NBER WORKING PAPER SERIES

WHAT U.S. DATA SHOULD BE USED TO MEASURE THE PRICE ELASTICITY OF DEMAND FOR ALCOHOL?

Christopher J. Ruhm
Alison Snow Jones
William C. Kerr
Thomas K. Greenfield
Joseph V. Terza
Ravi S. Pandian
Kerry Anne McGeary

Working Paper 17578
http://www.nber.org/papers/w17578

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
November 2011

Support for this research by a grant from the National Institute on Alcohol Abuse and Alcoholism (R01AA017890) is gratefully acknowledged. We also wish to thank Deidre Patterson, Keshia Maughn and Daniela Zapata for outstanding assistance with this research. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

What U.S. Data Should be Used to Measure the Price Elasticity of Demand for Alcohol?
Christopher J. Ruhm, Alison Snow Jones, William C. Kerr, Thomas K. Greenfield, Joseph V. Terza, Ravi S. Pandian, and Kerry Anne McGeary
NBER Working Paper No. 17578
November 2011
JEL No. H2,I12,I18

ABSTRACT

This paper examines how estimates of the price elasticity of demand for beer vary with the choice of alcohol price series used. Our most important finding is that the commonly used ACCRA price data are unlikely to reliably indicate alcohol demand elasticities. Instead, the estimates obtained using ACCRA prices vary drastically and unpredictably. As an alternative, researchers often use beer taxes to proxy for alcohol prices. However, since beer taxes are actually likely to poorly indicate prices, it is not surprising that the estimated beer tax elasticities are close to zero. We believe that our most useful estimates are obtained using annual Uniform Product Code (UPC) or "barcode" scanner data on grocery store alcohol prices. These estimates suggest a relatively low price elasticity of demand for beer, probably around -0.3, with evidence that the elasticities are considerably overstated in models that control for beer but not wine or spirits prices.

Christopher J. Ruhm
Frank Batten School of
Leadership and Public Policy
University of Virginia
235 McCormick Rd.
P.O. Box 400893
Charlottesville, VA 22904-40893
and NBER
ruhm@virginia.edu

Alison Snow JonesÀ
Drexel University

William C. Kerr
Alcohol Research Group
Public Health Institute
6475 Christie Avenue, Suite 400
Emeryville, CA 94608-1010
wkerr@arg.org

Thomas K. Greenfield
Alcohol Research Group
Public Health Institute
6475 Christie Avenue, Suite 400
Emeryville, CA 94608-1010
tgreenfield@arg.org

Joseph V. Terza
Department of Economics
University of North Carolina at Greensboro
Greensboro, NC 27402-6165
jvterza@uncg.edu

Ravi S. Pandian
Department of Health Management and Policy
Drexel University
Philadelphia, PA 19102
rpandian68@yahoo.com

Kerry Anne McGeary
Department of Economics
Miller College of Business
Whitinger Business Building, RM 129
Ball State University
Muncie, IN 47306
and NBER
kmcgeary@bsu.edu

This paper examines how estimates of the price elasticity of demand for beer vary with the choice of alcohol price series used. The analysis is motivated by the demonstrated effectiveness of price in reducing both alcohol consumption and the negative social costs associated with high levels of drinking (Giesbrecht et al, 2004; Cook, 2007; Chaloupka et al, 2002). We focus on beer because it is the most important source of alcohol, constituting roughly 55% of ethanol consumed (NIAAA, 2010).

There is an enormous body of empirical research examining the price elasticities of demand for alcohol and for alternative types of alcoholic beverages, as well as for the consequences of price changes for outcomes such as motor vehicle fatalities, binge drinking, and alcohol related violence.[1] Understanding the responsiveness of drinking, and its consequences, to price is important both for its own sake and because of the information it provides on the potential efficacy of price versus non-price policies.[2]

Unfortunately, there are reasons to doubt the elasticity estimates obtained in prior studies because of the difficulties in correctly defining and measuring the relevant prices of alcohol. One issue, which we will not try to resolve in this paper, is that single measures of average beer, wine and spirits prices are generally used, even though consumers have incentives to substitute towards cheaper beverages in a given class when prices rise or relative prices shift. Putting this problem aside, it turns out that there are substantial difficulties in accurately measuring alcohol prices. Previous research has generally dealt with this problem inadequately, if at all, raising

[1] A recent meta-analysis of 112 studies by Wagenaar et al. (2009) finds that average reported price elasticities are -0.46 for beer, -0.69 for wine and -0.80 for spirits. However, the large majority of these investigations (e.g. 40 of 47 studies for beer consumption) use aggregate data. These tend to yield larger (absolute values of) elasticities than analyses using individual data, in part because of cross-border purchases whereby individuals make purchases in jurisdictions with lower prices. In an earlier review, Leung & Phelps (1993) estimate consensus beer, wine and spirits elasticities of -0.3, -1.0 and -1.5. Chaloupka et al. (2002) review the literature examining how prices are related to drinking and related alcohol problems (motor vehicle crashes, health, violence and crime) among youths and young adults.

[2] Examples of nonprice policies include minimum legal drinking ages, drunk driving penalties, or alcohol availability constraints.

doubts about the elasticity estimates obtained.

Prior U.S. investigations (e.g. Kenkel, 1993; Sloan et al, 1994; Manning et al, 1995; Grossman et al, 1998; Williams et al, 2005; Arcidiacono et al, 2007) have often used alcohol prices from the ACCRA Cost of Living Index, a quarterly publication originally compiled by the American Chamber of Commerce Research Association and, since 1998, by the Council for Community and Economic Research. A principle advantage is that the ACCRA series provides information on prices for 120 to 300 medium and large cities, thus supplying one of the few sources of geographic information that is more detailed than the state level.[3] However, the ACCRA data are subject to significant measurement error, potentially yielding imprecise and biased elasticity estimates (Young & Bielinska-Kwapisz, 2003; Dave & Kaestner, 2002). A primary shortcoming is that prices are collected for just one brand each of beer, wine and blended whiskey, as detailed below, introducing considerable error if these brands do not reflect the purchases of "typical" drinkers or subgroups of particular interest (e.g. youths). In addition, ACCRA spirits prices stopped being collected after 2004.[4]

Given these problems, many researchers instead use beer taxes to proxy price variations (e.g. Chaloupka et al, 1993; Ruhm, 1996; Freeman, 2000; Markowitz et al, 2005). Taxes have at least two advantages: they are directly amenable to policy interventions (i.e. state and national alcohol taxes are set by governments) and they are determined independently of demand, whereas prices need not be.[5] However, taxes present other issues. First, it is difficult to determine the tax on distilled spirits and wine in "control" states, where sales occur only through state

[3] The exact number of cities varies by year. Cities with populations of 50,000 or more are eligible for inclusion, although some smaller cities were "grandfathered" in when the population criteria were originally established. General information on the ACCRA data is available at: http://coli.org/.
[4]Additional problems are that prices in discount outlets are specifically excluded, even if these represent the bulk of market sales, and that the collectors of ACCRA prices are also not specifically trained as data gatherers.
[5]An outward shift of the demand curve increases both prices and quantities of alcohol consumed.

liquor stores.[6] One result is that the aforementioned investigations control only for beer taxes and not also those on wine and spirits. Second, state taxes constitute only a small share (3 to 5 percent) of retail alcohol prices. Third, since states change excise taxes relatively infrequently, most of the temporal variation in real tax rates is due to inflation rather than changes in nominal taxes. Finally, state taxes may be endogenously determined. For instance, high taxes in states with strong anti-drinking sentiments would introduce a spurious negative correlation between alcohol taxes and use.

For these reasons, we compare results using ACCRA prices or beer taxes to those obtained using an alternative source of price data – annual Uniform Product Code (UPC) or "barcode" scanner data, collected by AC Nielsen. The UPC data offers detailed and precise information on alcohol sales for detailed geographic markets. Specifically, using these data, we are able to calculate the total value of sales (in dollars) and volume of sales, by brand and beverage type, for beer, wine, and spirits sold in grocery stores in 51, 37 and 21 markets respectively.[7]

Although superior to other sources of price information, the scanner data have limitations. First, the Nielsen markets tend to represent more densely populated areas and correspond to one or more Standard Metropolitan Statistical Areas (SMSA). Consequently, UPC data are not available for some rural areas (most notably the entire states of Montana, the Dakotas, and Maine). Second, the data are not available for liquor stores or other sellers of alcohol (such as Costco and Walmart), nor in control states that restrict alcohol sales in

[6] There are 18 such states for spirits and five for wine. This paragraph draws heavily on a more detailed discussion in Young & Bielinska-Kwapisz (2002).

[7] UPC data have previously been used in alcohol-research by Bray et al. (2007, 2009). UPC data on sales in convenience stores were also available in 19 markets for 2008 (but not 2004). Using 2008 data, we confirmed a strong relationship between UPC grocery store and convenience store beer prices—the correlation between the two prices was 0.92, with an average difference of 8 cents per ounce of ethanol. The number of markets is smaller for wine and spirits than for beer because more states allow beer to be sold in grocery stores than wine or spirits.

supermarkets.[8] To reduce the effect of the last exclusion, missing UPC wine and spirit prices in the control states were supplemented with price information obtained from the National Alcohol Beverage Control Association's (NABCA) Statistics for Alcohol Management (SAM) database, which includes monthly brand-level pricing and sales, and container size for all products sold in each state. We utilize the shelf price series, which averages prices in effect during a given time period, by their sales volume during that period to accurately reflect price changes and sale prices.

Rather than relying on general measures of alcohol sales as dependent variables in our alcohol consumption regression models, we obtain detailed cross-sectional information on drinking from the first and second waves of the National Epidemiological Survey of Alcohol and Related Conditions (NESARC 1 and 2), conducted in 2001-02 and 2004-05 respectively. These national surveys were sponsored by the National Institute on Alcohol Abuse and Alcoholism and designed to provide nationally representative estimates of alcohol consumption, abuse and dependence for non-institutionalized adults aged 18 and older.[9]

We use two basic analysis strategies. First, we examine whether elasticity estimates obtained with the commonly used ACCRA data are robust to the years over which alcohol prices or drinking are measured. Second, we examine the sensitivity of the estimated consumption elasticities to: 1) the use of alternative price series (i.e. ACCRA, beer taxes or UPC prices), measured in a given year; 2) the geographic area of analysis; and 3) whether wine and distilled spirits prices are also included as regressors.

Our most important finding is that demand elasticities obtained using ACCRA prices are extremely unstable, with plausible specifications providing results consistent either with no

[8] Supermarkets account for around 40% of beer sales (Bray, et al., 2007).
[9] See http://aspe.hhs.gov/hsp/06/catalog-ai-an-na/nesarc.htm for general information on the NESARC surveys and Grant et al. (2003), Chen et al. (2006) or Dawson et al. (2007) for detailed discussions and examples of analysis.

responsiveness of consumption to beer prices or with extremely large negative own-price elasticities. This makes it likely that the results obtained in previous research, using ACCRA data, are unreliable and sensitive to the choice of data years and estimation samples. We do not directly test whether the same problems apply to longitudinal analyses identified by within-locality changes in ACCRA prices, although we are doubtful that these will be more useful, since measurement error is particularly problematic in fixed-effect models.[10] Second, our results suggest that estimates of demand elasticities are attenuated when using taxes rather, than direct measures of prices, although these findings are less definitive. We conclude that there are benefits from using more detailed price information, such as the scanner data that we employ.

