[6] The BLS calculates and assigns weights to Survey data to approximate proper geographic and demographic representation when aggregated. As we evaluate individual households, rather than the aggregate, we do not incorporate the BLS weights into our analysis.
[7] Our thanks to Kurt Krueger for his gracious provision of the SAS code underlying his original analysis and tables.
[8] Expenses not directly related to personal consumption were considered irrelevant. For a more detailed description, see Krueger (2007).

household by family composition.

The Diary Survey data are arranged in a similar manner. Monthly expenditure files are merged with family demographics to allow for consumption allocation within each household surveyed. As with the Interview Survey data, irrelevant expenditures are removed and the remaining UCCs are allocated within each household based on Krueger's (2007) divisibility rules. This allows for calculation of PCEs for the male and female heads of each household surveyed.

To minimize the effects of unobservable variables and simplify our analysis, we impose additional restrictions on our data set. Households with annual incomes below $10,000—a base approximation of the poverty line—are removed. Other households with income in the uppermost decile, that is, greater than $185,000, are also not included in this analysis. Within these bounds, a small number of households with PCEs at or below zero, or greater than 100 percent of household income are also excluded. We further restrict our sample such that only the husband, the wife, or both are earning income (i.e., children are not working), following the example of Krueger (2007). Due to sample constraints, and to enhance comparability with Krueger's work, we limit the number of children per household from zero to four; hence, households with five or more children are removed from the analysis. We also exclude households with one or more non-child dependents.

Under the assumption that expenses involving infants affect household consumption differently than expenses for other dependents, and ought to be treated as such, we exclude households with persons younger than two years from our analysis and define "children" to be those persons aged two to 17 years old. When allocating expenses, as Krueger (2015) noted, the survey data lumps 16 and 17-year-olds with adults 18 and older in expenditure categorization; therefore, we include 16 and 17-year-olds in adult expenditure allocation, where appropriate. For example, expenses described as "Age 16 males" are divided among the males aged 16 years or older in the household, though we consider 16 and 17-year-olds to be "children" elsewhere in our analysis. Our use of microdata not only for expenditure allocation but also for later regressions grants us flexibility to allocate expenditures more accurately without altering our description of "children" in the process.

We limit the sample to only husband and wife-headed households. This avoids problems with aggregate data, which reflects households of various other compositions. Krueger (2007), noted that:

> If a traditional two-person household personal consumption table were used to offset the husband's earnings loss, such an analysis would mix the expenditure data of working and retired husbands and wives along with mixing in the data of households consisting of two single persons or one single person living with a child, etc. (p. 15)

Also excluded are households with positive or negative farm or self-employment income.

Using Krueger's (2007) method, expenditures are allocated to husbands and wives in each microdata household to derive PCEs. Expenditures are divided by household income to obtain personal consumption percentages (PCPs) for husbands and wives in each microdata household.

Use of microdata allows for a much richer analysis than using the aggregated consumer expenditure tables (CE Tables) available on the BLS Web site.[9] The CEX Tables generally categorize the data according to a single characteristic; for example, one table shows data for:

- All Consumer Units
- Married Couples, further classified as:
  - Married Couple Only
  - Married Couple with Oldest Child under 6
  - Married Couple with Oldest Child 6 – 17
  - Married Couple Oldest Child 18 or Older
- One Parent, as Least one Child Under 18
- Single Person and others

[9] https://www.bls.gov/cex/tables.htm.

There is no way to further disaggregate based on the number of children. Other tables disaggregate by age or income grouping or some other characteristic. A newer feature on the BLS page cross tabulates the tables by two categories, such as age and income; however, even these tables aggregate data into broad groupings. By using the microdata, it is possible to develop specific family groupings more relevant to use by forensic experts.

Another difficulty of using the CEX Tables is that the data on expenditures are fairly aggregated. There are fewer than 50 detailed expenditure categories, as opposed to the hundreds of UCCs. This aggregation can complicate expenditure allocation; in the "Food at home" category, for instance, there is no distinction made for baby food, and the category "Public and other transportation" includes both taxi and school bus charges. By enabling researchers to address these expenditures individually, UCCs provide a clear advantage over the aggregated BLS tables.