National Epidemiological Survey of Alcohol and Related Conditions

Information on alcohol use and personal characteristics are obtained from the first and second waves of the National Epidemiological Survey of Alcohol and Related Conditions. NESARC 1 data collection occurred in 2001-02 (with around 85 percent of interviews in 2001 and the remaining 15 percent in 2002). The follow-up NESARC 2 interviews took place in 2004-05 (with 82 percent on interviews occurring the earlier year and 18 percent in the later one). The timing of the surveys is relevant since restrictions in the availability of the UPC data imply that we can match it only to the second wave of the NESARC. Conversely, when using the ACCRA price data, we estimate models for both NESARC 1 and NESARC 2.[11] Since the ACCRA and UPC information are unavailable for rural areas and small towns, we restrict our analysis to NESARC respondents residing in metropolitan areas.

The NESARC contains detailed data on alcohol use (including the specific types of

[10] Nor do we directly examine the effects of instrumenting ACCRA prices with taxes, as has been done by Young &Bielinska-Kwapisz (2003).
[11] We do not, however, utilize the longitudinal nature of the two waves of the NESARC.

beverages consumed), abuse and dependence; treatment for alcohol problems; and family history of alcoholism or mental illness. Although we plan to use this information in future research, the goal of the current project is to use relatively simple models to examine whether estimates of average alcohol demand elasticities are sensitive to the price measures employed. For this reason, we focus on two basic components of alcohol use: whether the individual had consumed beer during the previous period and, conditional on beer drinking, the quantity consumed over the same period. This basic information will be converted to ethanol equivalent ounces of beer consumption in the econometric models, using procedures detailed below.

The NESARC data are also the source of supplementary demographic characteristics related to: sex, marital status, race/ethnicity (black, Hispanic, other non-Hispanic nonwhite), family size, education (less than high school graduate, some college), occupation (blue collar, white collar, service), geographic region (Midwest, South, West), and household income.[12]

Alcohol Prices and Sample Construction

ACCRA prices for beer, wine, and spirits were obtained for each of the years 2000-2004. As mentioned, the ACCRA data are limited to one brand for each type of alcohol.[13] We calculated ethanol equivalent prices per ounce of alcohol using information on the published alcohol content of the respective beverages obtained from a variety of sources.[14] Each ACCRA

---

[12] The reference group includes non-Hispanic white non-employed high school graduates living in the Northeast. Household income refers to money received by all household members from: jobs, self-employment, Social Security, Railroad Retirement, SSI, Veterans payments, retirement/disability/survivor pensions, interest, dividends, workers compensation, unemployment insurance, child support, alimony, educational assistance (tuition, books, living expenses), or public assistance (AFDC, ADC, WIC or any other public assistance/welfare payments).
[13] Data were provided for six packs (of 12 ounce containers) of Heineken (beer), 1.5 liter bottles of Gallo or Livingston Cellars Chablis (wine) and 750 ml bottles of J&B Scotch (spirits) in the years we study.
[14] These included information directly in the UPC data and the NABCA database for spirits, and liquor control board price lists from Washington and Pennsylvania for wine. Beer data were obtained from the Kansas Department of Revenue (https://www.kdor.org/brands/default.aspx), manufacturer websites (e.g. www.millercoors.com/our-beers), and other related websites such as the Beer Advocate (www.beeradvocate.com).

price value was next linked to corresponding US counties, using geographic tables obtained from the census, and assigned a population weight (for the population aged 15 years and older). Weighted State and UPC market prices were then calculated from these county-level values.

Uniform Product Code (UPC) scanner data on alcohol prices were obtained from AC Nielsen. The UPC data are collected for a 60-month rolling window from grocery stores in 51 markets with annual sales in excess of $2 million. Figure 1 provides an example of the type of information available for a single market (Buffalo-Rochester) and beverage type (Budweiser beer). Conversion of the UPC data to obtain the price per ounce of ethanol involved several steps. First, volume was expressed in "equivalent units" to account for differences in packaging sizes – for instance, beer could be sold as single bottles (of varying sizes), six packs, 12 packs, or cases.[15] Next, the percent alcohol by volume (%ABV) was calculated for each beer, wine and spirits brand.[16] Multiplication of % ABV by number of ounces in each package size for each Nielsen line item yielded total ounces of ethanol, which price was then divided into.

Sales volume weights were employed to obtain a single "average" price for the specified beverage type (beer, wine and spirits) in each ACCRA and UPC market.[17] Prices were then aggregated to the state level, using county population when there were multiple markets in the state. Analysis was restricted to NESARC respondents who were residents of urban and

---

[15] Beer sold in kegs, half kegs, and quarter kegs were excluded from these calculations, although nearly identical average prices were obtained when they were included. Wines were restricted to the following categories: Imported Dry Table, Domestic Dry Table, Flavored Refreshment, and Sparkling.

[16] We were not able to determine %ABV from external sources for 269 out of 500 beers. However, these 269 beers comprised only 0.9% of total beer sales across the 51 Nielsen markets. For these beers, we estimated %ABV from a regression of %ABV on price, package size, beer type (Ice, Pale, Amber, Dark, Pilsner, etc.), higher order terms, interactions, and market fixed effects. For wine, ABV values were obtained for 314 (out of 6489) different brands. These 314 brands accounted for 57% of the wine sold in the UPC sales records. For the remaining brands, an average ABV was assigned based on the wine type (ex. chardonnay, pinot noir, etc). For spirits, each of the UPC and NABCA sales records contained a proof value, permitting direct calculation of ethanol content.

[17] It is not clear that average prices are best when estimating price elasticities, since customers may respond to price differences, between brands or choices within brands, by substituting towards less expensive products. We are investigating this issue in current research; such potential substitution bias is also present in previous research.

suburban areas in states with price data.[18]

The estimation sample varies across models, with an effort made to: 1) estimate at least some specifications using the widest geographic area for which the specified price data were available; and 2) to provide comparability of estimates for models that utilize more restricted geographic samples. Specifically, for analyses exclusively focusing on ACCRA prices, the sample includes the 42 states for which we were able to obtain ACCRA beer, wine and spirits prices throughout the 2000-2004 period.[19] When estimating models for 2004 only, we have ACCRA prices for 45 states, our most comprehensive sample. We are able to match ACCRA and UPC beer prices for 35 states and ACCRA beer, wine and spirits prices with corresponding UPC prices for 25 states. This allows us to estimate models on all of these different samples, when comparing the results using ACCRA and scanner prices.[20] We also have information on beer taxes for all states and so estimate models where these are our key policy of interest, using samples with 25, 35 and 45 states.

Table 1 presents descriptive statistics for all respondents and for persons with some beer consumption for the 25, 35 and 45-state NESARC 2 samples. Respondent characteristics are similar when varying the number of states, except that the West and Midwest are over-represented in the samples with fewer states. However, beer drinkers are more likely (than the full sample) to be male, non-Hispanic white, college educated, and to have high incomes.

Analytic Methods

Previous researchers (e.g. Coate & Grossman, 1988; Grossman et al. 1987; Leung &

[18] Alternative specifications were estimated that included rural residents.
[19] Details on the states included in the various specifications are contained in the table notes.
[20] We have scanner data for fewer states because the UPC markets do not include spirits in many states and because we do not have beer prices in some of the control states where spirits prices are available.

Phelps, 1993; Giesbrecht, 1999; Laixuthai & Chaloupka; 1993 Kenkel, 1996; Farrell, Manning & Finch, 2003; Manning et al, 1995) have employed models derived from economic theory in which a utility maximizing consumer allocates income to purchase goods and services subject to preferences, market prices, and other demand determinants. Because income is a binding constraint in the short-run, the consumer's only option in responding to price changes is to alter the mix of goods and services purchased conditioned on preferences and other demand determinants (e.g., availability of a good or service). This leads to substitution away from more costly preferred goods and toward less costly preferred goods as relative prices change. With additional assumptions, this framework yields functional relationships between quantity demanded and relevant prices, income, other individual traits, and market characteristics:

$$A_i = A_i(P_i, P_j, Y, X) \qquad \textbf{(1)}$$

Where A_i is the quantity of alcoholic beverage i demanded ,i and j index preferred beverage types (beer, wine, and/or spirits), P denotes real price, Y is income, and X is a vector of demand shifters (e.g., age, race, gender, and education).

We estimate the elasticity of beer consumption based on a two-part framework comprising distinct model components representing: 1) the probability of any beer consumption; and 2) the natural log of the quantity of beer consumed conditional on some drinking.[21] Following Manning et al. (1995), we estimate the price elasticity of demand for alcohol obtained from this model as:

$$\eta_p = \left(1 - \hat{P}\right)\hat{\beta}_{1p} + \hat{\beta}_{2p} \qquad (2)$$

[21] The two-part model allows the determinants of drinking participation to diverge from those for the amount of drinking conditional on some consumption. The error terms in the two equations may also have different distributions.

where $\hat{P}$ is the estimated proportion of the sample having non-zero beer consumption, $\hat{\beta}_{1p}$ denotes the coefficient of log-price in the first part of the model (corresponding to whether or not any beer is consumed–the *extensive margin*), and $\hat{\beta}_{2p}$ is the estimated coefficient of log-price in the second part (corresponding to how much beer is consumed for individuals who consume at all–the *intensive margin*). Note also that

$$\eta_{1p} = (1 - \hat{P})\hat{\beta}_{1p} \quad (3)$$

the first additive component on the right-hand side of (2), represents the contribution of the extensive margin to the overall price elasticity. Our methods of calculating asymptotic standard errors for the elasticities specified by (2) and (3) are detailed in appendix.

Comparison of ACCRA and UPC Prices

ACCRA data are likely to poorly indicate the actual alcohol prices faced by consumers for the reasons discussed above, the most important being that information is collected for only a single brand of beer, wine and spirits. Unless these brands are representative of the "average" purchase, they will poorly proxy the relevant prices. To provide one example, ACCRA beer prices are collected for Heineken, a "super-premium" brand that is generally considerably more expensive than typical beers purchased. (Kerr, 2008). We provide evidence that this concern is salient through comparisons of market-specific 2004 ACCRA prices for beer, wine and spirits, and corresponding UPC sales volume-adjusted prices for actual grocery store purchases.[22]

Figure 2 shows ACCRA and UPC prices, per ounce of ethanol, averaged across all available markets. ACCRA beer prices averaged $2.21 per ounce of ethanol, which is 74 percent

[22] Volume-adjustment implies that the most heavily consumed brands and types receive the greatest weight in the price calculations.

higher the corresponding weighted UPC beer price ($1.27), as expected since ACCRA prices were for high-priced Heineken beer. Similarly, average ACCRA spirits prices were 91 percent above UPC prices ($2.12 vs. $1.11), because ACCRA collected data on J&B Scotch, a relatively expensive brand of distilled spirits. Conversely, since ACCRA measures prices of the non-premium Gallo or Livingston Cellars Chablis wine brands, average ACCRA wine prices were 40 percent below corresponding UPC prices ($1.12 vs. $1.87).

These disparities suggest that estimates exploiting geographic variations in ACCRA prices are likely to be biased, unless the ratio of ACCRA to UPC prices is similar across markets. Even if this condition holds, ACCRA will not correctly indicate the *relative* prices across beverage types, so that the cross-price elasticities will almost certainly be inaccurate. For example, the UPC data indicate that alcohol from beer is almost one-third cheaper than that from wine, on average, whereas the ACCRA data misleadingly indicate that ethanol from beer costs nearly twice as much.

Figures 3 through 5 provide corresponding comparisons of UPC and ACCRA prices for beer, spirits, and wine on a market-specific basis.[23] The top panel of each figure shows prices that are volume-adjusted but do not account for differences in the ethanol content of the beverages actually purchased. Thus, these refer to six-packs of (12 ounce containers) of beer, 750 ml bottles of spirits and 1.5 liter bottles of wine. The lower panels provide corresponding price information per ounce of ethanol, which is used in the regressions below. For each figure, crosses show ACCRA prices, dots and diamonds respectively display weighted (by sales volume) mean and median UPC prices, and the shaded areas indicate the 25th through 75th percentile of UPC prices.

[23] Several states (NY, Fl, TX, CA, OH and NC) contain more than one Neilsen market.

The overall patterns observed when aggregating across all markets in Figure 2 – higher ACCRA than UPC prices for beer and spirits but lower ACCRA prices for wine – are present in most individual markets. ACCRA beer prices are higher than the UPC average or median in all 49 markets and exceed the 75th percentile in all markets except Denver (where only 3.2% alcohol by weight (ABW) beer can be sold in supermarkets), when measured on a per ounce of ethanol basis. That said, the ratio of ACCRA to UPC prices differs substantially across markets. For instance, the ACCRA beer price per ounce of ethanol exceeds the UPC level by 102, 98 and 95 percent in Milwaukee, Charlotte and Cincinnati but by a much smaller 4, 24 and 30 percent in Denver, Oklahoma City and Minneapolis (all states where only 3.2% ABW beer is sold in supermarkets).[24]

ACCRA spirits prices similarly exceed the UPC average and 75th percentile for all 21 markets, whether or not the alcoholic content of the beverages is adjusted for. Once again, however, relative prices differ substantially across markets, with the ACCRA price per ounce of ethanol being 144 and 120 percent greater than UPC prices in Milwaukee and Tampa, but just 33 and 66 percent higher in Boston and New Orleans/Mobile.

Figure 5 shows a more nuanced picture for wine. On a per ounce of ethanol basis, ACCRA prices are below the UPC average in all 37 markets but they are at or within 15 percent of the median price in 4 markets (Las Vegas, St. Louis, Milwaukee, and West Texas) while being below the 25th percentile in six (Baltimore, Little Rock, Miami, San Diego, San Francisco and Seattle). In the three markets with the smallest differentials (Las Vegas, St. Louis, Boston),

[24] In preliminary research, we also compared grocery store beer prices (used in the regressions below) to those for sales in convenience stores, for the 19 markets in which such data were available. Prices were typically slightly lower in convenience than grocery stores ($5.94 versus $6.21 per six pack and $1.39 versus $1.44 per ounce of ethanol) but much lower in either case than ACCRA measured prices ($7.98 per six pack and $2.25 per ounce of ethanol).

ACCRA prices are 22, 25 and 30 percent below the UPC average but they are 53, 52 and 51 percent lower in the three markets with the largest gap (San Diego, Des Moines, Seattle).

ACCRA Data Does Not Provide Robust Elasticity Estimates

We next use the econometric methods discussed above to show that use of the ACCRA data fail to yield stable estimates of the price elasticity of demand for beer. Indeed, using plausible specifications, the range of estimates is so wide as to provide little helpful guidance.

Specifically, we estimate price and income elasticities using NESARC 2 data for respondents interviewed in 2004-2005, with ACCRA prices measured either in 2004 or 2003, as well as for NESARC 1 respondents from 2000-2001 with ACCRA prices collected in 2001 or 2000. Since the large majority (82 percent) of NESARC 2 interviews occur in 2004, 2004 ACCRA prices are approximately contemporaneous while those from 2003 are lagged approximately one year. Similarly, 2001 prices are approximately contemporaneous for 85 percent of NESARC 1 respondents, and those from 2000 are lagged by around one year. We do not have a strong theoretical argument for including current versus recent lags of prices (and an argument could certainly be made for incorporating both) but would generally not expect the estimated elasticities to be strikingly different, since prices are extremely highly correlated from one year to the next. Therefore, if the ACCRA prices are useful, we would generally expect to obtain similar elasticity estimates across all four specifications or, at a minimum, for the two estimates using contemporaneous prices (2004 prices with NESARC 2 and 2001 prices with NESARC 1) and for the two using a one-year lag (2003 prices with NESARC 2 and 2000 prices with NESARC 1).

Table 2 summarizes the results. Each model includes the full set of demographic variables, household incomes, and controls for beer, wine and spirits prices.[25] The top panel shows the total elasticity of beer consumption, combining the effects of changes at the extensive and intensive margins. The bottom panel displays the first-stage elasticities, related to changes in the probability of consuming any beer (the extensive margin).

Estimates for the own price elasticity of total beer consumption range from a small and insignificant -0.2 in column (c) to a very large and statistically significant -1.9 in column (d). Nor is there any consistency across the two time periods. Using NESARC 2 data and approximately contemporaneous prices, the estimated demand elasticity is -1.5; this compares to -0.2 for the corresponding NESARC 1 specification. Controlling for prices one year earlier, the elasticity estimate is decreased substantially (to -0.6) for the NESARC 2 sample but increases dramatically (to -1.9) for NESARC 1; the standard errors are sufficiently large that these differences are not always significant.[26] Similar patterns are observed in the lower panel of Table 2. Thus, using the point estimates, one can conclude only that the own price elasticity of total beer consumption ranges between -0.2 and -1.9 (top panel) and while that of beer drinking participation ranges from -0.3 to -1.1 (lower pane).[27] Such wide variation of estimates provides little useful guidance for policy-making and is obtained despite having fairly large samples.

There are analogous, albeit less severe, problems when estimating cross-price elasticities. The point estimates always suggest that wine and spirits are substitutes for beer (higher prices for

---

[25] Coefficients on the supplementary covariates are consistent with our expectations and previous research. Females, married persons, older individuals, and nonwhites or Hispanics drink relatively little beer. College educated persons drink beer relatively often but consume relatively small amounts when they do. Blue collar and service workers consume relative large quantities and the unemployed the least. Regional variations are small, but with some evidence of more beer drinking in the Midwest and West.

[26] Using 2002 ACCRA prices for the NESARC 2 data, corresponding to approximately a two-period lag, the estimated demand elasticity (standard error) is 0.4 (0.6).

[27] The 95 percent confidence intervals are cover a range from -3.0 to 0.7 for the elasticity of total beer drinking. Estimates obtained for models incorporating sampling weights exhibit similar instability.

these products are associated with greater beer consumption) but they are usually not statistically significant and vary across models. Interestingly, the data suggest that higher wine prices increase both the probability of drinking beer, whereas higher spirits prices mainly raise beer drinking at the intensive margin. The estimated income elasticities are not sensitive to the choice of specifications and indicate that higher incomes primarily raise beer drinking at the extensive margin.

Elasticity Estimates are Sensitive to Changes in Samples and Sources of Price Data

We next examine whether the estimated price elasticity of demand for beer is sensitive to the choice of price series and samples. For this analysis we face several data restrictions, as already mentioned. First, although we have ACCRA data on beer, wine and spirits prices for 45 states, Nielsen collects corresponding grocery store scanner prices for markets in only 35 of these.[28] Furthermore, since distilled spirits sales are restricted to state liquor stores in some states, the UPC data containing spirits and wine prices is limited to 25 states. Since wine and spirits tax rates are complicated to calculate in the control states, we follow previous research in by estimating tax models that control for beer taxes only. We therefore estimated a wide variety of models with alternative sampling criteria and price/tax controls. As discussed, UPC data were not available to us prior to 2004, therefore all of these models control for 2004 prices or taxes, with consumption measured using NESARC 2 data.

The findings are displayed in Table 3. Once again, the top panel estimates total demand elasticities and the bottom one indicates elasticity estimates for drinking participation. From a theoretical perspective, it would be desirable to always include wine and spirits price regressors,

[28] Our analysis excludes the five states (Utah, Colorado, Minnesota, Kansas and Oklahoma) where grocery stores are not permitted to sell beer with an alcohol content exceeding 3.2% ABW.

as well as those for beer, but the data do not permit this for the 35-state sample, when using UPC prices, or when using tax data. Therefore, results for wine and spirits prices are not reported on the table but these are controlled for in columns (b), (d), (f) and (h). Models with ACCRA prices, columns (a) through (f), are estimated with and without controls for wine and spirits prices and for 25, 35 and 45 states. Specifications with UPC prices, columns (g) through (i), are estimated with and without wine and spirits prices for 25 states and with beer prices only for 35 states. Models controlling for beer taxes, columns (j) through (l), are estimated for the 25, 35 and 45 state samples. All specifications also control for the full set of demographic and geographic characteristics.

The first noteworthy finding is that the own price demand elasticity estimates obtained using the ACCRA data are extremely sensitive to states included in the sample. When wine and spirits prices are also controlled for, the estimated elasticity is attenuated from -3.9 in the 25 state sample to -1.5 when 45 states are included. Although wider geographic variation is presumably preferable, the smaller sample still contains many large states (including California and Florida) and the 35 state sample, which yields a similar elasticity estimate (-3.8), includes the five largest states.

Second, the use of ACCRA prices leads to quite different, and much larger, estimates of own-price elasticities than corresponding specifications using UPC prices. For instance, using the 25 state model with controls for wine and spirits prices, the own price total elasticity is estimated to be -3.9 with ACCRA prices (column b) versus a statistically insignificant -0.3 with UPC prices (column h). The elasticity estimates are attenuated for the ACCRA models that exclude wine and spirits prices (columns a, c and e versus b, d and f) but increase in absolute value with their exclusion in the UPC price models (column g versus f). Importantly, when estimating corresponding specifications, there is essentially no change in estimated own price elasticities when increasing the number of states from 25 to 35 and using the UPC data (column g versus column i), in contrast to the already noted instability obtained with the ACCRA data.

Third, total tax elasticities of beer consumption are always close to zero and statistically insignificant (columns j through l). Interestingly, higher taxes do appear to have a small negative effect on beer drinking participation, but this is offset by an imprecisely estimated positive effect at the intensive margin. As with the UPC data, but in contrast to the models controlling for ACCRA prices, the elasticity estimates are unaffected by changes in the number of states sampled.

Finally, the estimated income elasticities are extremely stable across specifications and sources of price data. They indicate that beer drinking is a normal good with income effects concentrated at the extensive margin. The coefficient estimates are similarly stable for the supplemental covariates measuring demographic and geographic characteristics.

Discussion

Our most important finding is that the commonly used ACCRA price data are unlikely to reliably indicate demand elasticities for alcohol. The estimates obtained using ACCRA prices vary drastically and unpredictably depending on the: year examined, exact sample within a given year analyzed, or the lag structure of prices included in the model. In plausible specifications, we obtain point estimates of own-price beer elasticities varying between -0.2 and -3.9, with considerable imprecision around even this wide range. Such sensitivity could easily explain discrepancies shown in the literature and, even more importantly, suggest that the “sensible” elasticities obtained in much previous work may have occurred because researchers had the good luck to choose years and samples that provided such estimates, or because extreme results were less likely often reported or published.

As an alternative, researchers have often used beer taxes as the proxy for alcohol prices, and we replicate such methods for comparison purposes. However, beer taxes are likely to poorly indicate prices (Young and Bielinska-Kwapisz, 2002) and, since real tax rates have fallen dramatically over time–from $0.10 per standard 12 ounce drink in 1960 to $0.03 in 2010 (in 2011 dollars)–they constitute only a small share of prices and even a doubling or tripling of state beer taxes would not be expected to have much effect on consumption. [29] Given this, it is not surprising that we estimate beer tax elasticities to be close to zero, although the data do suggest a negative tax elasticity of drinking participation.