III. Method of Analysis

The analysis begins by assigning husband and wife-headed households from the CEX microdata into seven different demographic categories:

1. Husband and wife only households with either one or two working spouses
2. Husband and wife only households with only one working spouse
3. Husband and wife only households with two working spouses
4. Husband and wife households with up to four children under age 18 and at least one working spouse
5. Husband and wife households with one child under age 18 and at least one working spouse
6. Husband and wife households with two children under age 18 and at least one working spouse
7. Husband and wife households with three children under age 18 and at least one working spouse

For each demographic category, we perform the traditional analysis - allocating microdata expenditures among family members, then aggregating households into income strata and calculating mean income and PCEs for husbands and wives in each income stratum. PCEs aggregate diary and interview consumption into a combined estimate. A quadratic equation estimating PCEs as a function of income is then fit across the mean of each stratum, j, for spouse s (meaning *husband* or *wife)*:

$$PCE_j^s = \beta_0^s + \beta_1^s Income_j + \beta_2^s Income_j^2 + \epsilon_j \tag{1}$$

The resulting coefficient estimates allow for the estimation of individual PCEs, as well as upper and lower 95-percent confidence boundaries for the estimated PCEs. These can be divided by income to generate individual and confidence-bounded personal consumption percentages (PCPs).

We then turn to the microdata. As each observation is unique, and there is no concordance between the Interview and Diary samples, separate regressions are run for Interview and for Diary Survey data. Based on a visual observation of the data, rather than estimate PCEs, we estimate interview personal consumption percentages (IPCPs) and diary personal consumption percentages (DPCPs) as a function of income. The following quadratic functions are estimated separately for husbands and wives, where i represents an individual household and s indicates either a *husband* or *wife*:

$$IPCP_i^s = \gamma_0^s + \gamma_1^s Income_i + \gamma_2^s Income_i^2 + \varepsilon_i \tag{2a}$$

$$DPCP_i^s = \delta_0^s + \delta_1^s Income_i + \delta_2^s Income_i^2 + \mu_i. \tag{2b}$$

The coefficients in equations (2a) and (2b) are combined to estimate overall PCPs as a function of income. Our microdata estimation accounts for potential heteroskedasticity by incorporating White (1980) heteroskedasticity-consistent covariance matrix estimators.

Logarithmic power functions are also estimated for interview personal consumption percentages (IPCPs) and diary personal consumption percentages (DPCPs) as a function of income, taking the forms:

$$log(IPCP_i^s) = \theta_0^s + \theta_1^s \log(Income_i) + \varepsilon_i' \quad (2c)$$

$$\log(DPCP_i^s) = \pi_0^s + \pi_1^s \log(Income_i) + \mu_i' \quad (2d)$$

Using equations (2c) and (2d) to estimate overall PCPs as a function of income is a bit trickier than with quadratic equations. Hill, et al. (2011) (p. 154) show that in larger samples, the best predicted values for the Interview and Diary PCPs are:

$$\widehat{IPCP_i^s} = \exp\left(\hat{\theta}_0^s + \hat{\theta}_1^s \log(Income_i) + \widehat{\sigma_I^2}/2\right) \quad (2e)$$

$$\widehat{DPCP_i^s} = exp\left(\hat{\pi}_0^s + \hat{\pi}_1^s \log(Income_i) + \widehat{\sigma_D^2}/2\right) \quad (2f)$$

where $\widehat{\sigma_I^2}$ and $\widehat{\sigma_D^2}$ are the Interview and Diary regressions' respective mean squared errors. Final PCPs are then calculated as $\widehat{IPCP_i^s} + \widehat{DPCP_i^s}$ from equations (2e) and (2f).

IV. Results

Table 1 contains coefficient estimates generated from estimating quadratic functions of PCEs across the ten mean income-strata observations for each of the seven demographic groupings. The estimation methodology is similar to methods found in previous PCE studies. In all cases, we find that PCEs are increasing in income. In six of the seven demographic groupings, the increase occurs at a decreasing rate. The adjusted R^2 values of these models range from 0.95 to 0.99.