In addition, heroic efforts are needed to estimate tax rates on spirits in the 18 states and wine in the 5 states restricting such sales to state liquor stores, as would be required for models that include beer, wine and spirits taxes. We attempted such an exercise but viewed the final estimates to be unreliable because they required strong assumptions about the typical mark-up at the wholesale and retail levels and since the resulting tax estimates are positively related to the assumed price.[30]

---

[29] Using ACCRA prices, Young (2010) estimates that state taxes averaged 1.7 percent of the purchase price of beer and 4.4 percent of the price of wine in 2009, and 6.1 percent of the price of spirits in 2004.

[30] We initially attempted to calculate tax rates in these cases using the method of Benson et al. (2003), which compares prices for the same brands across open and control states. However, this assumes that control and open state wholesalers pay the same price to producers, which we determined was not the case for the control states where this data is available. As an alternative, we used the following procedure: 1) compute an average freight on board (FOB) price for specified types of alcohol (e.g. 750 ml bottles) in a given year; 2) calculate the corresponding retail price in each control state utilizing that state's mark-up formula; 3) calculate the expected open state price using typical wholesale and retail mark-up percentages ; 4) treat the difference between each calculated control state price and the expected open state price as a tax estimate that includes the typical open state mark-up on the tax because the tax is levied before the wholesale mark-up. 5) Remove this mark-up on the tax to get the tax estimate for each state. Obviously, this procedure makes an assumption about the typical mark-up at the wholesale and retail levels. Also, the tax estimates vary with the price of the beverage chosen since, assuming a constant percentage mark-up, the computed excise tax increases approximately proportionately with the assumed price.

Given these issues, we believe that the most our most useful estimates are obtained using the detailed scanner data for grocery purchases. These suggest a relatively low price elasticity of demand for beer, probably around -0.3, with evidence that responsiveness of consumption to price is considerably overstated in models that control for beer but not wine or spirits prices. We caution that these estimates are not without problems. Most importantly, using cross-sectional data, the elasticities are likely to be understated if geographic variations in prices are dominated by demand factors that differ across markets.

One potential strategy for future research would be to obtain longitudinal scanner price data and then to estimate models identified by within-market changes in prices. It would also be useful to employ such data to estimate demand elasticities for other types of alcohol, although the large number of beverage types, particularly for wine, increases the difficulty in calculating percent alcohol by volume when doing so. The UPC price data we examine is limited to grocery stores, underscoring the importance of subsequent studies accounting for sales in liquor, convenience and warehouse stores, and for differences in prices for alcohol consumed in bars and restaurants versus that purchased in stores for "off-premise" consumption. Finally, we have treated individuals as homogenous and so calculated average price-elasticities of demand. However, it is likely that the demand elasticities vary considerably across consumers in ways that are currently poorly understood.

Literature Cited

Arcidiacono P, Sieg H, Sloan F. (2007), Living Rationally Under The Volcano? An Empirical Analysis Of Heavy Drinking And Smoking, *International Economic Review*, 48(1): 37-65.

Benson BL, Rasmussen DW, Zimmerman PR (2003), Implicit taxes collected by state liquor monopolies. Public Choice 115(3-4): 313-331.

Bray JW, Loomis BR, Engelen M. (2007), Correlates of In-Store Promotions for Beer: Differential Effects of Market and Product Characteristics, *Journal of Studies on Alcohol and Drugs*, 68(2): 220-227.

Bray JW, Loomis BR, Engelen M. (2009), You Save Money When You Buy in Bulk: Does Volume-Based Pricing Cause People to Buy More Beer? *Health Economics*, 18(5): 607-618.

Chaloupka FJ, Saffer H, Grossman M. (1993), Alcohol-control Policies and Motor Vehicle Fatalities, *Journal of Legal Studies*, 22(1): 161-186.

Chaloupka FJ, Grossman M, Saffer H. (2002), The Effects of Price on Alcohol Consumption and Alcohol-Related Problems, *Alcohol Res Health*, 26(1): 22-34.

Chen CM, Yi H-y, Falk DE, Stinson FS, Dawson DA, Grant BF. (2006), *Alcohol Use and Alcohol Use Disorders in the United States: Main findings from the 2001-2002 National Epidemiologic Survey on Alcohol and Related Conditions (NESARC).* Bethesda, MD: National Institute on Alcohol Abuse and Alcoholism, National Institutes of Health; January.

Coate D, Grossman M (1988), Effects of Alcoholic Beverage Prices and Legal Drinking Ages on Youth Alcohol Use, *Journal of Law and Economics*, 31(1): 145-71.

Cook PJ. *Paying the Tab: The Costs and Benefits of Alcohol Control*. Princeton, NJ: Princeton University Press; 2007.

Dave D, Kaestner R. (2002), Alcohol Taxes and Labor Market Outcomes, *Journal of Health Economics*, 21(3): 357-371.

Dawson DA, Goldstein RB, Grant BF. (2007), Rates and Correlates of Relapse Among Individuals in Remission from DSM-IV Alcohol Dependence: A 3-year Follow-up,*Alcohol ClinExp Res,* 31(12):2036-2045.

Farrell, S, Manning, WG, Finch, MD (2003), Alcohol Dependence and the Price of Alcoholic Beverages,*J Health Econ*.22:117-47.

Freeman DG. (2000), Alternative Panel Estimates of Alcohol Demand, Taxation and the Business Cycle, *Southern Economic Journal*, 67(2): 325-344.

Grant BF, Kaplan K, Shepard J, Moore T. *Source and Accuracy Statement for Wave 1 of the 2001–2002 National Epidemiologic Survey on Alcohol and Related Conditions.* Bethesda, MD: National Institute on Alcohol Abuse and Alcoholism; 2003.

Giesbrecht N, Greenfield TK, Anglin L, Johnson S. (2004), Changing the Price of Alcohol in the United States: Perspectives from the Alcohol Industry, Public Health, and Research. *Contemporary Drug Problems,* 31(4):711-736.

Grossman M, Chaloupka FJ, Sirtalan I. (1998), An Empirical Analysis of Alcohol Addiction: Results from the Monitoring the Future Panels, *Economic Inquiry*, 36(1), 39-48.

Grossman M, Coate D, Arluck, GM. (1987), Price Sensitivity of Alcoholic Beverages in the United States, in Moore, MH, Gerstien, DR, Eds. *Control Issues in Alcohol Abuse Prevention: Strategies for states and Communities.* Greenwich, CT: JAI Press, 169-98.

Kenkel, DS (1996), New Estimates of the Optimal Tax on Alcohol, *Economic Inquiry,*34(2): 296-319.

Kenkel, DS (1993), Drinking, Driving and Deterrence: The Effectiveness and Social Costs of Alternative Policies”, *Journal of Law and Economics*, 36(2), 877-913.

Kerr WC (2008) Ethanol content of beer sold in the U.S.: variation over time, across states and by individual drinks, in Encyclopedia Handbook of Beer in Health and Disease Prevention, Preedy VR, Watson RR eds, pp 255-264. Academic Press (Elsevier), London.

Laixuthai A, Chaloupka FJ. (1993), Youth Alcohol Use and Public Policy,*Contemporary Policy Issues,*11(4): 70-81.

Leung SF, Phelps CE. (1993), A Review of Estimates of the Price Sensitivity of Demand for Alcoholic Beverages, in Hilton, ME, Bloss, G, Eds.,*Economics and the Prevention of Alcohol-related Problems*. NIAAA Research Monograph 25, NIH Pub. No. 95-3513. Bethesda, MD: National Institute on Alcohol Abuse and Alcoholism, 123-148.

Manning WG, Blumberg L, Moulton LH. (1995), The Demand for Alcohol: the Differential Response to Price,*Journal of Health Economics,*14(2): 123-48.

Markowitz S, Kaestner R, Grossman M. (2005), An Investigation of the Effects of Alcohol Consumption and Alcohol Policies on Youth Risky Sexual Behaviors□, *American Economic Review*, 95(2): 263-266.

National Institute on Alcohol Abuse and Alcoholism, (2010), Apparent Per Capita Ethanol Consumption for the United States, 1850–2007, http://www.niaaa.nih.gov/Resources/DatabaseResources/QuickFacts/AlcoholSales/consum01.htm, accessed June 18, 2010.

Ruhm CJ (1996), Alcohol Policies and Highway Vehicle Fatalities, *Journal of Health Economics*, 15(4: 435-454.

Sloan FA, Reilly FA, Schenzler C. (1994), Effects of Prices, Civil and Criminal Sanctions, and Law Enforcement on Alcohol-Related Mortality, *Journal of Studies on Alcohol*, 55(4): 454-465.

Wagenaar A, Salois MJ, Komro KA. (2009), Effects of Beverage Alcohol Price and Tax Levels on Drinking: A Meta-Analysis of 1003 Estimates from 112 Studies, *Addiction*, 104(2): 179-190.

Williams J, Chaloupka FJ, Wechsler H. (2005), Are There Differential Effects of Price and Policy on College Students 'Drinking Intensity? *Contemporary Economic Policy*, 23(1): 78-90.

Young DJ (2010), Alcohol Taxes, Beverage Prices, Drinking and Traffic Fatalities in Montana, mimeo, University of Montana, January.

Young DJ, Bielinska-Kwapisz A (2003), Alcohol Consumption, Beverage Prices and Measurement Error. *Journal of Studies on Alcohol*, 64(2): 235-8.

Young DJ, Bielinska-Kwapisz A. (2002), Alcohol Taxes and Beverage prices. *National Tax Journal,* 55(1): 57-73.

Table 1: Descriptive Statistics for Analysis Variables, NESARC 2 samples

Variable	25-State Sample		35-State Sample		45-State Sample	
	All	**Beer Drinkers**	**All**	**Beer Drinkers**	**All**	**Beer Drinkers**
Daily Ethanol from Beer (ounces)	0.151 (0.005)	0.408 (0.013)	0.153 (0.005)	0.424 (0.012)	0.152 (0.004)	0.417 (0.011)
Beer Drinker During Past Year	0.370 (0.004)	1.000	0.360 (0.003)	1.000	0.363 (0.003)	1.000
Female	0.576 (0.004)	0.400 (0.006)	0.581 (0.003)	0.403 (0.005)	0.581 (0.003)	0.403 (0.005)
Age (years)	48.69 (0.13)	44.88 (0.20)	48.54 (0.11)	44.65 (0.16)	48.68 (0.11)	44.74 (0.15)
Household Income ($1000's)	58.75 (0.44)	69.29 (0.79)	57.69 (0.36)	68.11 (0.65)	58.04 (0.34)	68.30 (0.62)
Family Size (#)	2.671 (0.012)	2.724 (0.019)	2.667 (0.01)	2.716 (0.016)	2.656 (0.009)	2.711 (0.015)
Non-Hispanic Black	0.190 (0.003)	0.137 (0.004)	0.207 (0.003)	0.152 (0.004)	0.203 (0.002)	0.149 (0.004)
Hispanic	0.214 (0.003)	0.214 (0.005)	0.22 (0.003)	0.218 (0.004)	0.211 (0.003)	0.207 (0.004)
Other Nonwhite	0.049 (0.002)	0.042 (0.003)	0.044 (0.001)	0.039 (0.002)	0.045 (0.001)	0.039 (0.002)
< High School Graduate	0.15 (0.003)	0.114 (0.004)	0.156 (0.002)	0.114 (0.003)	0.154 (0.002)	0.111 (0.003)
1-3 Years of College	0.321 (0.004)	0.329 (0.006)	0.317 (0.003)	0.328 (0.005)	0.313 (0.003)	0.325 (0.005)
4+ years of College	0.28 (0.004)	0.333 (0.006)	0.275 (0.003)	0.328 (0.005)	0.276 (0.003)	0.331 (0.005)
Midwestern Residence	0.282 (0.004)	0.296 (0.006)	0.215 (0.003)	0.229 (0.005)	0.196 (0.002)	0.208 (0.004)

Southern residence	0.310 (0.004)	0.273 (0.006)	0.39 (0.003)	0.358 (0.005)	0.354 (0.003)	0.322 (0.005)
Western residence	0.360 (0.004)	0.38 (0.006)	0.249 (0.003)	0.271 (0.005)	0.230 (0.003)	0.247 (0.004)
Married	0.509 (0.004)	0.521 (0.006)	0.505 (0.003)	0.52 (0.005)	0.505 (0.003)	0.521 (0.005)
Blue-collar Occupation	0.157 (0.003)	0.185 (0.005)	0.152 (0.002)	0.186 (0.004)	0.152 (0.002)	0.185 (0.004)
White-collar Occupation	0.543 (0.004)	0.596 (0.006)	0.538 (0.003)	0.591 (0.005)	0.538 (0.003)	0.592 (0.005)
Service occupation	0.143 (0.003)	0.135 (0.004)	0.151 (0.002)	0.14 (0.004)	0.151 (0.002)	0.14 (0.004)
Beer Tax	0.002 (8.3E-6)	0.002 (1.3E-5)	0.002 (7.5E-6)	0.002 (1.2E-5)	0.002 (7.4E-6)	0.002 (1.2E-5)
UPC Beer price	1.248 (0.001)	1.245 (0.001)	1.253 (0.001)	1.252 (0.001)	---	---
UPC Wine price	1.848 (0.001)	1.839 (0.002)	---	---	---	---
UPC Spirits price	1.142 (0.002)	1.136 (0.003)	---	---	---	---
ACCRA Beer price	2.101 (0.001)	2.101 (0.001)	2.091 (0.001)	2.091 (0.001)	2.112 (0.001)	2.112 (0.001)
ACCRA Wine price	1.033 (0.001)	1.029 (0.001)	1.058 (0.001)	1.053 (0.001)	1.088 (0.001)	1.086 (0.001)
ACCRA Spirits price	2.114 (0.001)	2.106 (0.002)	2.120 (0.001)	2.114 (0.001)	2.140 (0.001)	2.135 (0.001)

Notes: Sample sizes are 16,437, 23,743 and 26,395 for all respondents in the 25-state, 35-state, and 45-state samples. For beer drinkers the sample sizes are 6,089, 8,543 and 9,591. Table shows (unweighted) means with standard errors in parentheses. Unless otherwise noted, all variables are dichotomous. Alcohol prices and taxes are measured in 2004 and are per ounce of ethanol.

Table 2: Effects of ACCRA-Based Alcohol Prices on Beer Consumption Elasticities

Prices/Income	**(a)**	**(b)**	**(c)**	**(d)**
		Total Beer Consumption		
Beer Prices	-1.567	-0.646	-0.213	-1.908
	(0.632)	(0.651)	(0.463)	(0.577)
Wine Prices	0.730	0.277	0.760	0.956
	(0.332)	(0.368)	(0.415)	(0.298)
Spirits Prices	0.249	0.149	0.275	0.705
	(0.456)	(0.535)	(0.391)	(0.414)
Household Income	0.073	0.074	0.077	0.079
	(0.030)	(0.030)	(0.023)	(0.023)
		Current Beer Drinker		
Beer Prices	-0.755	-0.319	-0.187	-1.105
	(0.261)	(0.272)	(0.182)	(0.227)
Wine Prices	0.422	0.170	0.277	0.259
	(0.137)	(0.154)	(0.162)	(0.116)
Spirits Prices	-0.315	-0.375	-0.079	0.223
	(0.187)	(0.220)	(0.152)	(0.163)
Household Income	0.125	0.125	0.088	0.089
	(0.012)	(0.012)	(0.009)	(0.009)
Data Source	NESARC 2	NESARC 2	NESARC 1	NESARC 1
ACCRA Year	2004	2003	2001	2000

Notes: Data are from the first and second National Epidemiological Surveys on Alcohol and Related Conditions (NESARC 1 and 2) conducted in 2001-02 and 2004-05. The sample includes residents of metropolitan areas with UPC price information in the 42 states (AL,AK,AZ,AR,CA,CT,DE,DC,FL,GA,ID,IL,IN,IA,KY,LA,MD,MA,MI,MS,MO,MT,NE,NV,NH,NJ,NM,NY,NC,ND,OH,OR,PA,SC,SD,TN,TX,VA,WA,WV,WI, and WY) for which ACCRA beer, wine and spirits prices were available in 2000-2004. (States that restrict the sale of beer in grocery stores to less than 3.2 percent alcohol by weight are also excluded.) Sizes of the analysis samples are 33,051 for NESARC 1 and 26,156 for NESARC 2. The outcome examined is ounces of average daily ethanol consumption from beer during the last year. Alcohol prices are measured in terms of ethanol equivalents. Elasticities are calculated using the procedures discussed in the text. In addition to alcohol prices and household incomes, the regression models also control for sex, marital status, age, race/ethnicity, family size, education, region, and occupation. Standard errors are in parentheses.

Table 3: Effects of Alternative Measures of Prices and Taxes on 2004 Beer Consumption Elasticities

Prices/Income	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)	(i)	(j)	(k)	(l)
				Total Beer Consumption								
Beer Prices	-3.718	-3.908	-3.592	-3.802	-0.627	-1.548	-0.963	-0.285	-1.073	0.027	0.006	0.002
	(0.903)	(1.011)	(0.700)	(0.777)	(0.479)	(0.621)	(0.453)	(0.499)	(0.375)	(0.059)	(0.048)	(0.045)
Household Income	0.090	0.091	0.097	0.097	0.076	0.077	0.092	0.092	0.099	0.088	0.095	0.076
	(0.037)	(0.037)	(0.031)	(0.031)	(0.030)	(0.030)	(0.037)	(0.037)	(0.032)	(0.037)	(0.031)	(0.030)
				Current Beer Drinker								
Beer Prices	-2.294	-2.252	-1.683	-1.552	-0.626	-0.840	-0.552	-0.297	-0.341	-0.051	-0.038	-0.047
	(0.373)	(0.418)	(0.286)	(0.318)	(0.200)	(0.257)	(0.189)	(0.207)	(0.155)	(0.024)	(0.020)	(0.019)
Household Income	0.142	0.142	0.140	0.140	0.124	0.124	0.142	0.142	0.140	0.138	0.138	0.123
	(0.015)	(0.015)	(0.013)	(0.013)	(0.012)	(0.012)	(0.015)	(0.015)	(0.013)	(0.015)	(0.013)	(0.012)
Price Measure	ACCRA	ACCRA	ACCRA	ACCRA	ACCRA	ACCRA	UPC	UPC	UPC	Taxes	Taxes	Taxes
# of States	25	25	35	35	45	45	25	25	35	25	35	45
Other Prices	No	Yes	No	Yes	No	Yes	No	Yes	No	No	No	No

Notes: Alcohol consumption data are from the second National Epidemiological Survey on Alcohol and Related Conditions (NESARC 2), conducted in 2004-05. Alcohol prices are for 2004, measured in ethanol-equivalents, and come from the American Chamber of Commerce Research Association (ACCRA), Uniform Product Code (UPC) scanner data provided by AC Nielsen, or from state beer taxes. Some estimates include the 25 states (AL, AZ, CA, FL, ID, IL, IA, LA, MD, MA, MI, MS, MO, NE, NV, NH, NM, NC, OH, OR, VA, WA, WV, WI, WY) for which beer, wine and spirits prices (ACCRA and UPC) were available. Others include the 35 states in which ACCRA and UPC beer prices, as well as beer taxes, were available. These include the 25 states mentioned above plus (AR, CT, DC, GA, IN, KY, NY, SC, TN, TX). Models with 45 states include all of those where ACCRA beer, wine and spirits prices were available. (These models include DC and all states except CO, KS, ME, MN, OK, UT). All samples are restricted to residents in metropolitan areas. Sizes of the analysis samples are 16,437, 23,743 and 26,393 for the samples that include 25, 35 and 45 states. The outcome examined is average daily ethanol consumption from beer during the last year. Alcohol prices are measured in terms of ethanol equivalents. Elasticities are calculated using the procedures discussed in the text. The regression models also control for sex, marital status, age, race/ethnicity, family size, education, region, occupation and, where "other prices" are included, the natural logs of spirits and wine prices. Standard errors are in parentheses.

Figure 1: SAMPLE: BUDWEISER Buffalo-Rochester, 24 WEEKS ENDING 1/01/05 (Grocery Store Sales)																
	UNIVERSAL PRODUCT CODE	**BRAND DESCRIP-TION**	**SIZE**	**PRO-DUCT MODULE**	**STYLE**	**TYPE**	**BOTTLE TYPE**	**CONTAIN-ER**	**DOL-LAR SALES**	**DOL-LAR SHARE**	**EQ UNIT SALES**	**EQ SHARE**	**UNIT SALES**	**UNIT SHARE**	**AVERAGE SELLING PRICE**	**AVERAGE EQ SELLING PRICE**
TOTAL BUDWEISER		BUDWEISER		BEER					2,585,321	12.8	161,193	12.1	362,954	13.4	7.12	16.04
BUDWEISER BR NRB LN 24P 12 OZ	001820011349	BUDWEISER	12.00	BEER	DOMESTIC	REGULAR	LONGNECK	NON REFILLABLE BOTTLE	104,593	0.5	7,096	0.5	7,096	0.3	14.74	14.74
BUDWEISER BR CN 6P 12 OZ	001820000016	BUDWEISER	12.00	BEER	DOMESTIC	REGULAR	N/A	CAN	123,518	0.6	6,263	0.5	25,056	0.9	4.93	19.72
BUDWEISER BR CN 6P 16 OZ	001820000018	BUDWEISER	16.00	BEER	DOMESTIC	REGULAR	N/A	CAN	29,092	0.1	1,630	0.1	4,891	0.2	5.95	17.85
BUDWEISER BR NRB LN 16 OZ	001820000024	BUDWEISER	16.00	BEER	DOMESTIC	REGULAR	LONGNECK	NON REFILLABLE BOTTLE	0	0.0	0	0.0	0	0.0	0.00	0.00
BUDWEISER BR CN 6P 8 OZ	001820000042	BUDWEISER	8.000	BEER	DOMESTIC	REGULAR	N/A	CAN	11,457	0.1	443	0.0	2,659	0.1	4.31	25.86
BUDWEISER BR NRB 40 OZ	001820000116	BUDWEISER	40.00	BEER	DOMESTIC	REGULAR	REGULAR	NON REFILLABLE BOTTLE	0	0.0	0	0.0	0	0.0	0.00	0.00
BUDWEISER BR NRB 40 OZ	001820000126	BUDWEISER	40.00	BEER	DOMESTIC	REGULAR	REGULAR	NON REFILLABLE BOTTLE	46,991	0.2	2,902	0.2	20,903	0.8	2.25	16.19
BUDWEISER BR CN 24 OZ	001820000466	BUDWEISER	24.00	BEER	DOMESTIC	REGULAR	N/A	CAN	50,926	0.3	3,288	0.2	39,452	1.5	1.29	15.49
BUDWEISER BR NRB LN 22 OZ	001820000478	BUDWEISER	22.00	BEER	DOMESTIC	REGULAR	LONGNECK	NON REFILLABLE BOTTLE	51,569	0.3	3,067	0.2	40,140	1.5	1.28	16.81
BUDWEISER BR CN 24P 12 OZ	001820000639	BUDWEISER	12.00	BEER	DOMESTIC	REGULAR	N/A	CAN	246,531	1.2	16,126	1.2	16,126	0.6	15.29	15.29
BUDWEISER BR NRB LN 12P 12 OZ	001820000771	BUDWEISER	12.00	BEER	DOMESTIC	REGULAR	LONGNECK	NON REFILLABLE BOTTLE	308,351	1.5	19,111	1.4	38,222	1.4	8.07	16.13
BUDWEISER BR NRB LN 6P 7 OZ	001820000774	BUDWEISER	7.000	BEER	DOMESTIC	REGULAR	LONGNECK	NON REFILLABLE BOTTLE	2,357	0.0	97	0.0	660	0.0	3.57	24.30
BUDWEISER BR NRB LN 6P 12 OZ	001820000834	BUDWEISER	12.00	BEER	DOMESTIC	REGULAR	LONGNECK	NON REFILLABLE BOTTLE	97,461	0.5	4,972	0.4	19,892	0.7	4.90	19.60