Tables 2 and 3 contain coefficients generated from estimating quadratic functions of personal consumption percentages (rather than expenditures) across microdata for each of the seven demographic groupings. Table 2 is for husbands; Table 3 is for wives. Within each table, the first set of columns contains results from the interview survey samples and the second set for the diary. The last set of columns sums the interview and diary coefficients to generate final coefficients for estimating overall personal consumption percentages as a function of income.

Across all seven demographic groupings studied, personal consumption percentages are decreasing in income, at a decreasing rate. The adjusted R^2 values range from 0.01 to 0.15 and are higher for the diary samples than the interview samples. The relatively lower R^2s in comparison to the income-strata mean results are reasonable given that the income-strata data mask the variation in personal consumption rates found in the underlying microdata. It is also reasonable that the microdata diary results have higher R^2s than the interview data as the diary data cover more commonly and frequently purchased items like food, while the interview data contain infrequent purchases such as homes and automobiles. These latter expenses may be less taste-dependent, and, thus, more consistent across households of similar structure and income.

Tables 4 and 5 contain coefficients generated from estimating logarithmic functions of personal consumption percentages across the microdata for each of the seven demographic groupings. The first table is for husbands; the second, for wives. Within each table, the first set of columns contains results from the interview samples, and the second set for the diary samples. For each demographic grouping, the last line in the table shows the adjusted R^2 value, followed by the appropriate mean squared error; the adjusted R^2s are within the range of those generated in the quadratic microdata. Due to this model's logarithmic structure, the coefficient estimates cannot be added together to estimate overall consumption as a function of income. Rather, equations (2e) and (2f) above must first be used to estimate diary and interview personal consumption rates before those rates can be added to determine overall PCPs as a function of income.

Appendix 1 contains numerical comparisons of estimated personal consumption percentages across the three models. There are 14 sections to the appendix. The first seven sections are for husbands with one section for each family type; the second seven are for wives, again, with one section for each family type. Within each section, there are six columns. The first column shows income in $5,000 increments. The second and third columns contain the estimated PCPs using the microdata, estimated with the quadratic and logarithmic functions, respectively. Columns four through six contain information from the traditional income-strata estimates. In order, thecolumns display the lower bound of a 95 percent confidence interval, the estimated PCPs and the upper bound of a 95 percent confidence interval. Table 6 below reproduces the results for husbands in a husband and wife only household with either one or two spouses working. This table is abridged in that income increases in $10,000 increments rather than in $5,000 increments, as in the appendix. The results for husbands from Table 6 are shown graphically in Figure 3. From Table 6 and Figure 3, for husbands in a husband and wife only household with either one or two spouses working, the microdata quadratic estimate PCPs almost always fall out of the 95 percent confidence interval for the income-strata results. The microdata quadratic estimates start under the interval, pass over it at relatively low income and then fall under the income-strata confidence interval at income over about $75,000. The divergence, however, is not that great–typically one to two percentage points as incomes move beyond the lowest levels studied. The microdata logarithmic estimates also start under the mean income-strata confidence interval, but track within or just above the confidence interval for incomes greater than approximately $35,000. Comparing the microdata quadratic results to the microdata logarithmic results, the former appear more linear at lower incomes and display more curvature at higher income levels.

The comparisons between Table 6 and Figure 3 generally hold true for husbands and wives across the seven family types. The microdata quadratic estimates appear more linear at lower incomes and more convex at higher incomes than the microdata logarithmic estimates. The logarithmic estimates tend to lie below the confidence intervals for the mean income-strata estimates at low incomes and rise to within or above the confidence intervals at middle incomes. The logarithmic estimates stay within or just above the confidence intervals at higher incomes while the quadratic results may fall below; it is worth noting, however, that the degree of divergence between the microdata estimates and the mean income-strata confidence intervals varies by household type. Figure 4 displays consumption rates for wives in households with three children, and offers a good example of this variance. In Figure 4, both microdata estimates remain within the income-strata confidence interval at almost all income levels. Comparing Figure 3 to Figure 4, the better fit is most likely due to Figure 4's wider confidence interval.

Appendix 2 contains graphical comparisons of estimated personal consumption rates across the three models. Consider the three demographic groups that contain no children; for incomes below $35,000, the income-strata personal consumption rate estimates are higher than either of the microdata estimates. This is particularly true in households with no children and two working spouses, where, for incomes of $15,000, the divergence is 13.6 percentage points for husbands and 13.2 percentage points for wives. The divergence narrows as income increases; for example, for incomes of $55,000, all three models generate personal consumption rates within two to three percentage points from the largest to the smallest. The microdata log-linear estimates typically lie within or just outside of the confidence interval for each income-strata. By comparison, the microdata quadratic estimates tend to lie not far beyond the respective confidence intervals. In the $75,000 - $135,000 income range, the microdata quadratic rates are slightly lower than rates from the other two methods, but again, the divergence is by no more than 3.1 percentage points.

For households with children at very low incomes, the three models again diverge in their estimated personal consumption rates. This divergence is much smaller than for households without children, and more quickly approaches one percentage point or less. The microdata logarithmic results follow the income-strata estimates closely, and almost always fall well within the latter's 95 percent confidence interval. For incomes below about $75,000, the microdata quadratic model generates slightly flatter personal consumption rates than do the other two methods. At higher incomes, the three methods generate very similar results, and the microdata logarithmic estimates are nearly identical to the mean income-strata rates, lying well within the appropriate confidence interval.

V. Conclusion

Early studies of personal consumption were restricted to the use of Consumer Expenditure Survey data aggregated across predetermined expense categories and income groupings. Later studies were able to access household-level microdata, which allowed for the allocation of expenditures on individual items to relevant household members. This enhanced the calculation of personal consumption rates and expenditures; however, estimation still occurred across aggregated income-strata groups. By averaging expenditures and incomes across all households within a given income stratum, the aggregate estimates masked the variation in expenditures within that stratum.

This analysis extends the literature by estimating personal consumption rates at the household level. Household-level microdata from the 2011-2013 Consumer Expenditure Surveys are used to estimate diary and interview personal consumption expenditures and associated personal consumption rates for husband and wife-headed households. To facilitate comparison to earlier studies, households are initially aggregated into traditional income strata, and the interview and diary expenditures are combined. Mean income and expenditures are estimated for each stratum, and a quadratic function is fit through the mean income-strata data. The expenditure estimates are then divided by income to generate estimated personal consumption percentages, the crux of our analysis. Sample statistics and estimation results are used to generate 95 percent confidence intervals around the income-strata estimates.

Next, we turn to estimation at the microdata level. Quadratic and log-linear functions are individually estimated for interview and diary survey expenditure rates as functions of income. The quadratic coefficients and the log-linear estimates are combined to generate personal consumption rates for husbands and wives. These microdata-level results are compared and contrasted to initial income-strata estimates.

Results from all three models show that for any level of income, husbands and wives in households with no children consume greater proportions of household income than do husbands and wives in households with children. Among those households with children, personal consumption rates for husbands and wives both decline as the number of children increases.

Comparing models, the estimated personal consumption rates are very similar across the income-strata model and both microdata models for all but the lowest incomes. For a household income of $55,000, the three models predict personal consumption rates within just a few percentage points of each other. The quadratic microdata model tends to estimate a lower initial consumption rate, with consumption declining more slowly at lower incomes and increasing more rapidly with higher incomes than the other two models. The log-linear microdata model and the quadratic income-strata model produce very similar results to each other at all but the lowest incomes. In fact, the microdata logarithmic estimates fall within the 95 percent confidence interval for the income-strata estimates; this is especially true in households with children.

Two general conclusions can be drawn from this analysis. First, personal consumption rates are particularly sensitive to model specification at low-income levels. This topic merits further investigation. Second, given the similarity in results, forensic experts have reason to be confident in using the traditional income-strata results for all but the lowest-income families. The masking of the variation in the underlying households does not appear to influence significantly the resulting estimates.

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