Figure 2: Average UPC and ACCRA Prices Per Ounce of Ethanol in 2004, By Beverage Type

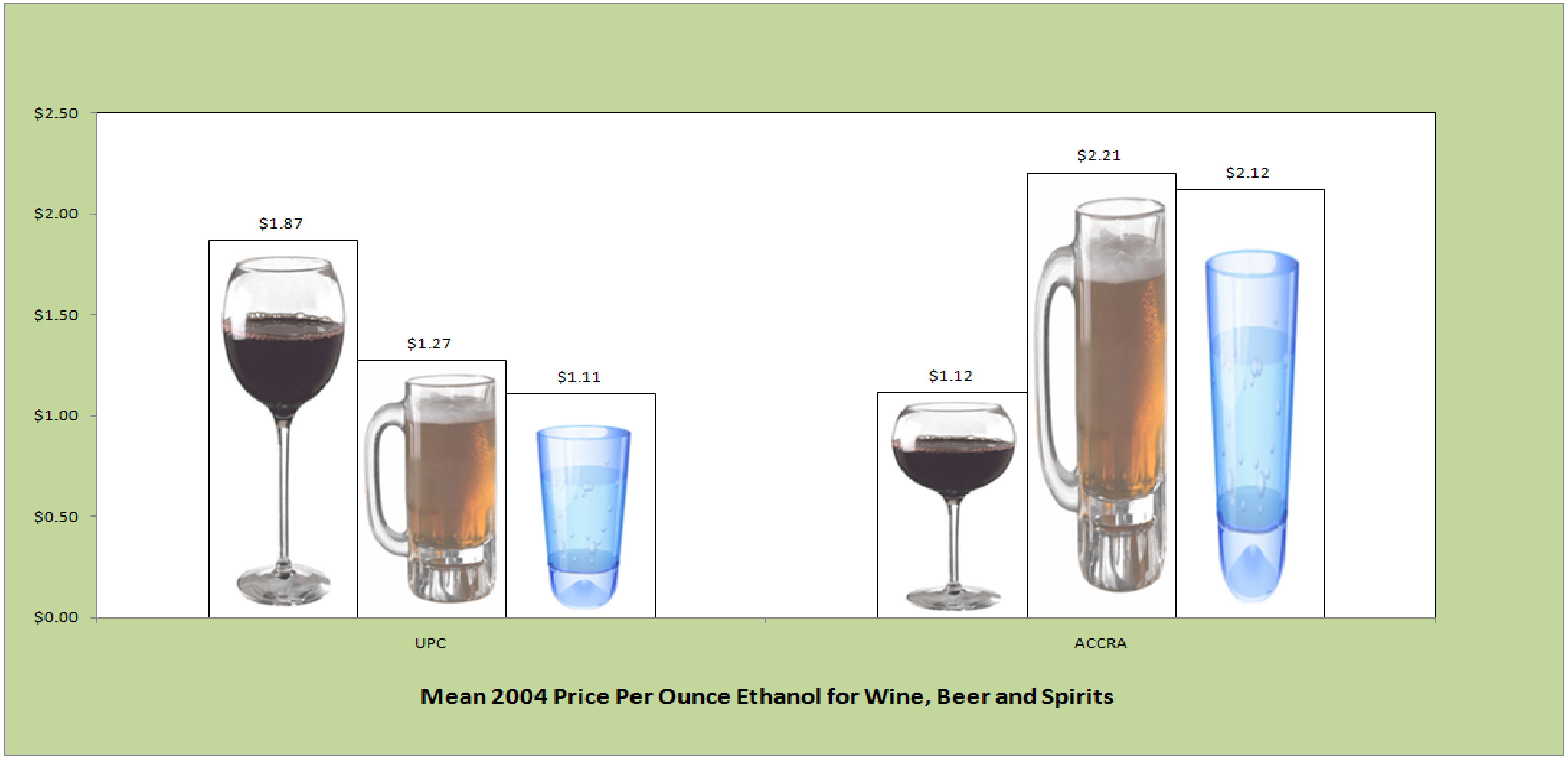
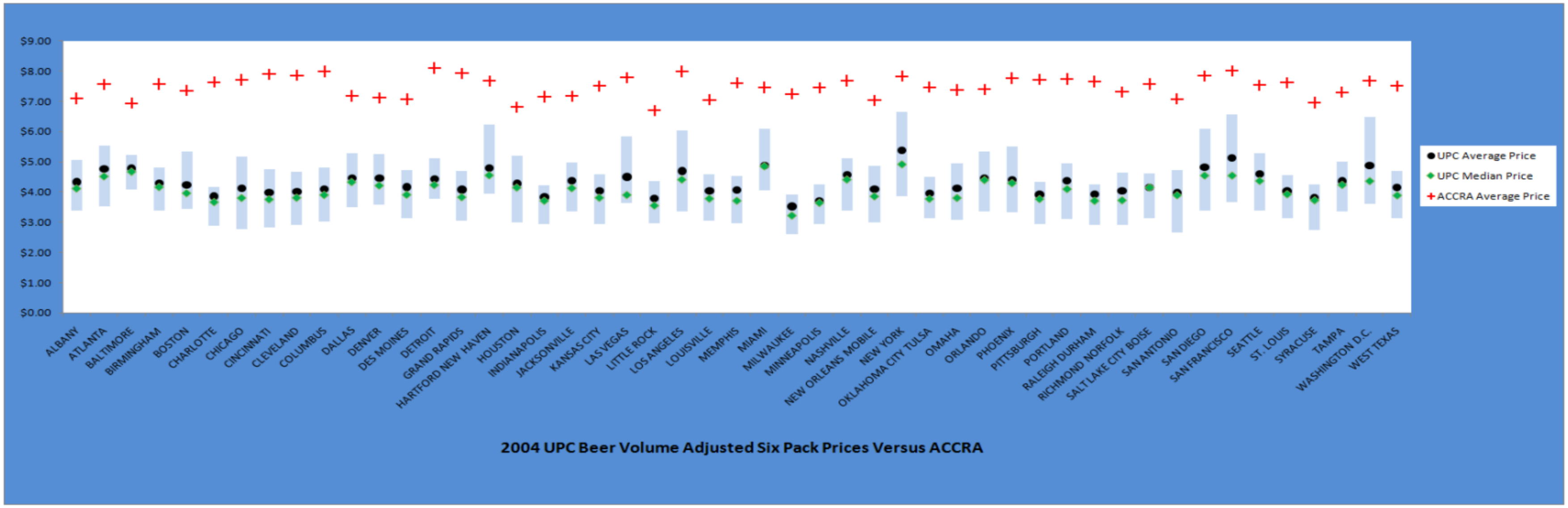


Figure 3: Market-Specific UPC and ACCRA Beer Prices, 2004



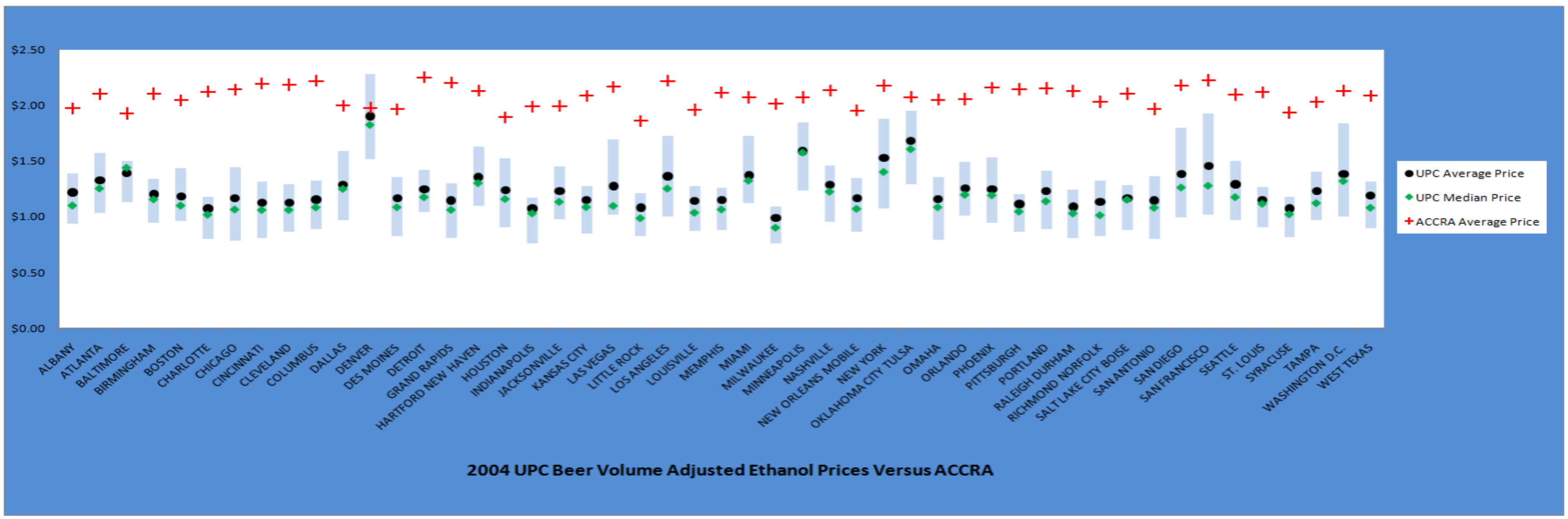
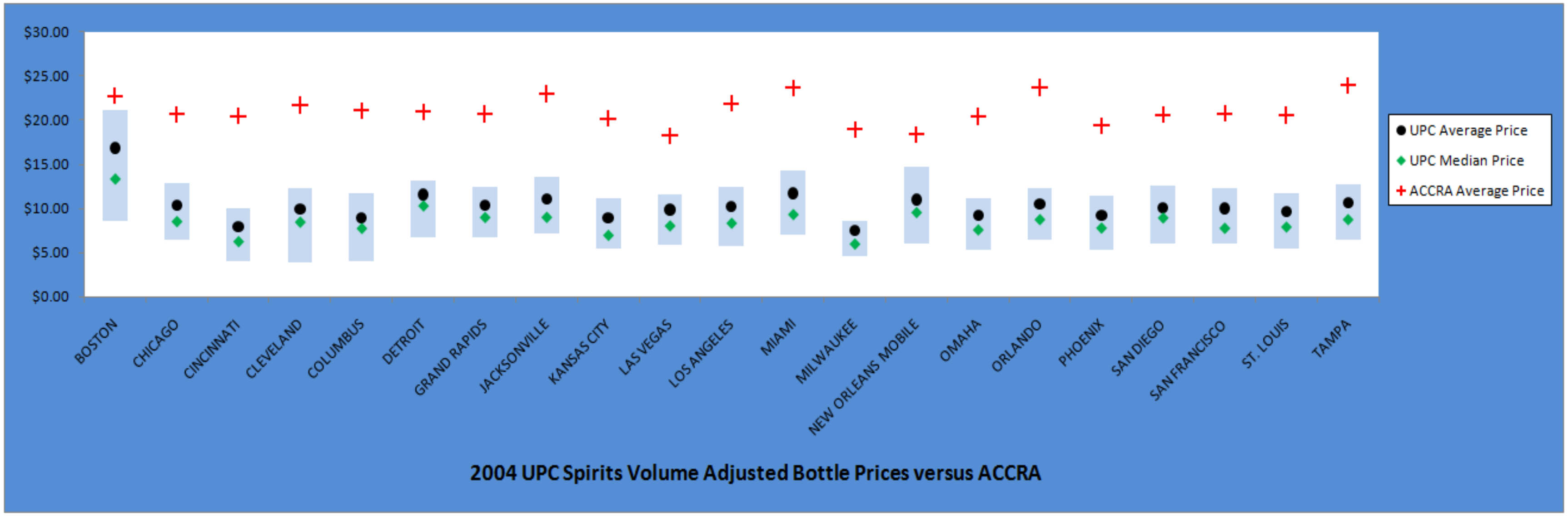


Figure 4: Market-Specific UPC and ACCRA Spirits Prices, 2004



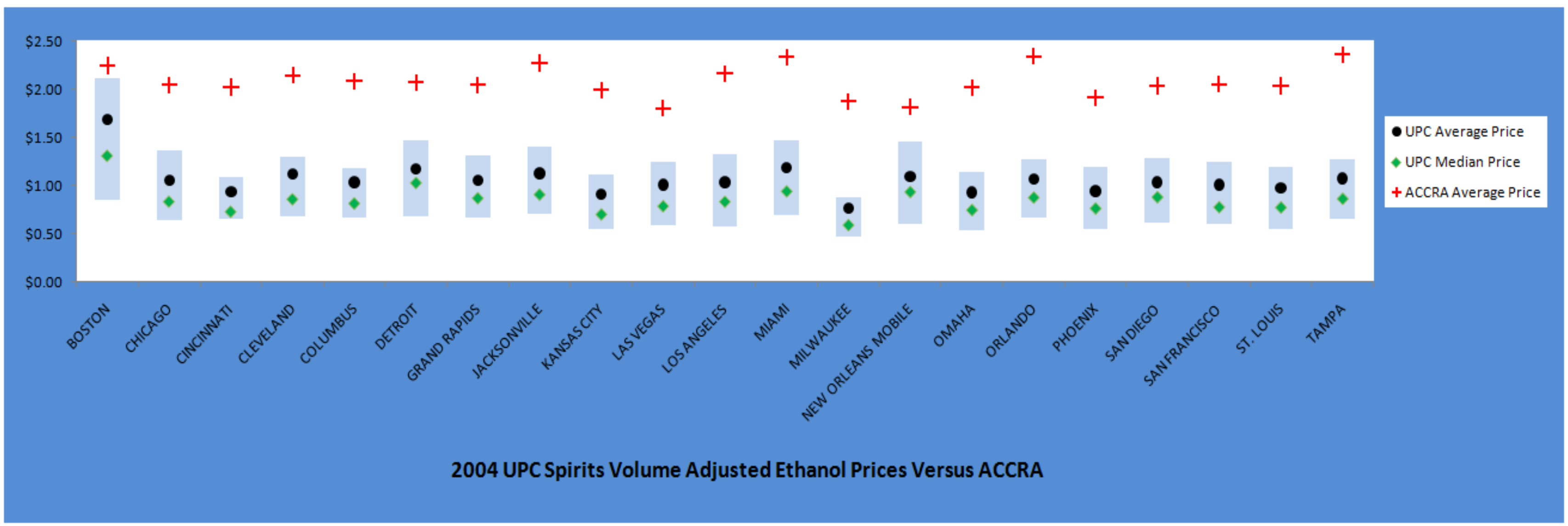
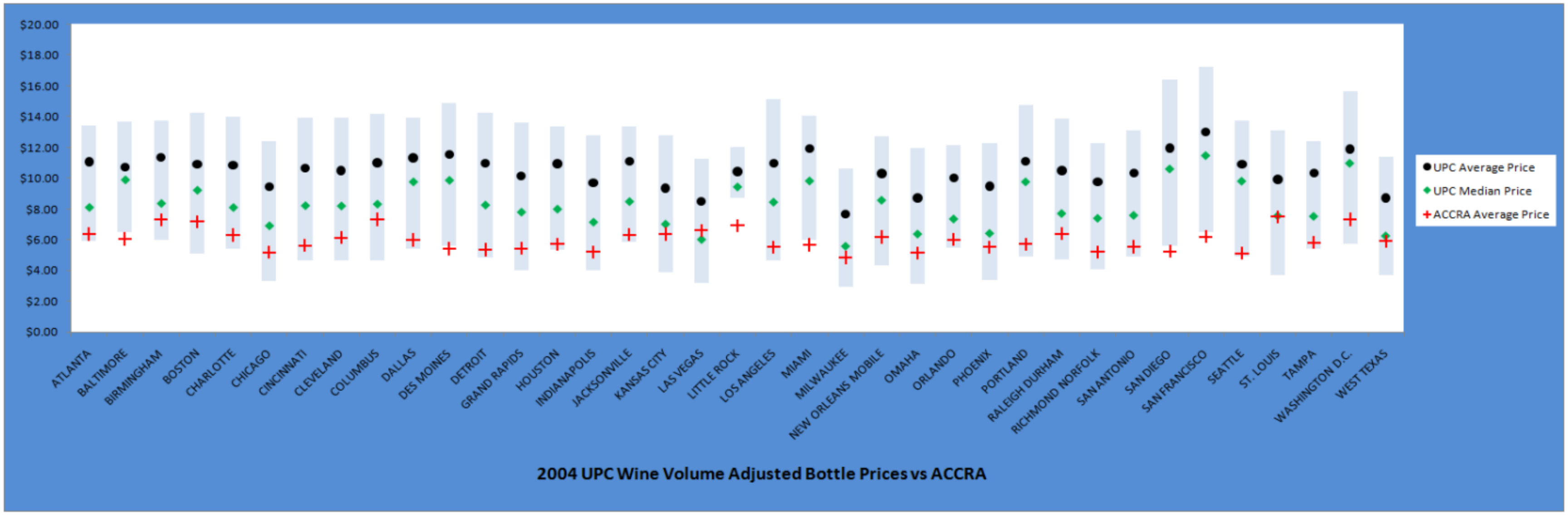
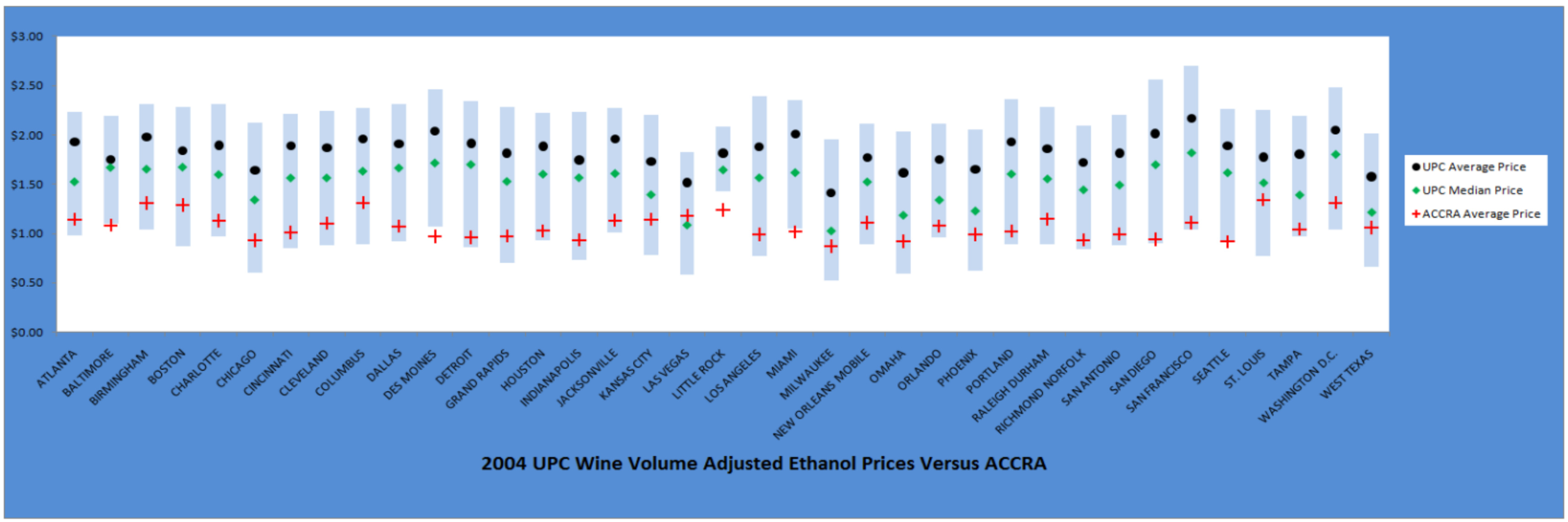


Figure 5: Market-Specific UPC and ACCRA Wine Prices, 2004





Appendix

A.1 Asymptotic Standard Error and t-stat for the Overall Elasticity Estimator (2)

Although this is not explicitly discussed by Manning et al. (1995), one can surmise that the population parameter targeted by (2), the overall elasticity measure, is

$$\eta_{x_p} = E\left[\frac{\partial \ln E[y \mid \ln(x_p),\ x_o]}{\partial \ln(x_p)}\right] \tag{A-1}$$

where y denotes observed beer consumption, x_p represents the price of beer(denoted simply as p in the text), and x_o is the vector of observable control variables in the beer demand equation. Given the usual assumptions underlying the conventional two-part model,[A1] we have that

$$E[y \mid \ln(x_p),\ x_o] = \Lambda(x\beta_1)\ \exp(x\beta_2)\,\psi \tag{A-2}$$

where $x = [\ln(x_p)\quad x_o]$, $\beta_1' = [\beta_{p1}\quad \beta_{o1}']$, $\beta_2' = [\beta_{p2}\quad \beta_{o2}']$, $\Lambda(\ )$ denotes the logistic distribution function, ψ is the smearing factor which is assumed to be constant,[A2] and the βs are parameters (and parameter vectors) to be estimated. Combining (A-1) and (A-2) we obtain

$$\eta_{x_p} = E\left[\frac{\partial \ln\left(\Lambda(x\beta_1)\exp(x\beta_2)\psi\right)}{\partial \ln(x_p)}\right] = E\left[\frac{\partial\left(\ln\Lambda(x\beta_1) + \ln\exp(x\beta_2) + \ln(\psi)\right)}{\partial \ln(x_p)}\right]$$

[A1] See Mullahy (1998) for details.
[A2] See Duan (1983) and Duan et al. (1983) for a detailed discussion of smearing.

$$= E\left[\frac{\lambda(x\beta_1)}{\Lambda(x\beta_1)}\beta_{1p} + \beta_{2p}\right] = E\left[\frac{\Lambda(x\beta_1)[1 - \Lambda(x\beta_1)]}{\Lambda(x\beta_1)}\beta_{1p} + \beta_{2p}\right]$$

$$= E\left[[1 - \Lambda(x\beta_1)]\beta_{1p} + \beta_{2p}\right]$$

$$= \beta_{1p} - E\left[\Lambda(x\beta_1)\right]\beta_{1p} + \beta_{2p}$$

$$= (1 - P)\beta_{1p} + \beta_{2p} \tag{A-3}$$

where P denotes the population proportion of beer drinkers. The corresponding sample analog elasticity estimator is (2). As is suggested by (A-3), we can equivalently re-write (2) as

$$\hat{\eta}_{x_p} = \sum_{i=1}^{n} \frac{1}{n}\left\{[1 - \Lambda(z_i\hat{\beta}_1)]\hat{\beta}_{p1} + \hat{\beta}_{p2}\right\} \tag{A-4}$$

where $\hat{\beta}' = [\hat{\beta}_1' \quad \hat{\beta}_2']$ denotes the conventional two part estimator of $\hat{\beta}' = [\beta_1' \quad \beta_2']$, $\hat{\beta}_1' = [\hat{\beta}_{p1}' \quad \hat{\beta}_{o1}']$, and $\hat{\beta}_2' = [\hat{\beta}_{p2}' \quad \hat{\beta}_{o2}']$. Using the notation of Terza (2011) section 4, we can write (A-4) as

$$\hat{\eta}_{x_p} = \sum_{i=1}^{n} \frac{1}{n}\hat{\eta}_{x_p i} \tag{A-5}$$

where

$$\hat{\eta}_{x_p i} = \eta(x_i, \hat{\beta}) = \hat{\beta}_{1p} - \Lambda(x_i\hat{\beta}_1)\hat{\beta}_{1p} + \hat{\beta}_{p2}$$

$$x_i = [\ln(x_{pi}) \quad x_{oi}]$$

Using expression (37) of Terza (2011), we have that the asymptotic variance of (A-5) is

$$\text{a var}(\hat{\eta}_{x_p}) = E\left[\nabla_\beta \eta\right] \text{AVAR}(\hat{\beta}) E\left[\nabla_\beta \eta\right]' + E\left[(\eta - \eta_{x_p})^2\right] \tag{A-6}$$

where

$$\eta = \eta(x,\beta) = \beta_{p1} - \Lambda(x\beta_1)\beta_{p1} + \beta_{p2}$$

$$\eta_{x_p} = E[\eta]$$

$$\nabla_\beta \eta = [\nabla_{\beta_{p1}}\eta \quad \nabla_{\beta_{o1}}\eta \quad \nabla_{\beta_{p2}}\eta \quad \nabla_{\beta_{o2}}\eta]$$

$$\nabla_{\beta_{p1}}\eta = 1 - \lambda(x\beta_1)\beta_{p1}\ln(x_p) - \Lambda(x\beta_1)$$

$$\nabla_{\beta_{o1}}\eta = -\lambda(x\beta_1)\beta_{p1}x_o$$

$$\nabla_{\beta_{p2}}\eta = 1$$

$$\nabla_{\beta_{o2}}\eta = 0 \text{ (a vector of the same column dimension as } x_o\text{)}$$

and $\mathrm{AVAR}(\hat{\beta})$ is the asymptotic covariance matrix of $\hat{\beta}$ (the block diagonal matrix whose upper left-hand block is the asymptotic covariance matrix of $\hat{\beta}_1$ and whose lower right-hand block is the asymptotic covariance matrix of $\hat{\beta}_2$. The asymptotic variance given in (A-6) can be consistently estimated using

$$\widehat{a\,\mathrm{var}}(\hat{\eta}_{x_p}) = \left(\frac{\sum_{i=1}^{n}\nabla_\beta \hat{\eta}_{x_p i}}{n}\right)\left(n\ \widehat{\mathrm{AVAR}}(\hat{\beta})\right)\left(\frac{\sum_{i=1}^{n}\nabla_\beta \hat{\eta}_{x_p i}}{n}\right)' + \left(\frac{\sum_{i=1}^{n}(\hat{\eta}_{x_p i} - \hat{\eta}_{x_p})^2}{n}\right) \qquad \text{(A-7)}$$

where

$$\nabla_\beta \hat{\eta}_{x_p i} = [\nabla_{\beta_{1p}}\hat{\eta}_{x_p i} \quad \nabla_{\beta_{1o}}\hat{\eta}_{x_p i} \quad \nabla_{\beta_{2p}}\hat{\eta}_{x_p i} \quad \nabla_{\beta_{2o}}\hat{\eta}_{x_p i}]$$

$$\nabla_{\beta_{1p}}\hat{\eta}_{x_p i} = 1 - \lambda(x_i\hat{\beta}_1)\hat{\beta}_{1p}\ln(x_{pi}) - \Lambda(x_i\hat{\beta}_1)$$

$$\nabla_{\beta_{1o}}\hat{\eta}_{x_p i} = -\lambda(x_i\hat{\beta}_1)\hat{\beta}_{1p}x_{oi}$$

$$\nabla_{\beta_{2p}}\hat{\eta}_{x_p i} = 1$$

$$\nabla_{\beta_{2o}}\hat{\eta}_{x_p i} = 0 \text{ (a vector of the same column dimension as } x_o\text{)}$$

and $\widehat{\text{AVAR}}(\hat{\beta})$ is the estimated asymptotic covariance matrix of $\hat{\beta}$ (the block diagonal matrix whose upper left-hand block is the estimated asymptotic covariance matrix of $\hat{\beta}_1$ and whose lower right-hand block is the estimated asymptotic covariance matrix of $\hat{\beta}_2$.[A3] In summary, $\hat{\eta}_{x_p}$ is consistent and

$$\sqrt{\frac{n}{\widehat{a\,\text{var}}(\hat{\eta}_{x_p})}}(\hat{\eta}_{x_p} - \eta_{x_p}) \xrightarrow{d} n(0,1). \tag{A-8}$$

A.2 Asymptotic Standard Error and t-stat for the Intensive Margin Elasticity Estimator (3)

It is clear from the derivation of (A-3) above that the population elasticity measure for the intensive margin is

$$\eta_{x_{p(1)}} = (1 - P)\beta_{1p}. \tag{A-9}$$

The corresponding sample analog elasticity estimator is (3). We can equivalently re-write (3) as

$$\hat{\eta}_{x_p} = \sum_{i=1}^{n} \frac{1}{n}[1 - \Lambda(z_i\hat{\beta}_1)]\hat{\beta}_{p1}. \tag{A-10}$$

Using the notation of Terza (2011) section 4, we can write (A-10) as

[A3] We have written (A-7) anticipating that this estimate would be computed using regression results from packaged software. As such, we highlight the "n" premultiplying $\widehat{\text{AVAR}}(\hat{\beta})$. Given that this matrix is obtained from packaged regression results, multiplication by n is required.

$$\hat{\eta}_{x_p(1)} = \sum_{i=1}^{n} \frac{1}{n} \hat{\eta}_{x_p(1)i} \qquad \text{(A-11)}$$

where

$$\hat{\eta}_{x_p(1)i} = \eta_1(x_i, \hat{\beta}) = \hat{\beta}_{1p} - \Lambda(x_i\hat{\beta}_1)\hat{\beta}_{1p}$$

$$x_i = [\ln(x_{pi}) \quad x_{oi}]$$

Using expression (37) of Terza (2011), we have that the asymptotic variance of (A-11) is

$$\text{a var}(\hat{\eta}_{x_p(1)}) = E\left[\nabla_{\beta_1}\eta_1\right]\text{AVAR}(\hat{\beta}_1)E\left[\nabla_{\beta_1}\eta_1\right]' + E\left[(\eta_1 - \eta_{x_p(1)})^2\right] \qquad \text{(A-12)}$$

where

$$\eta_1 = \eta_1(x, \beta_1) = \beta_{p1} - \Lambda(x\beta_1)\beta_{p1}$$

$$\eta_{x_p(1)} = E[\eta_1]$$

$$\nabla_{\beta_1}\eta_1 = [\nabla_{\beta_{p1}}\eta_1 \quad \nabla_{\beta_{o1}}\eta_1]$$

$$\nabla_{\beta_{p1}}\eta_1 = 1 - \lambda(x\beta_1)\beta_{p1}\ln(x_p) - \Lambda(x\beta_1)$$

$$\nabla_{\beta_{o1}}\eta_1 = -\lambda(x\beta_1)\beta_{p1}x_o$$

and $\text{AVAR}(\hat{\beta}_1)$ is the asymptotic covariance matrix of $\hat{\beta}_1$. The asymptotic variance given in (A-12) can be consistently estimated using

$$\widehat{\text{a var}}(\hat{\eta}_{x_p(1)}) = \left(\frac{\sum_{i=1}^{n}\nabla_{\beta_1}\hat{\eta}_{x_p(1)i}}{n}\right)\left(n\ \widehat{\text{AVAR}}(\hat{\beta}_1)\right)\left(\frac{\sum_{i=1}^{n}\nabla_{\beta_1}\hat{\eta}_{x_p(1)i}}{n}\right)' + \left(\frac{\sum_{i=1}^{n}(\hat{\eta}_{x_p(1)i} - \hat{\eta}_{x_p(1)})^2}{n}\right)$$

(A-13)

where

$$\nabla_{\beta_1}\hat{\eta}_{x_p(1)i} = [\nabla_{\beta_{1p}}\hat{\eta}_{x_p(1)i} \quad \nabla_{\beta_{1o}}\hat{\eta}_{x_p(1)i}]$$

$$\nabla_{\beta_{1p}}\hat{\eta}_{x_p(1)i} = 1 - \lambda(x_i\hat{\beta}_1)\hat{\beta}_{1p}\ln(x_{pi}) - \Lambda(x_i\hat{\beta}_1)$$

$$\nabla_{\beta_{1p}}\hat{\eta}_{x_p(1)i} = - \lambda(x_i\hat{\beta}_1)\hat{\beta}_{1p}x_{oi}$$

and $\widehat{AVAR}(\hat{\beta}_1)$ is the estimated asymptotic covariance matrix of $\hat{\beta}_1$.[A4] In summary, $\hat{\eta}_{x_p(1)}$ is consistent and

$$\sqrt{\frac{n}{\widehat{a\,var}(\hat{\eta}_{x_p(1)})}}(\hat{\eta}_{x_p(1)} - \eta_{x_p(1)}) \xrightarrow{d} n(0,1). \qquad \text{(A-14)}$$

[A4] We have written (A-12) anticipating that this estimate would be computed using regression results from packaged software. As such, we highlight the "n" premultiplying $\widehat{AVAR}(\hat{\beta}_1)$. Given that this matrix is obtained from packaged regression results, multiplication by n is required.